Coding with Dynamic Synapses and Receptive Fields

André Longtin

Jason Middleton, John Lewis, Len Maler

Jakub Cieniak, Dorian Gangloff

Physics, Cellular and Molecular Medicine
Center for Neural Dynamics
University of Ottawa

Benjamin Lindner
MPI für Physik komplexer Systeme Dresden

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Two Parts

- Both motivated by our work on weakly electric fish
- Two general coding principles

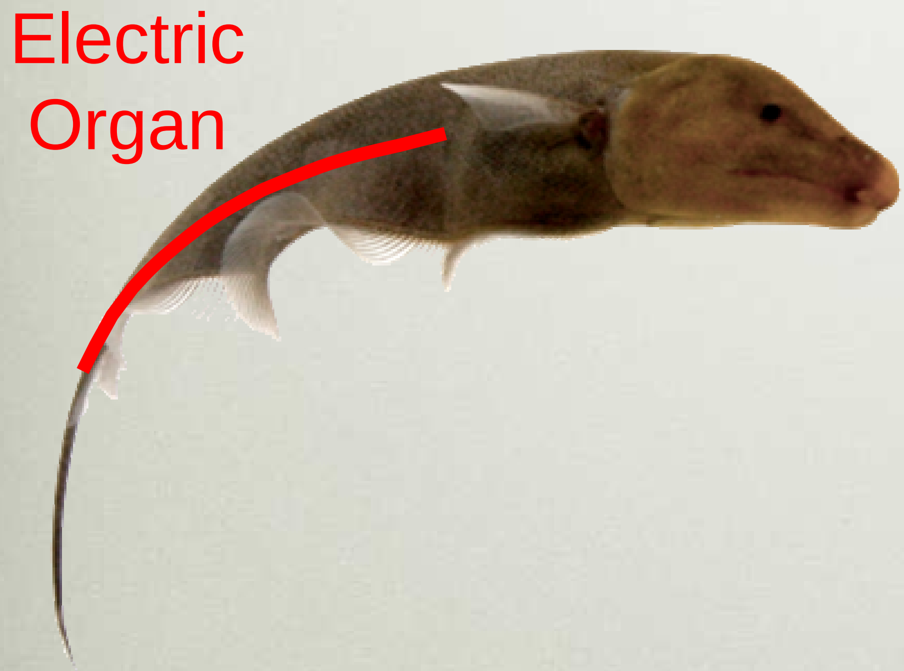
Part 1: Synchrony and Receptive Fields

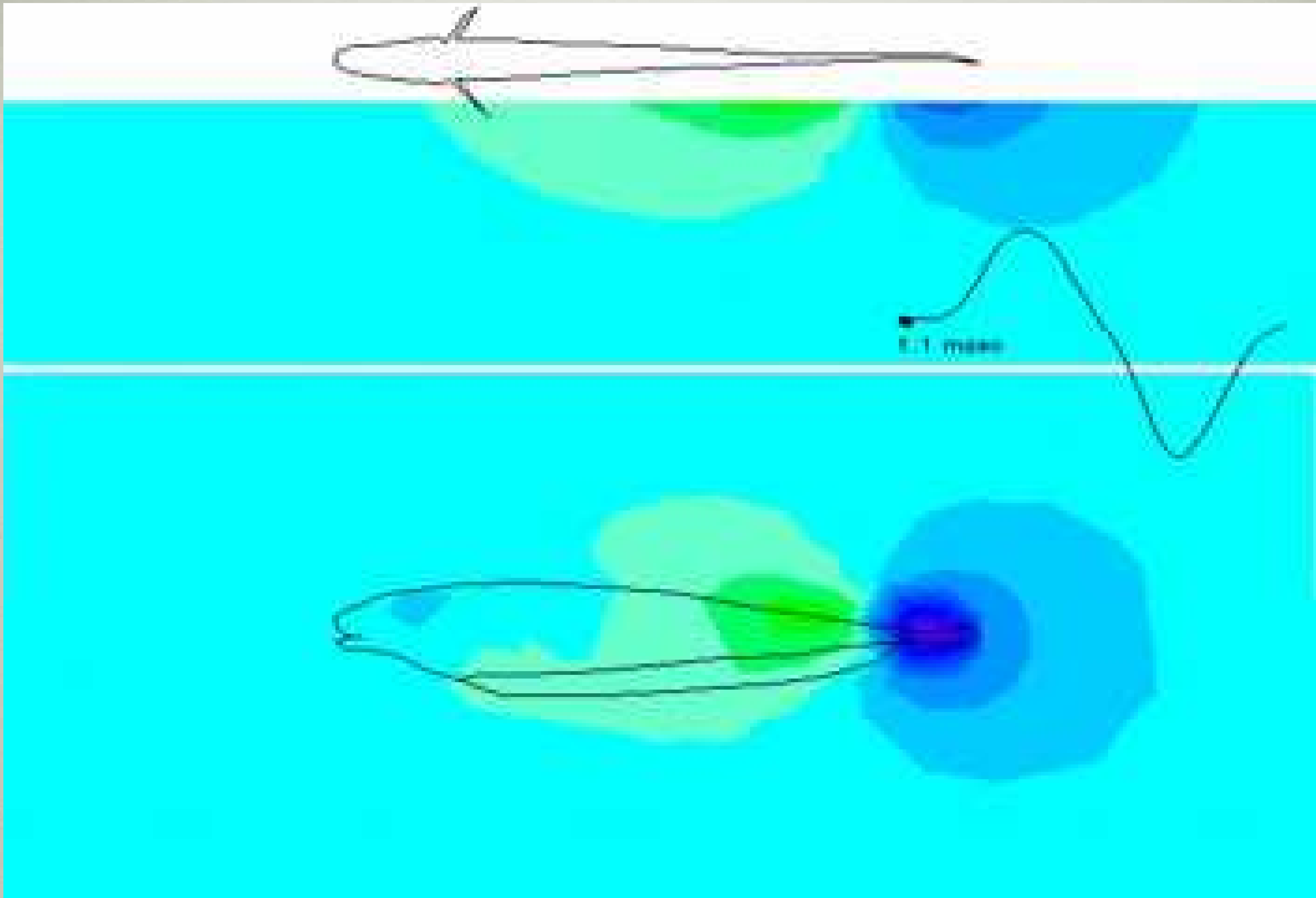
- Motivation: Electrosensory communication
- Synchrony data
- Neural modeling of decoding
- Synchrony decoded with large receptive fields

Middleton, Longtin, Benda, Maler, J. Neurophysiol. (2009)

Electrosensory system

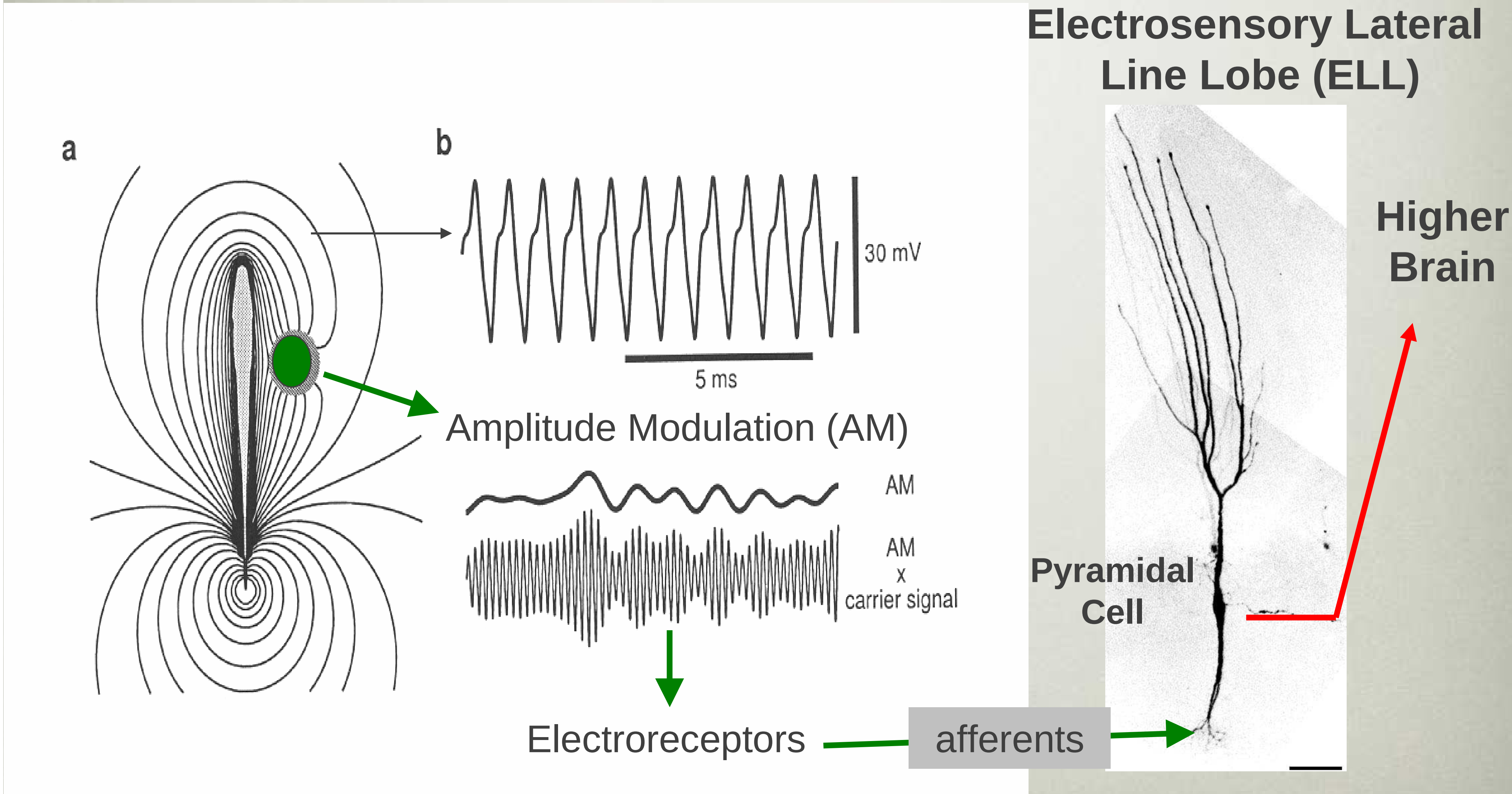
Weakly electric fish
(brown ghost)





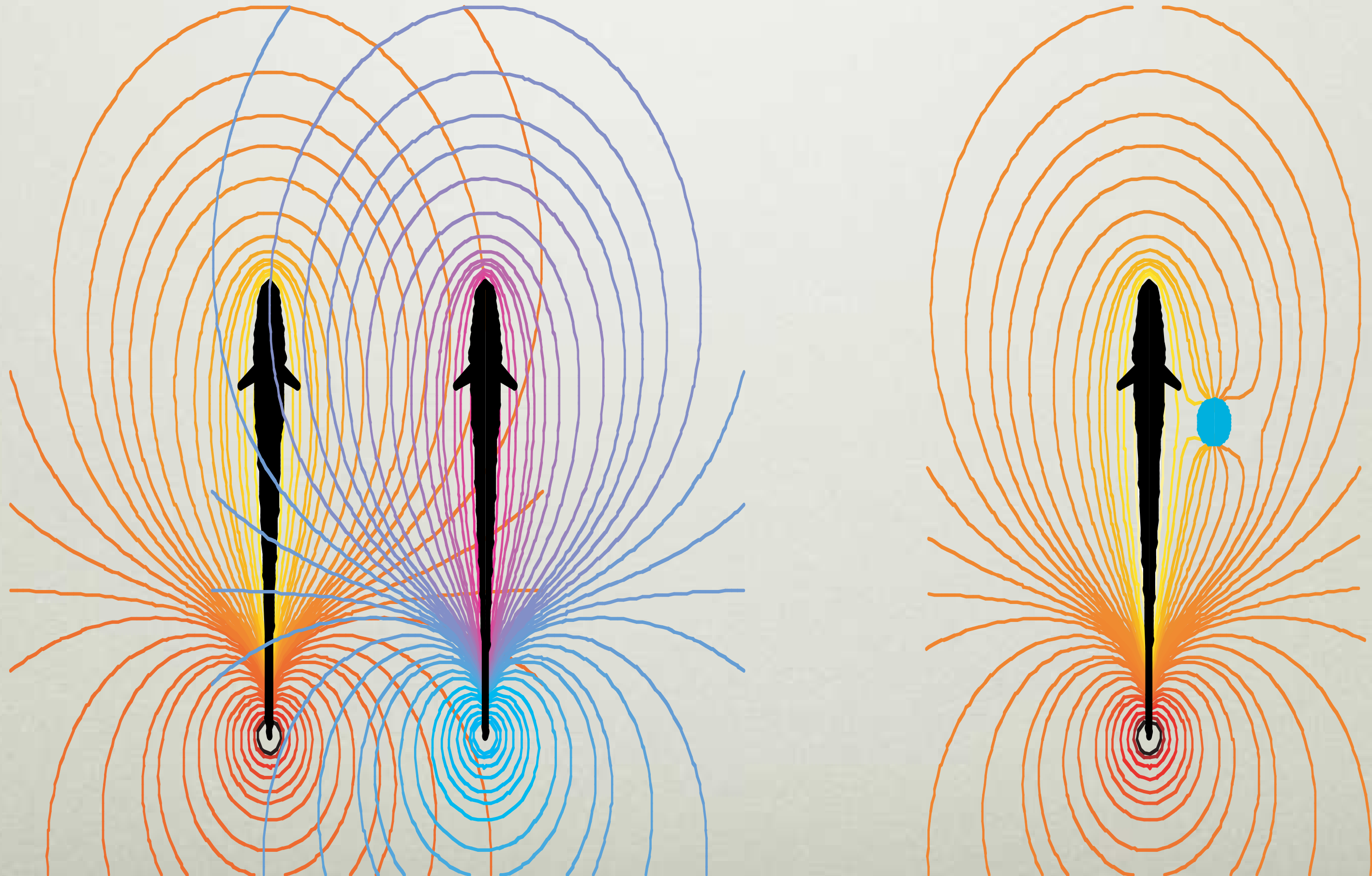
From Brian Rasnow, Caltech

Electrolocation

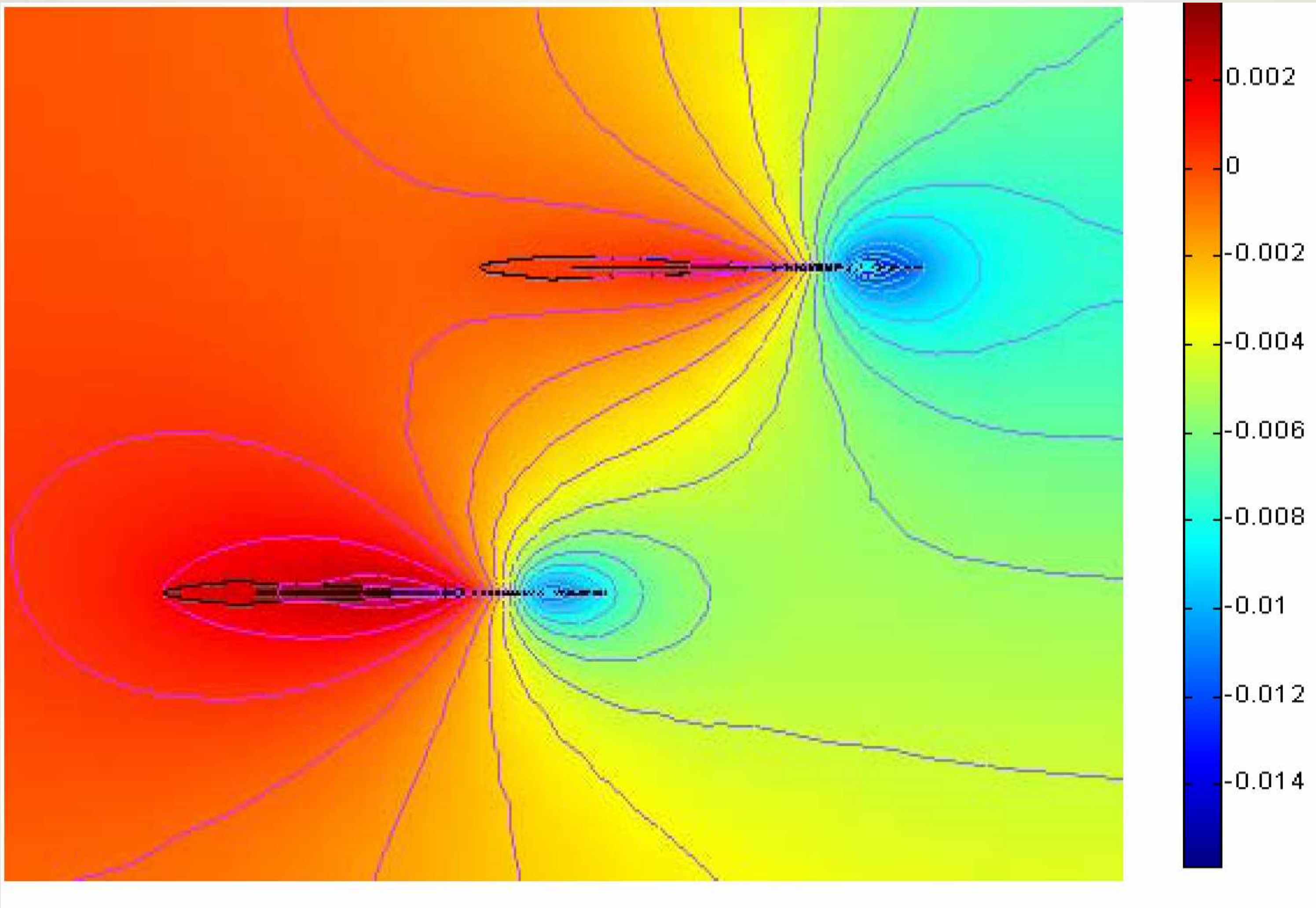


Krahe and Gabbiani (2004) *Nat. Neurosci.Rev*. 5:13-23

Beat patterns due to neighbors



Parallel Fish



Kelly, Babineau, Longtin, Lewis, Biol. Cybern. 2008

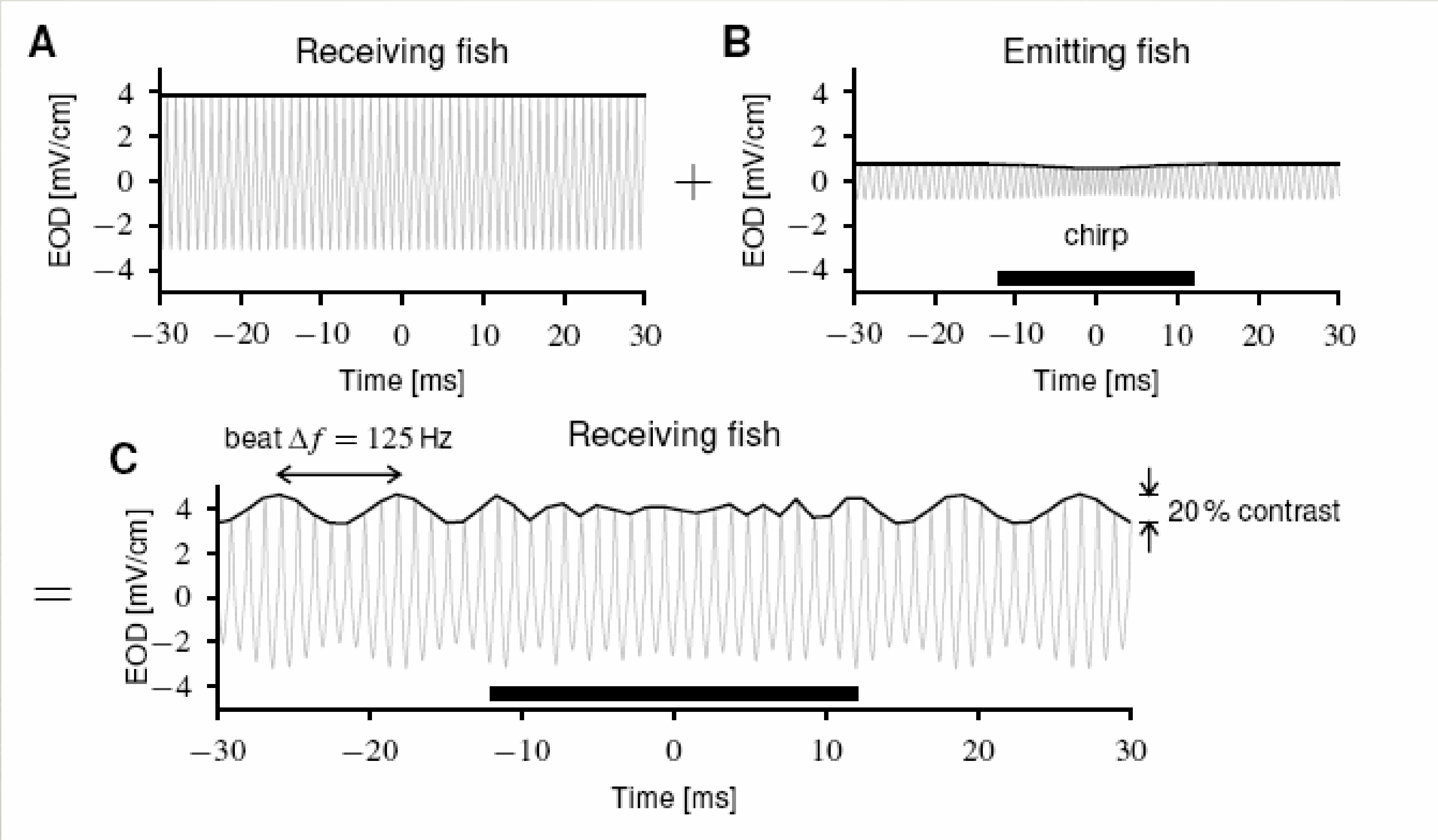
ELECTRORECEPTORS

- → ALL SPATIO-TEMPORAL SCALES
- **The EOD field excites 16,000 cutaneous electroreceptors.**

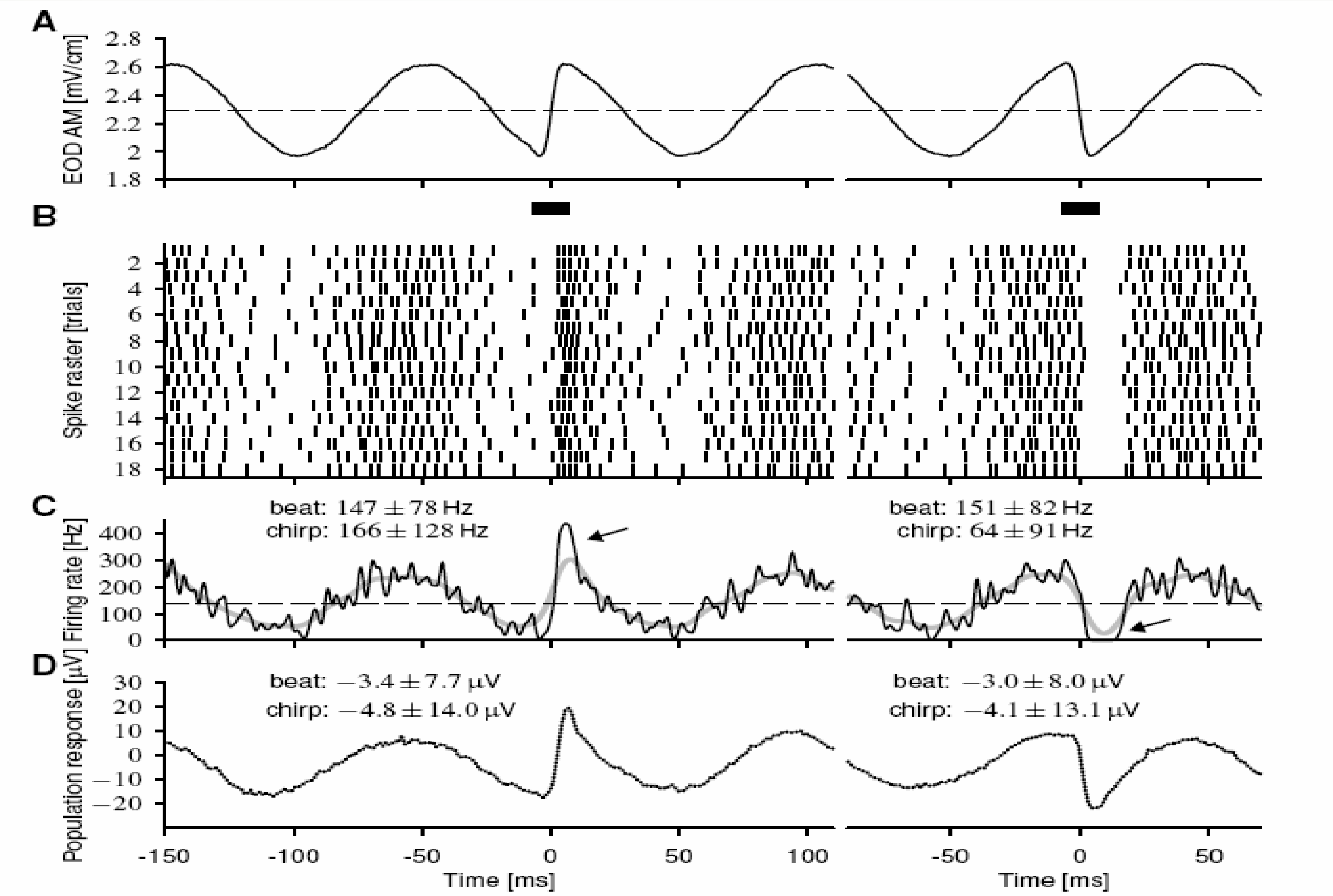
Electrocommunication

Female: EOD <800 Hz

Male: EOD >800 Hz

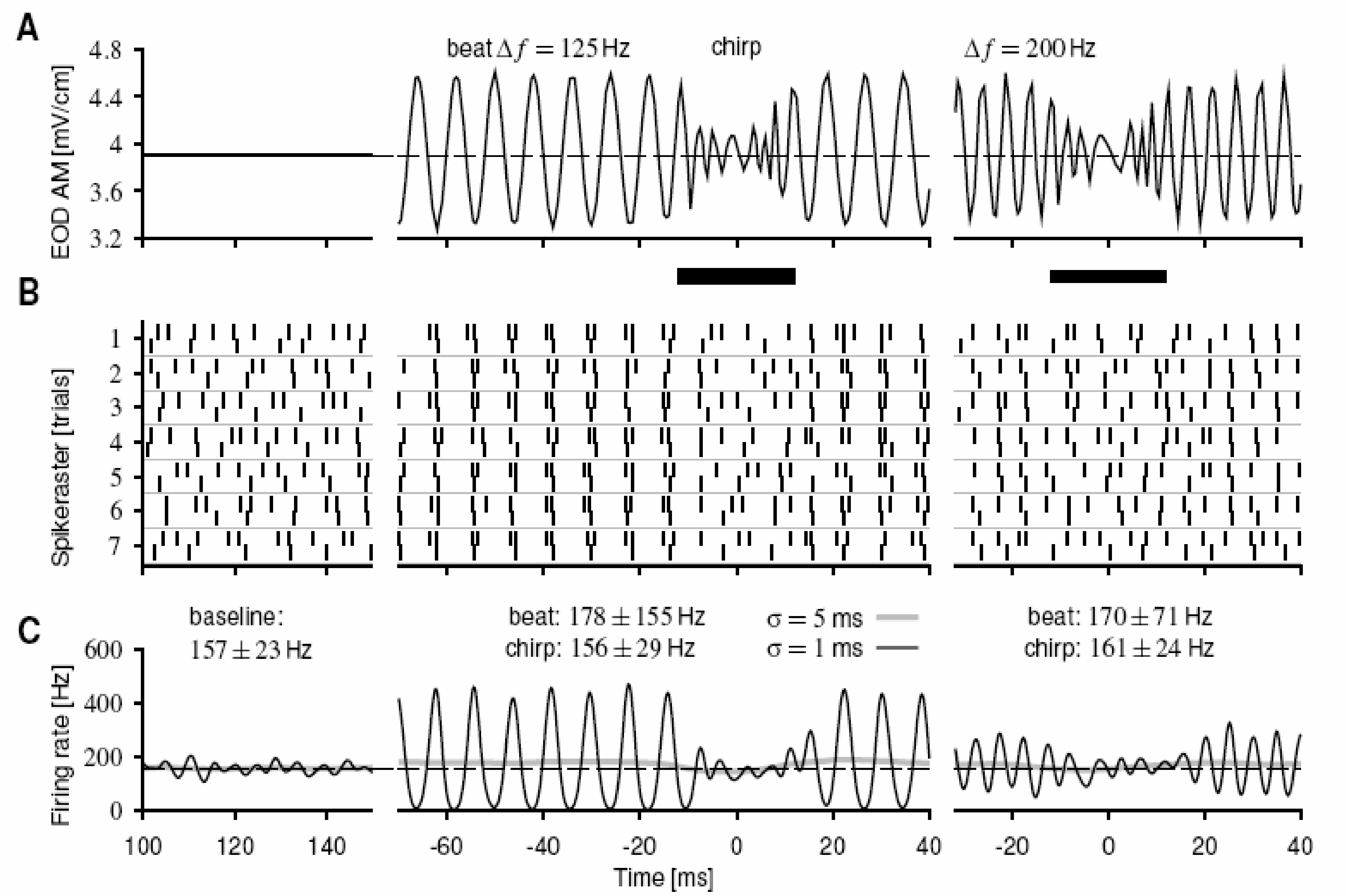


Same gender interactions: Calls synchronize receptors

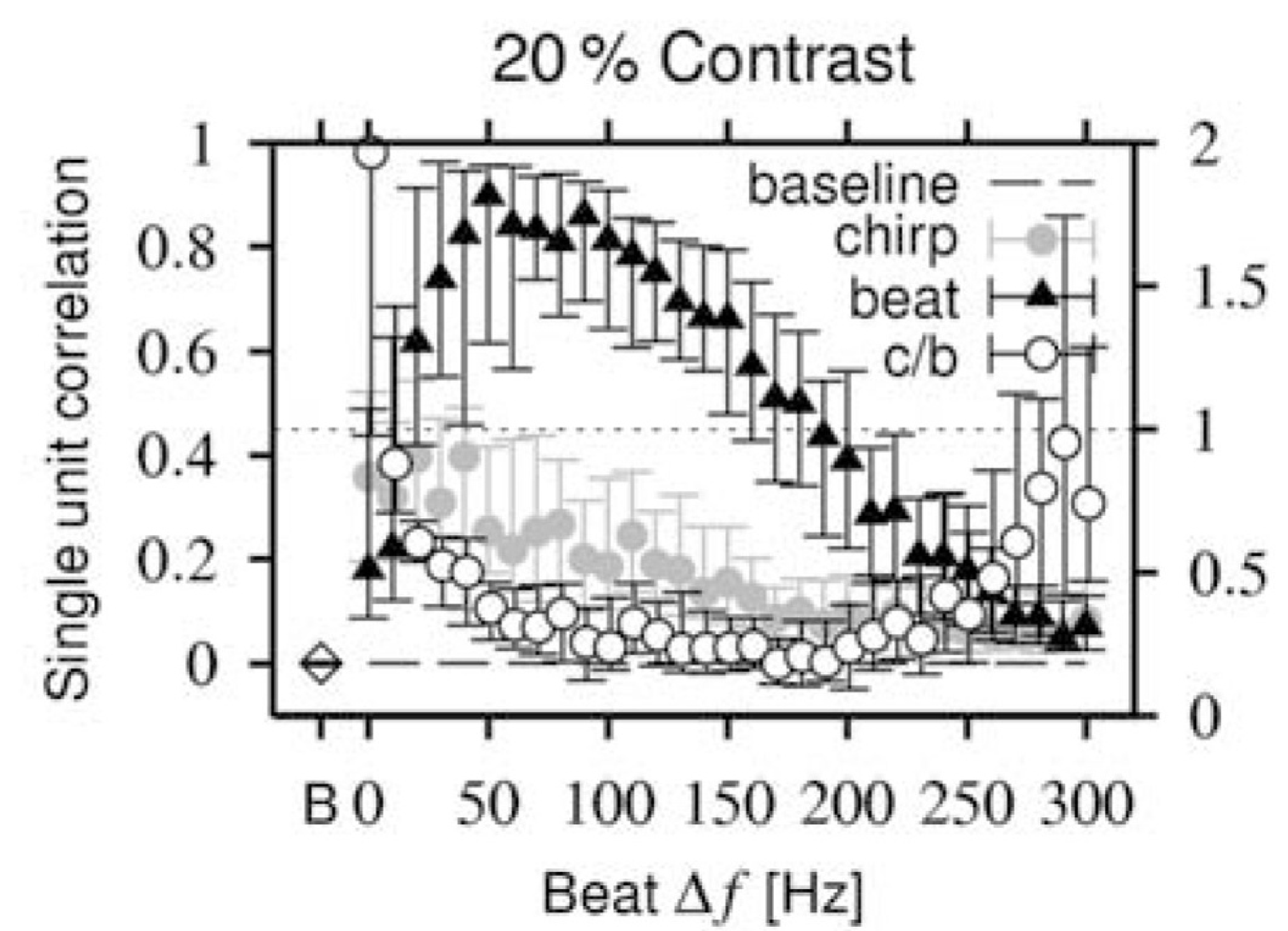


Benda, Longtin, Maler, J. Neurosci. 2005

Female-Male Interactions: Calls desynchronize receptors



Benda, Longtin, Maler, Neuron 2006


20 % Contrast
Single unit correlation
1
0.8
0.6
0.4
0.2
0
2
1.5
1
0.5
0
baseline
chirp
beat
c/b
B 0
50
100
150
200
250
300
Beat Δf [Hz]

Leaky Integrate-and-fire Model with Dynamic Threshold

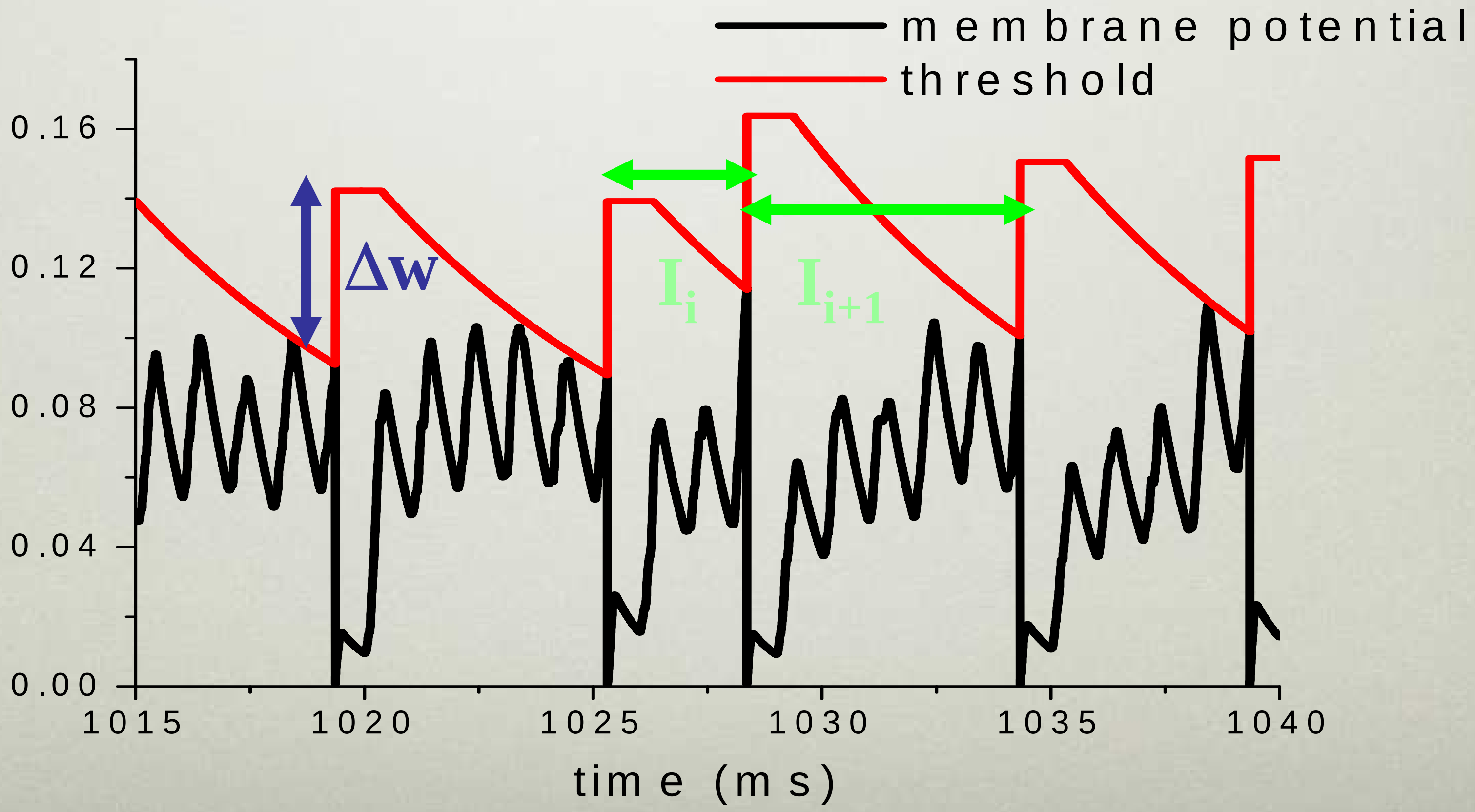
Chacron, Longtin, St-Hilaire, Maler, Phys.Rev.Lett. 85, 1576 (2000)

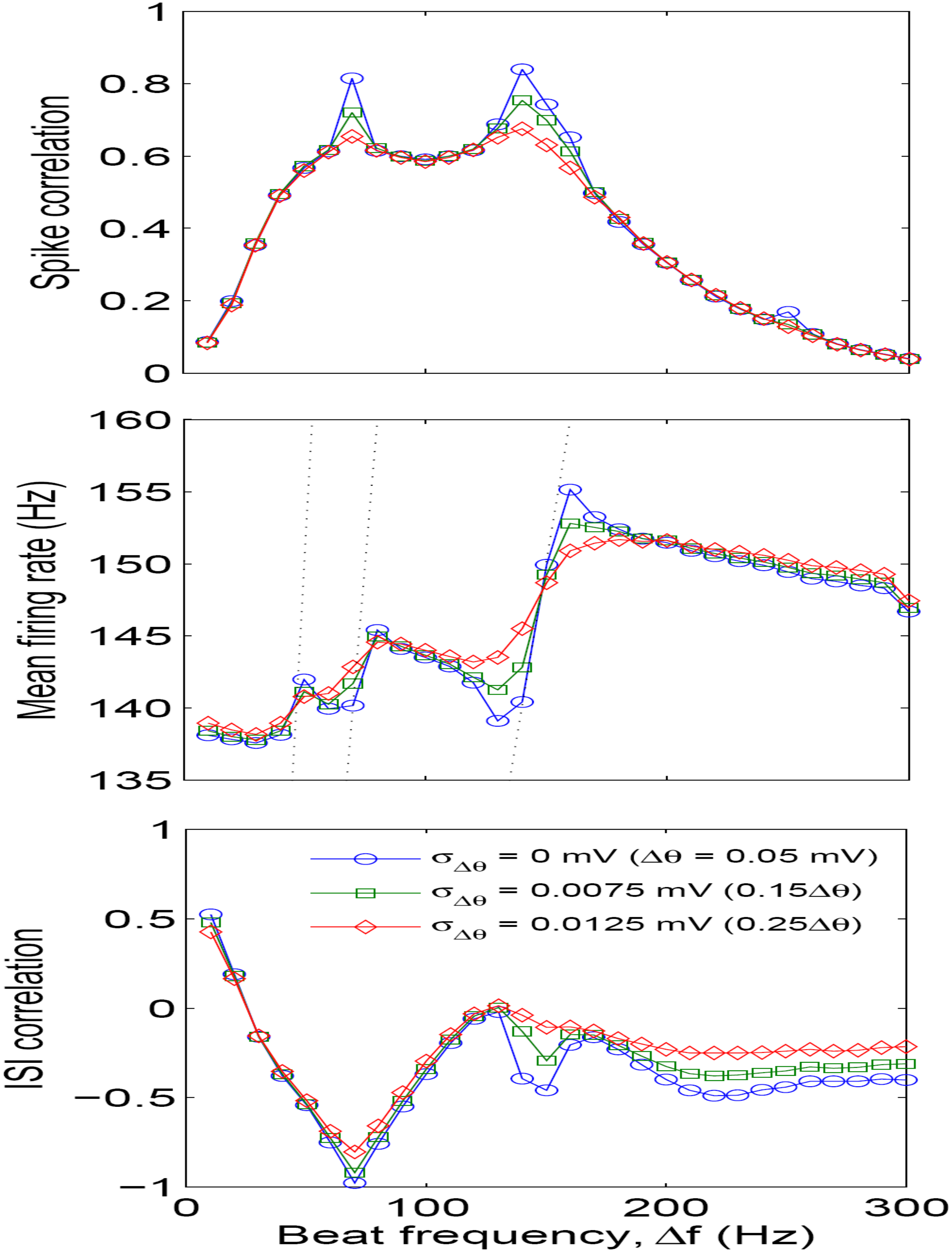
$$\dot{v} = -\frac{v}{\tau_v} + a(t)\sin(2\pi f t) + \xi(t)$$

$$\dot{w} = \frac{w_0 - w}{\tau_w}$$

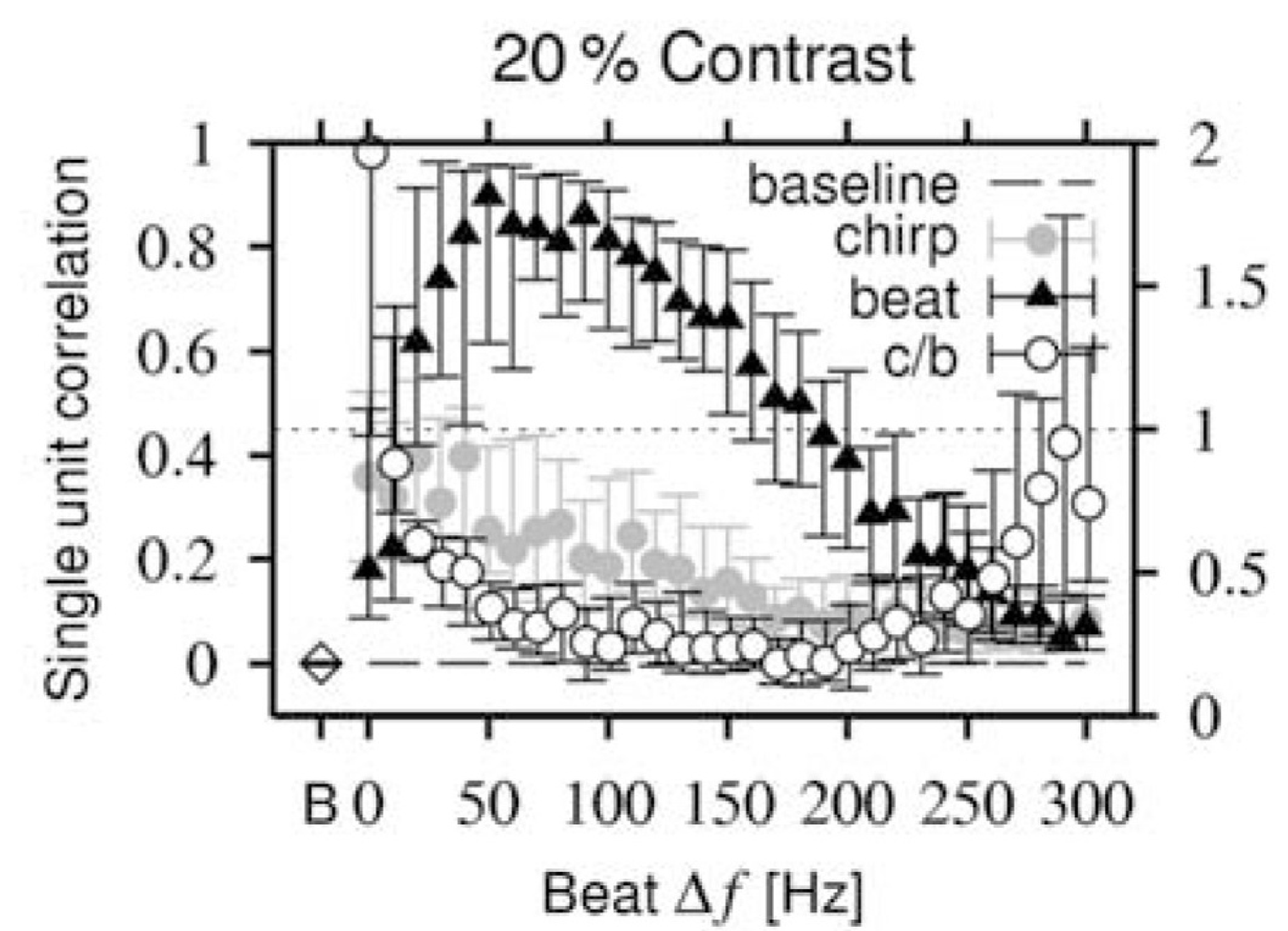
$$v(t^+_{fire}) = 0 \quad if \quad v(t_{fire}) = w(t_{fire})$$

$$w(t^+_{fire}) = w(t_{fire}) + \Delta w \quad if \quad v(t_{fire}) = w(t_{fire})$$





Spike correlation
Mean firing rate (Hz)
ISI correlation
$\sigma_{\Delta\theta}$ = 0 mV ($\Delta\theta$ = 0.05 mV)
$\sigma_{\Delta\theta}$ = 0.0075 mV (0.15$\Delta\theta$)
$\sigma_{\Delta\theta}$ = 0.0125 mV (0.25$\Delta\theta$)
Beat frequency, Δf (Hz)


20 % Contrast
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2
1.5
1
0.5
0
baseline
chirp
beat
c/b
B 0
50
100
150
200
250
300
Beat Δf [Hz]

How are changes in synchrony decoded?

Model of receptors

Models of ELL pyramidal cells driven by receptor data

Eventually include short-term plasticity between them

Spectral measures

Fourier transform

$$\tilde{x} = \frac{1}{\sqrt{T}} \int_0^T dt \;\; e^{2\pi i f t} x(t)$$

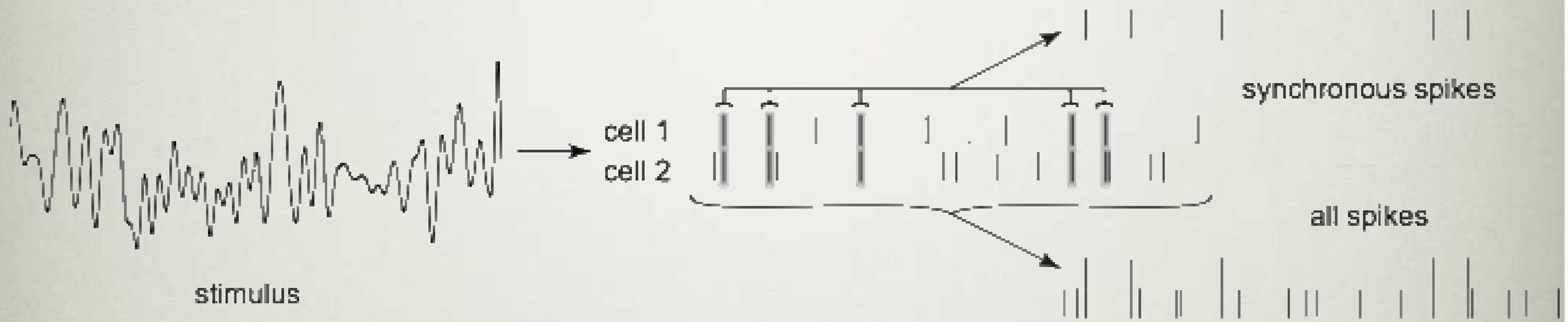
Cross spectra of synaptic input/voltage and input signal

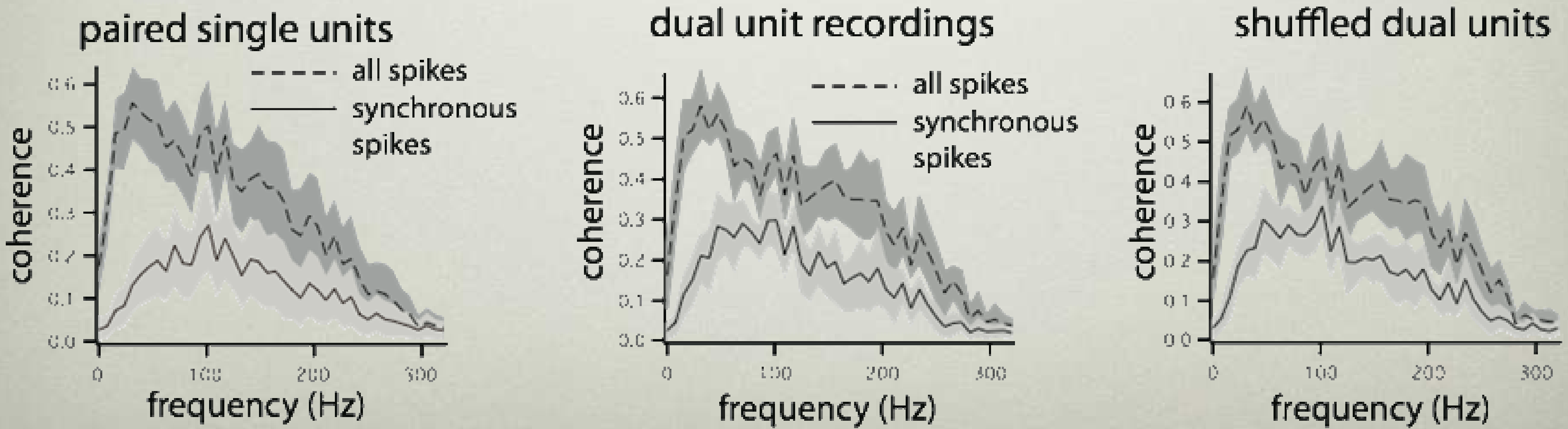
$$S_{Xs} = \langle \tilde{X} \tilde{s}^* \rangle \qquad S_{Vs} = \langle \tilde{V} \tilde{s}^* \rangle$$

Coherence functions

$$C_{Xs} = \frac{|S_{Xs}|^2}{S_{ss} S_{XX}} \qquad C_{Vs} = \frac{|S_{Vs}|^2}{S_{ss} S_{VV}}$$

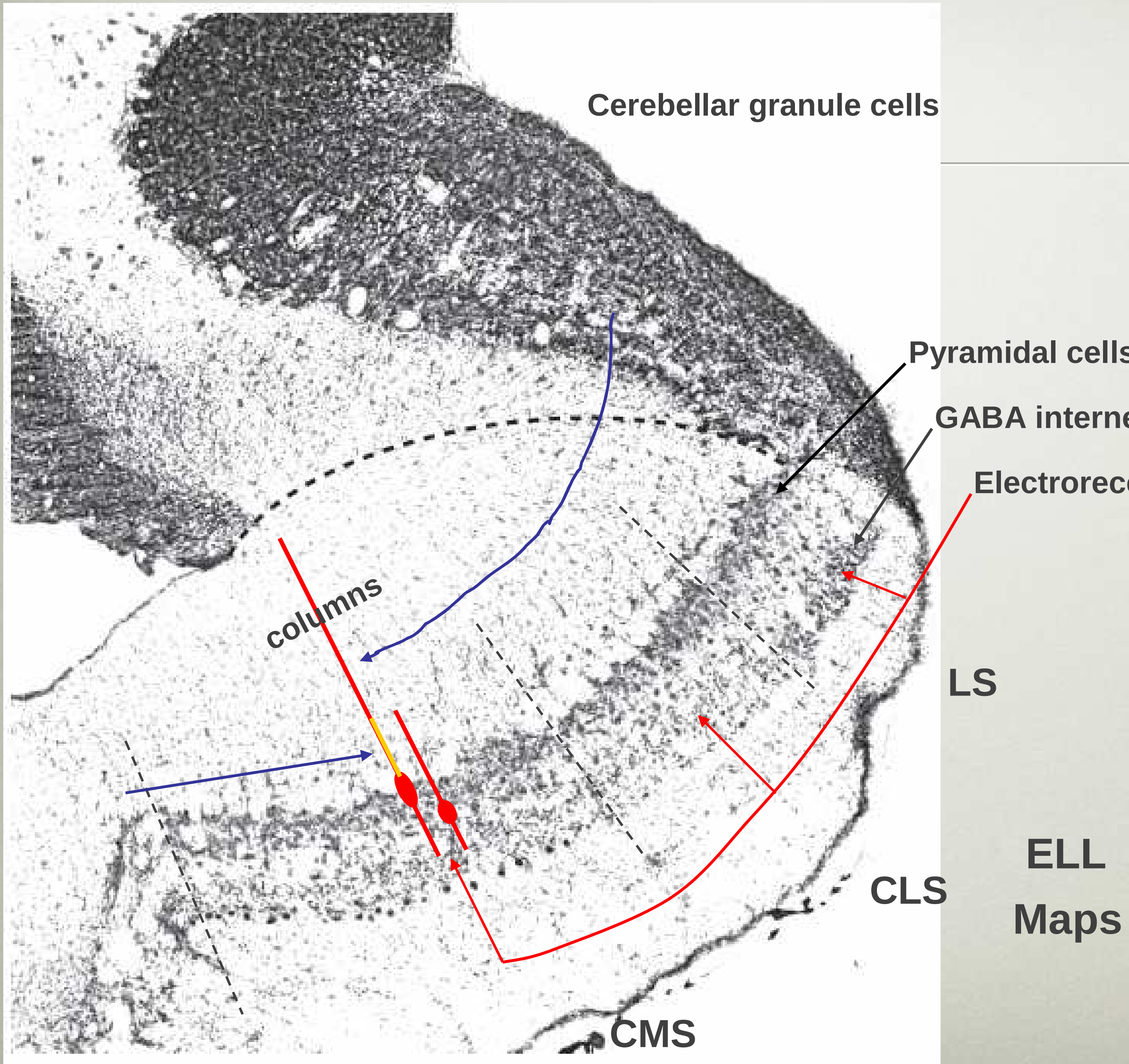
Data: synchronous spike coherence



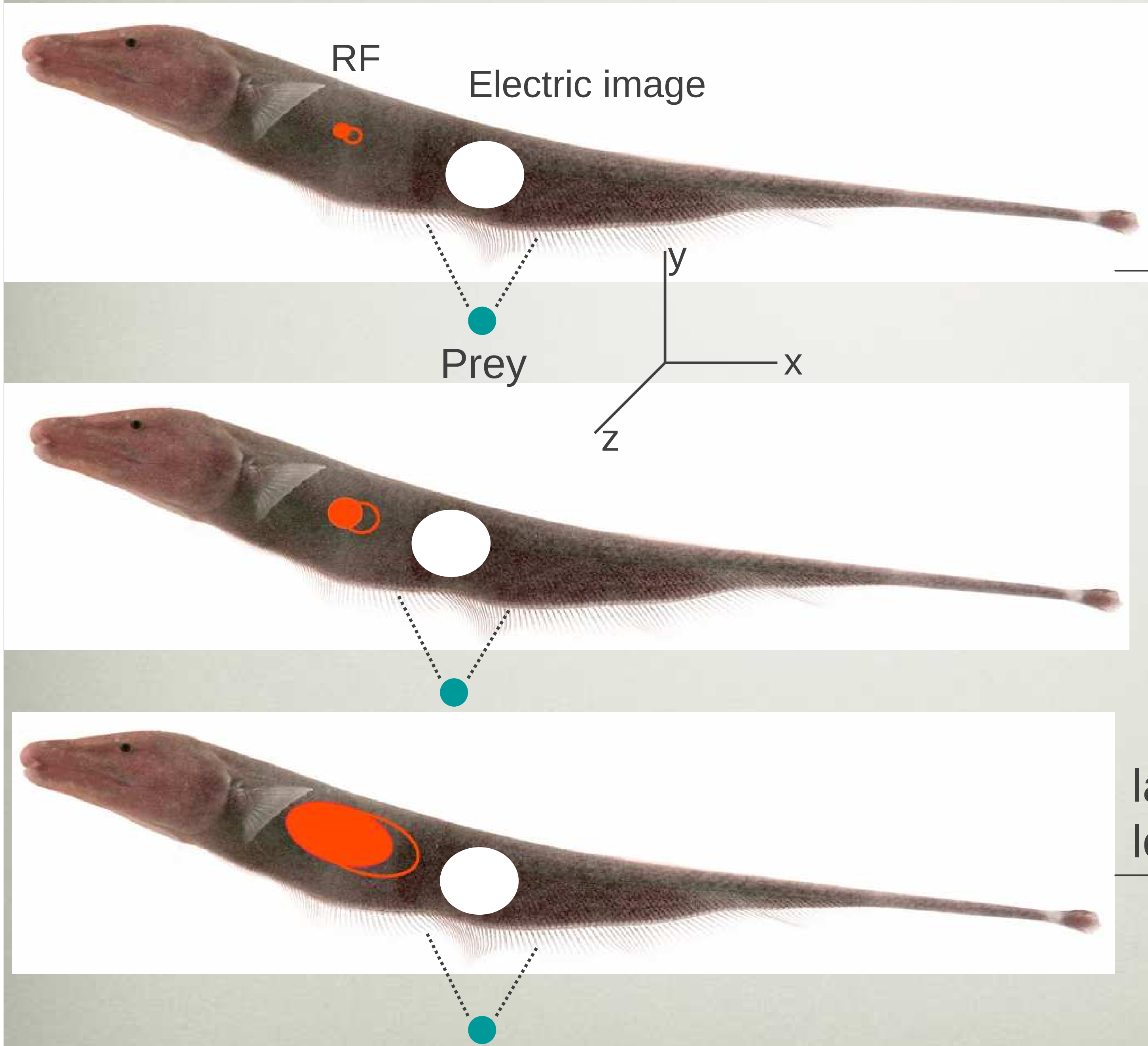


Postsynaptic Decoders

- **3 Somatotopic maps:**
- **Centro-medial (CMS)**
- **Centro-lateral (CLS)**
- **Lateral (LS)**


Cerebellar granule cells
Pyramidal cells
GABA interneurons
Electroreceptors
columns
LS
CLS
CMS
ELL
Maps

Receptive Fields



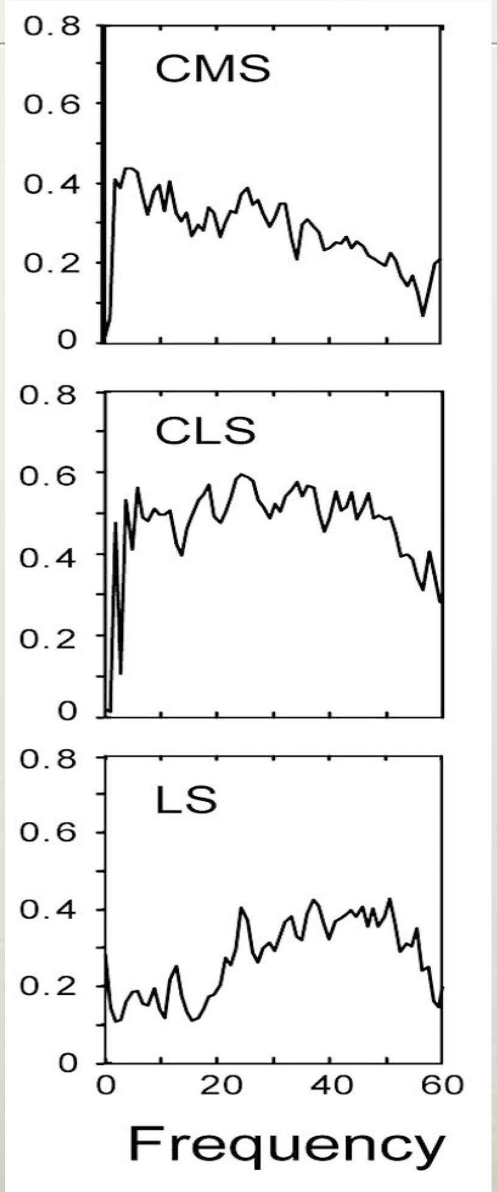
CMS map:
small receptive fields=
high spatial frequency

CLS map:
intermediate

LS map:
large receptive fields=
low spatial frequency

Temporal Filtering Properties

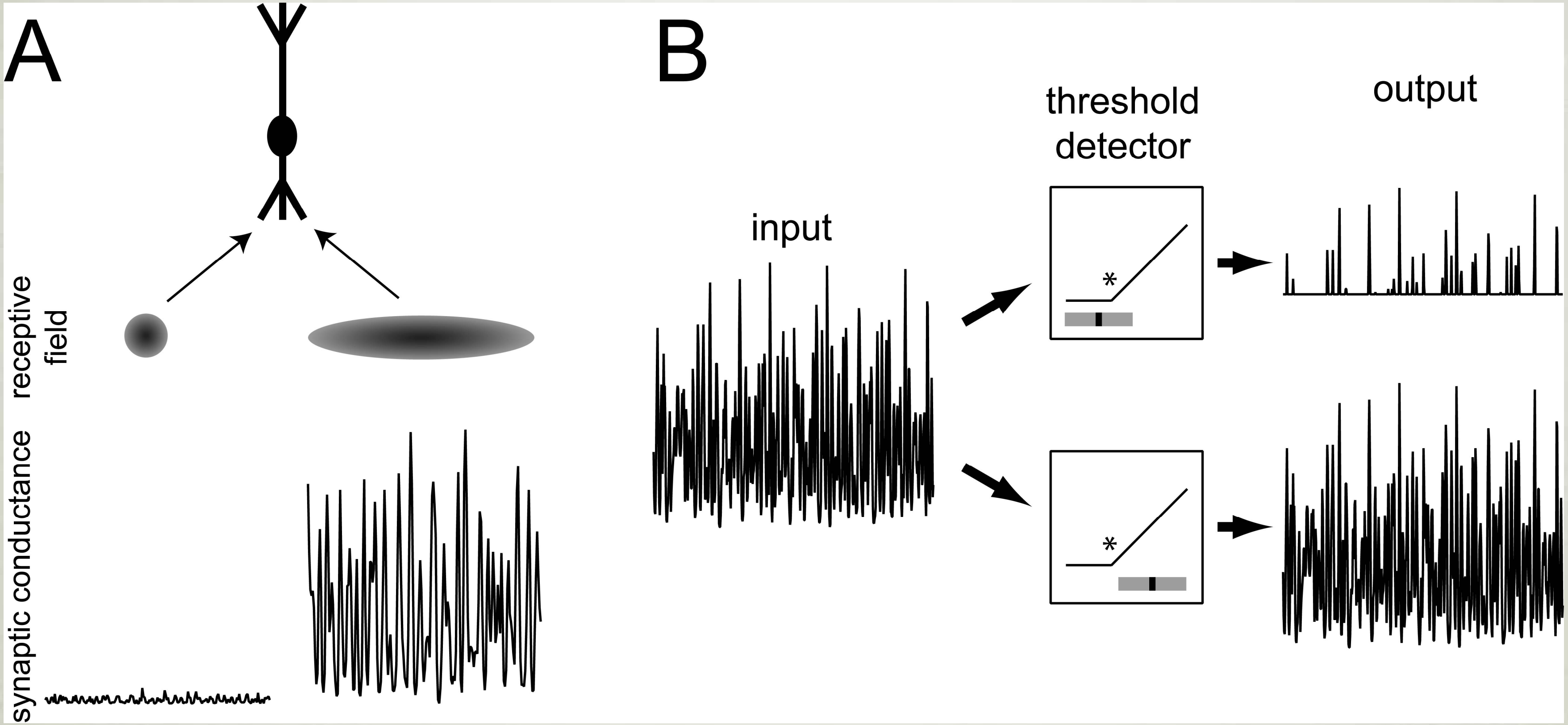
coherence



low-pass

high-pass

Mehaffey, *et al.* (2008)


A
receptive field
synaptic conductance
B
input
threshold detector
output
*
*

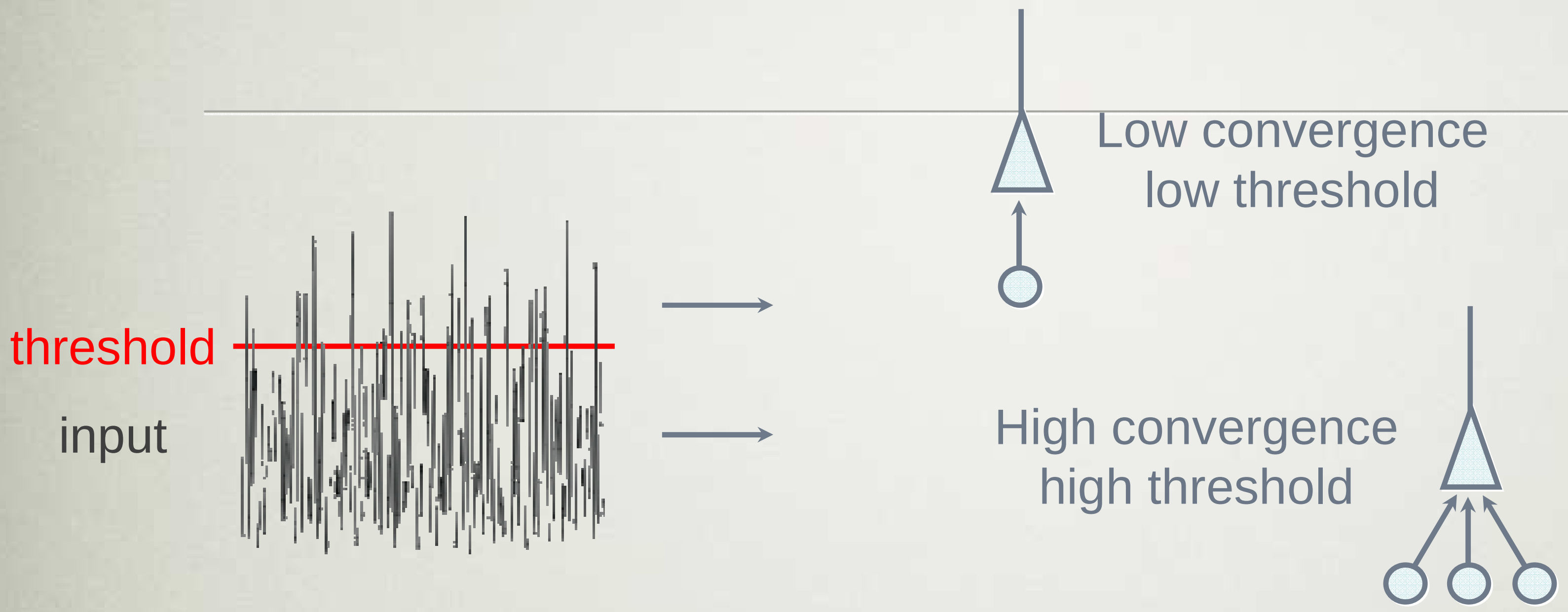
Neural models: experimental constraints

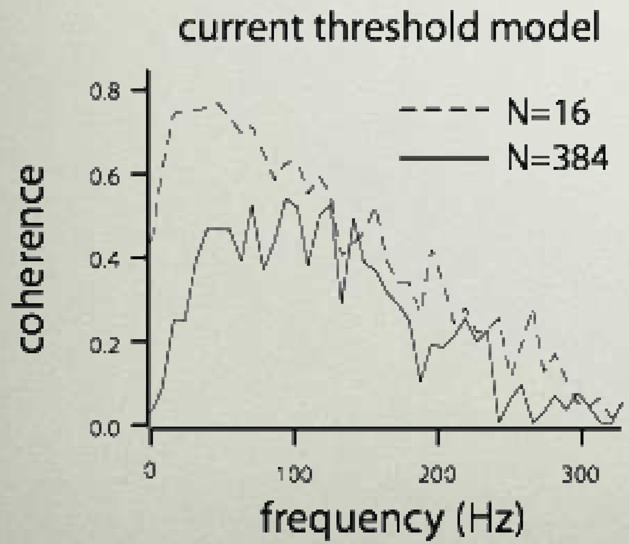
- Different receptive field (RF) sizes:
  - LS - large RFs (high convergence)
  - CMS - small RFs (low convergence)

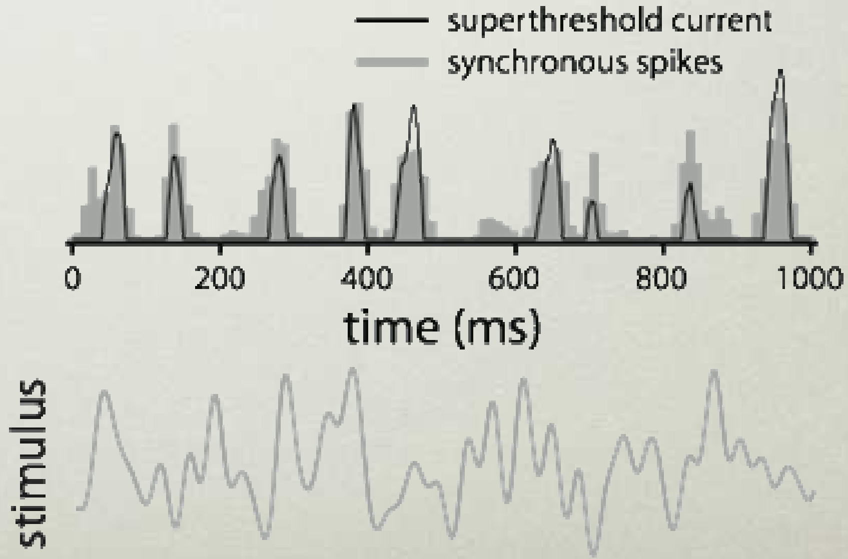
- Different spike thresholds:
  - LS - high threshold (-67mV)
  - CMS - low threshold (-61 mV)

- Output firing rates are roughly conserved across maps:
  - LS - 18 Hz
  - CMS - 14 Hz

Neural models: current threshold model

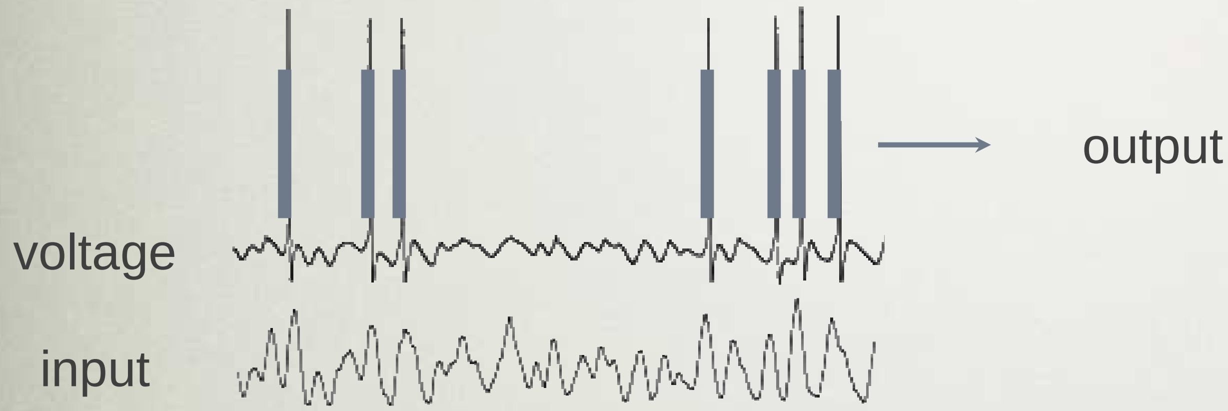


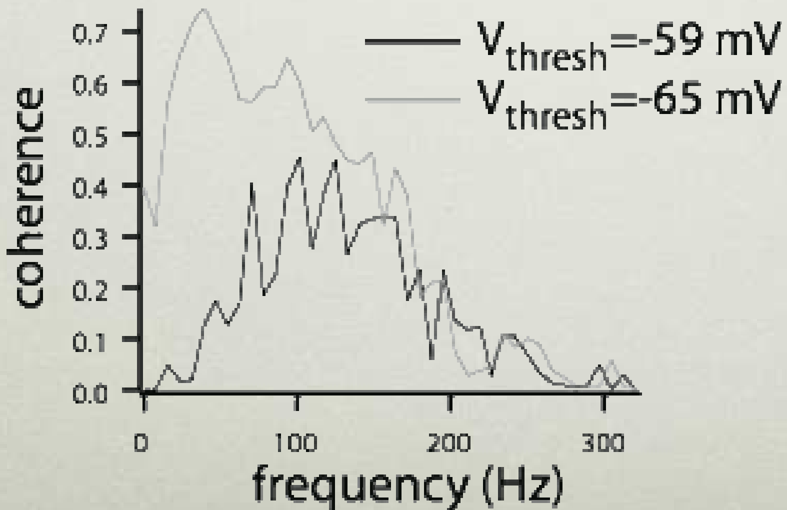




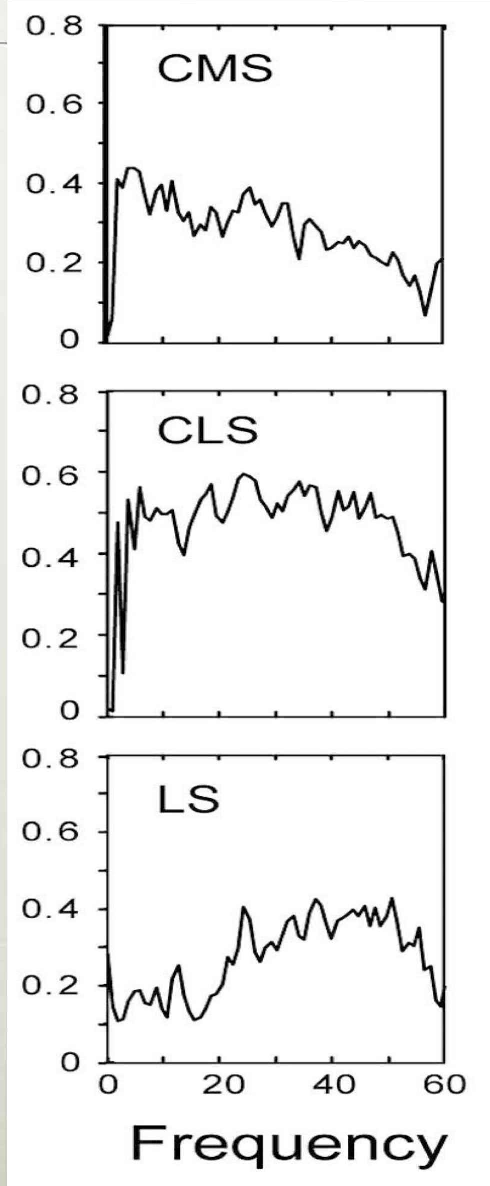
Conductance-based model

$$C\frac{dv(t)}{dt} = I_{DC} - g_{shunt}\left(v(t) - E_{shunt}\right) - g_{syn}x(t)\left(v(t) - E_{AMPA}\right)$$





Temporal Filtering Properties



coherence

low-pass

high-pass

Mehaffey, *et al.* (2008)

Summary

- Synchronous (electro)sensory afferent activity encodes high frequency information
- Summed activity encodes all frequencies
- Postsynaptic cells with high convergence and high spike threshold preferentially decode synchronous activity
- ELL: high convergence map (LS) decodes fast chirps
- Other sensory systems (visual: X and Y cells) could consist of parallel streams of different temporal information which are determined by transmission of synchronous activity

Part 2:
Coding with Plastic Synapses

- General properties of short term plasticity
- Amplitude-rate picture
- Frequency response picture
- Spontaneous Poisson activity
- Modulated Poisson activity
- Controlling Broadband Coding

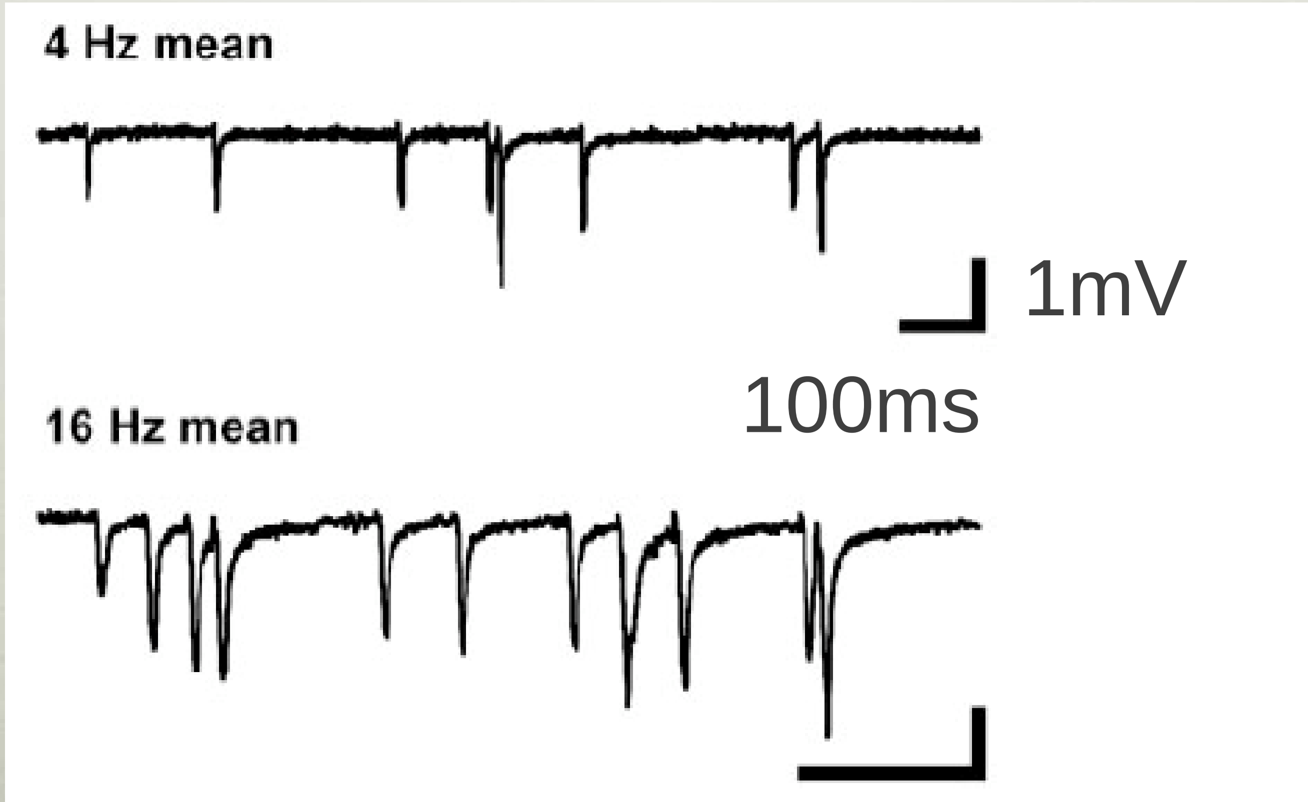
- *Lindner, Gangloff, Longtin, Lewis,*
- *Broadband Coding with Dynamic Synapses, J. Neurosci. (2009)*

Short-term plasticity

Change in the synaptic efficacy by incoming spikes

Increase in efficacy = synaptic facilitation

Decrease in efficacy = synaptic depression



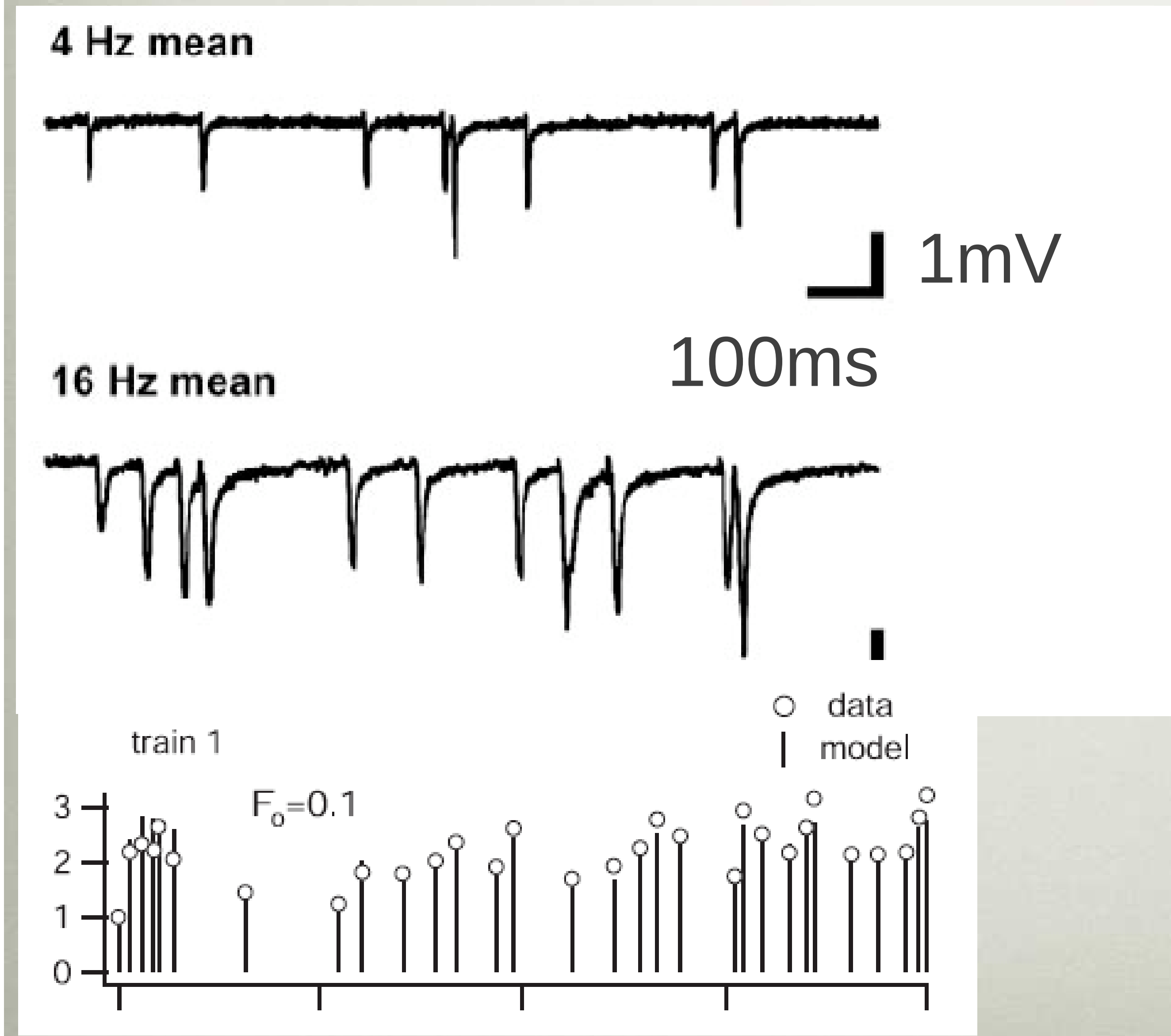
Possible roles of short-term plasticity

- input compression (Tsodyks & Markram 1997, Abbott et al. 1997)
- signaling of transients (Lisman 1997, Senn et al. 2000, Richardson et al. 2005)
- switching between neural codes (Tsodyks & Markram 1997)
- spectral filtering (Fortune&Rose 2001, Abbott et al. 1997, Dittman et al. 2000)
- synaptic amplitude can keep info about the presynaptic spike train seen so far (e.g. Fuhrmann et al. 2001)
- **redundancy reduction** (Goldman et al. 2002)
- sensory adaptation and decorrelation (Chung et al. 2002)

Information transfer

- Need more than synaptic amplitudes
- One also needs accompanying noise
- Noise comes mainly from (asynchronous) inputs
- Need to figure out how synaptic amplitudes and noise depend on time (due to signal)

Facilitation-depression model from experiments



Postsynaptic amplitude

$$A_j = F_j D_j$$

Lewis &Maler *J. Neurophysiol.* (2002,2004)

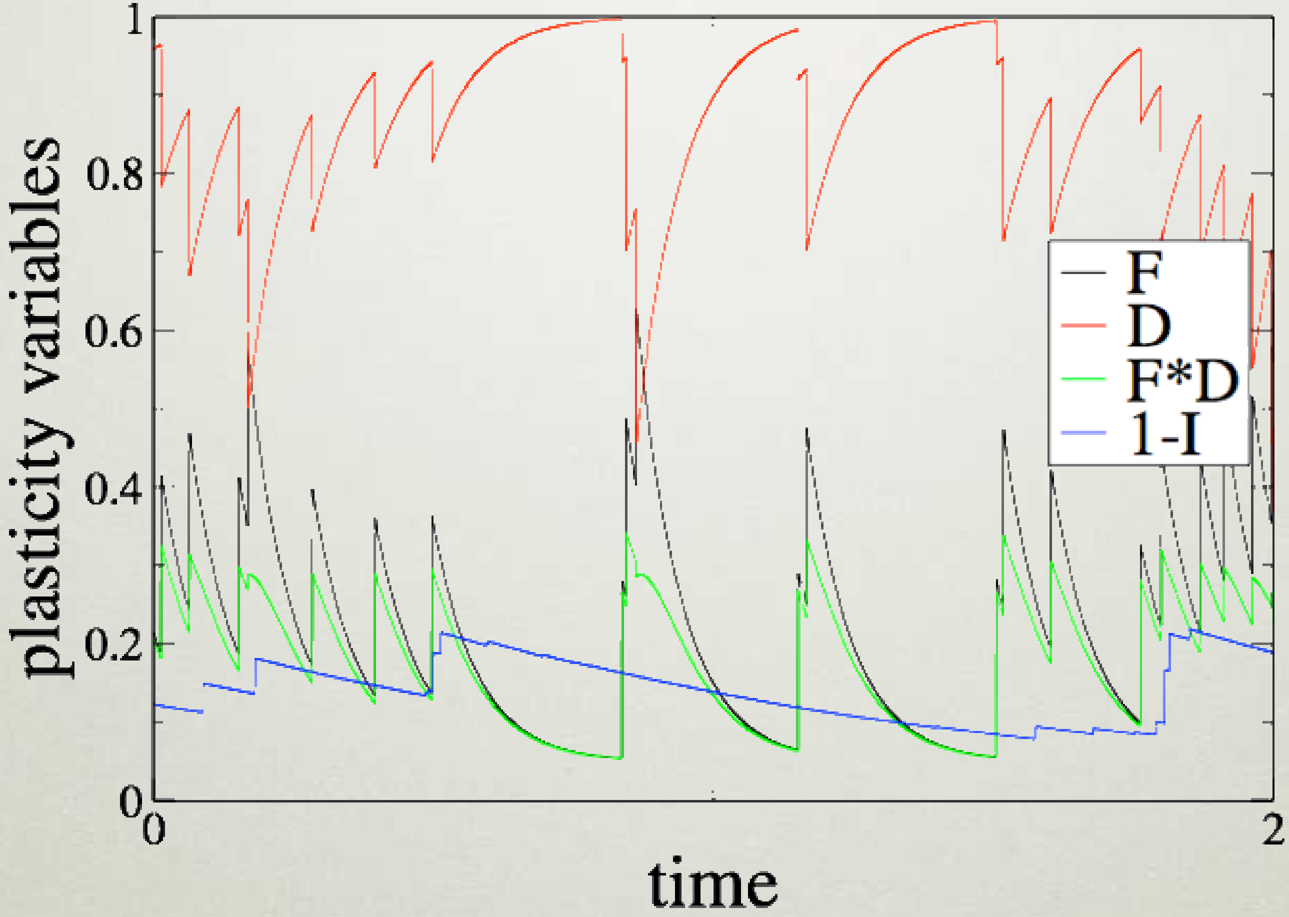
Facilitation and Depression Dynamics

$$\dot{D}_j = \frac{1 - D_j}{\tau_D}, \quad t = t_{i,j} \Rightarrow D_j \rightarrow D_j(1 - F_j)$$

$$\dot{F}_j = \frac{F_0 - F_j}{\tau_F}, \quad t = t_{i,j} \Rightarrow F_j \rightarrow F_j + \Delta$$

$$F_j(t) > 1 \Rightarrow F_j(t) \rightarrow 1; F_0 < F < 1$$

Trajectories for Poisson stimulus

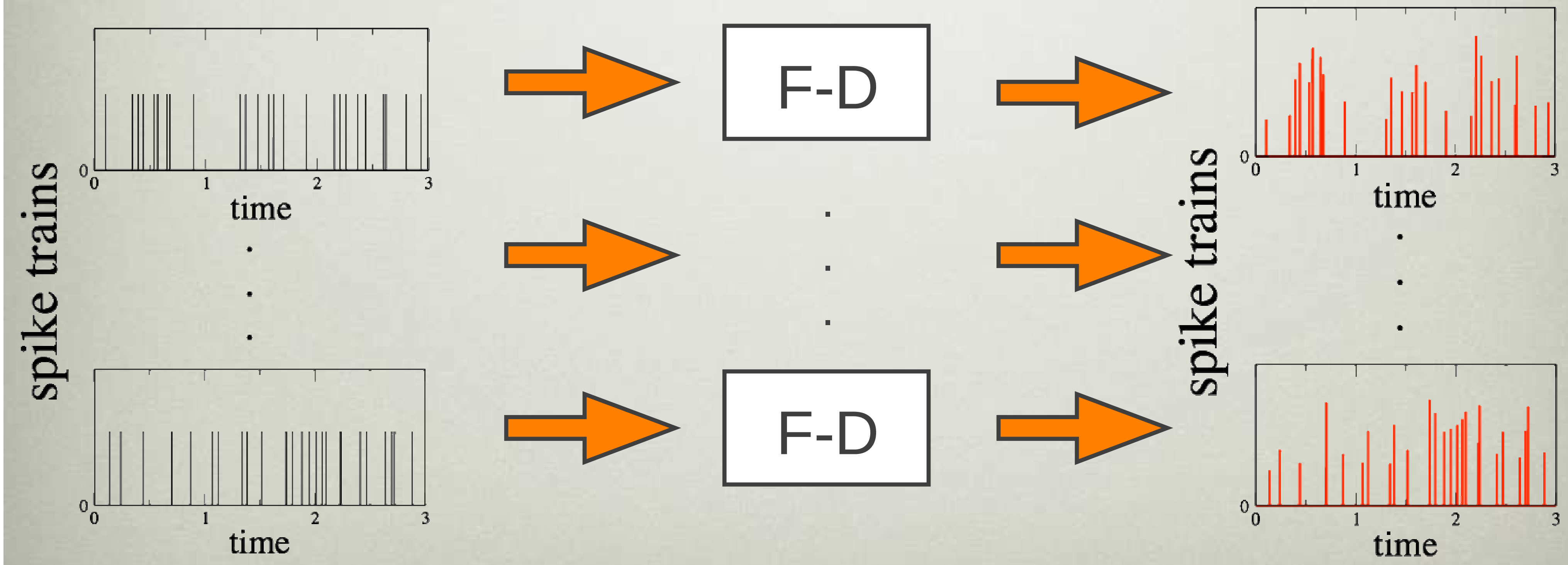


Model

Poisson input spike trains

Synaptic facilitation and depression

Synaptic input



Conductance and voltage dynamics

Synaptic inputs

$$x_j(t) = \sum_i A_{i,j}\delta(t - t_{i,j}), \quad X(t) = \frac{1}{N}\sum_j x_j(t)$$

Conductance dynamics

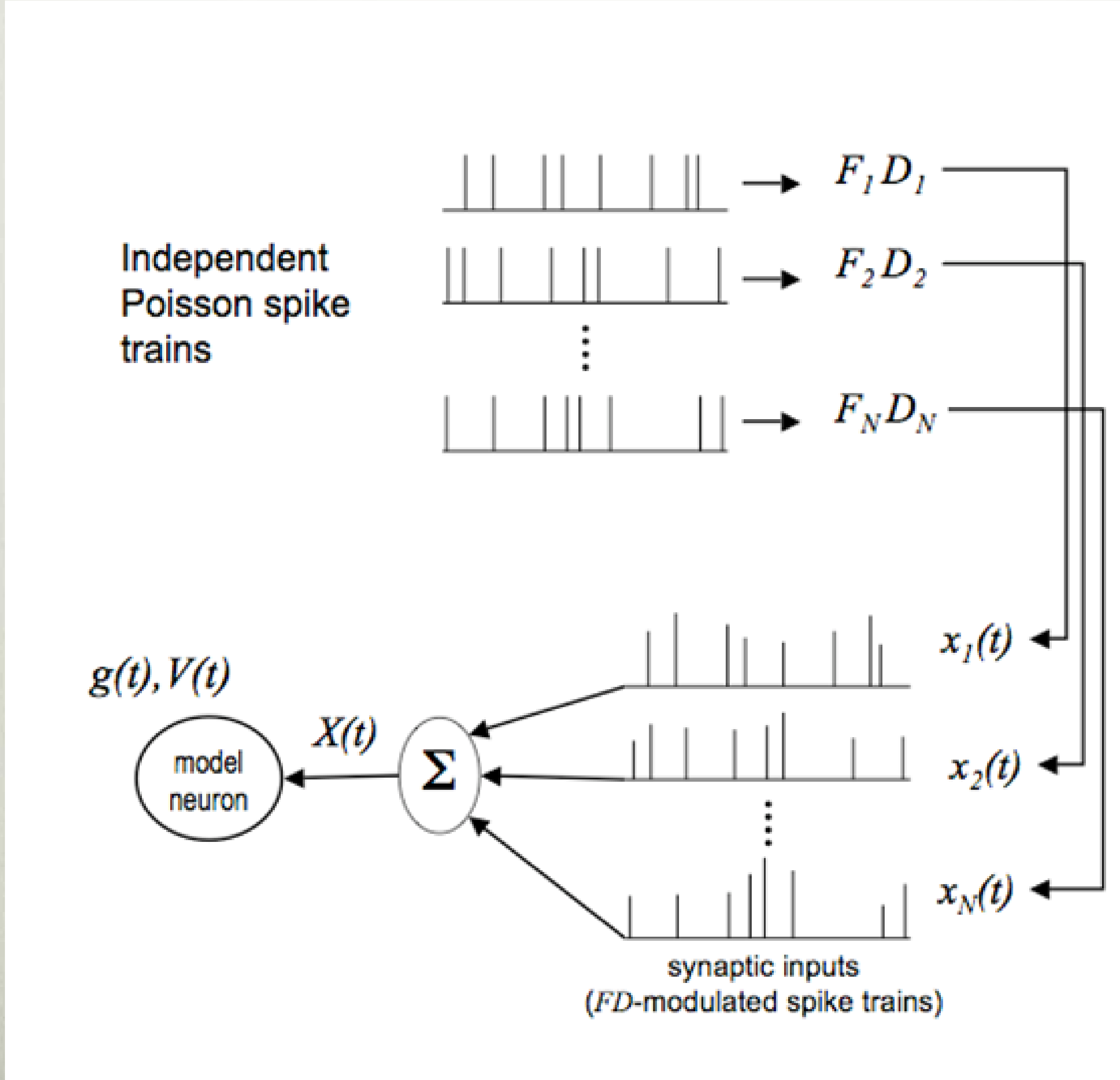
$$\dot{g} = -g/\tau + g_0 X(t)$$

Membrane voltage dynamics

$$C_m \dot{V} = -g_L(V - V_L) - g(t)(V - V_E)$$

Spontaneous activity

Model for spontaneous activity



Map description

Facilitiation (for small input rates)

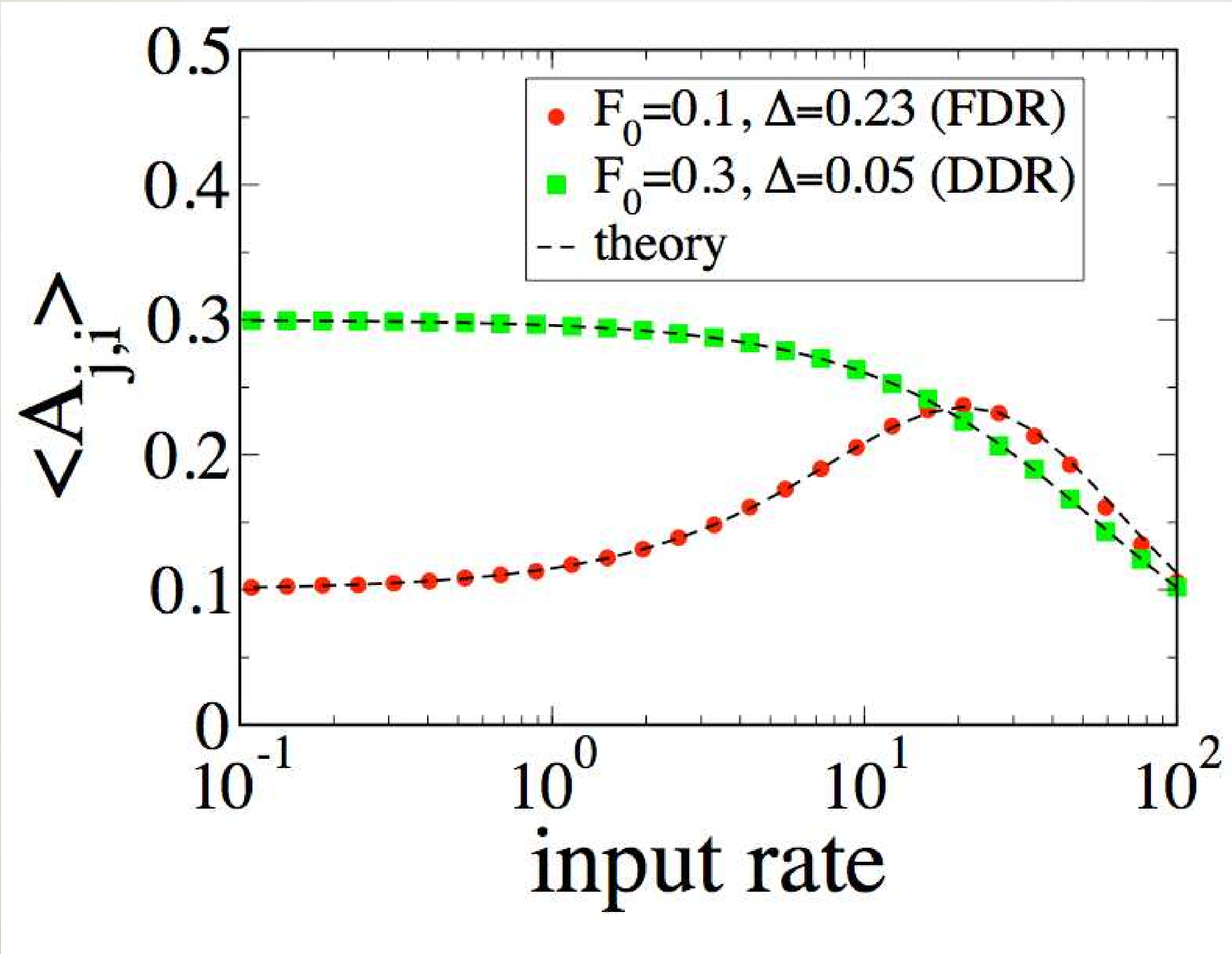
$$F_{i+1,j} = F_0 + (F_{i,j} - F_0 + \Delta)e^{-T_{i,j}/\tau_F}$$

Depression

$$D_{i+1,j} = 1 + (D_{i,j} - 1 - F_{i,j}D_{i,j})e^{-T_{i,j}/\tau_D}$$

$T_{i,j}$ input ISI

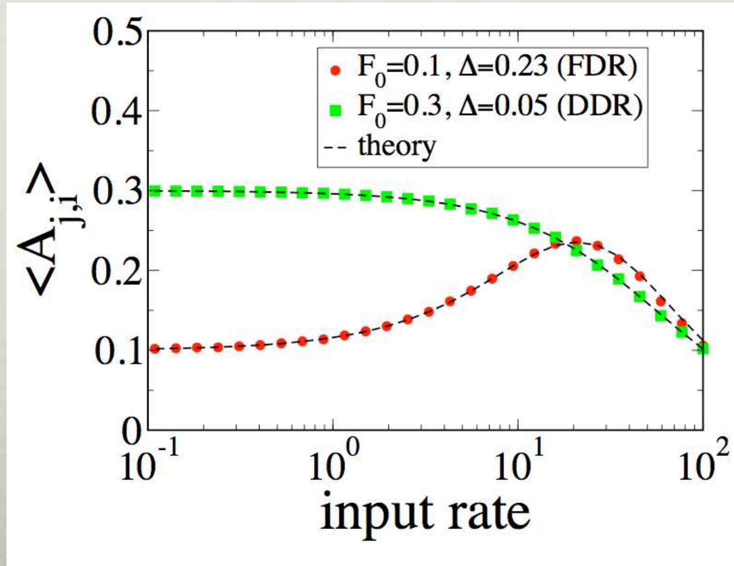
Mean value for low input rates



Distinction between different regimes

At low firing input rate

- Facilitation dominated regime (FDR) $$\left.\frac{d\langle A_j\rangle}{dr}\right|_{r=0} > 0$$
- **Depression dominated regime (DDR)** $$\left.\frac{d\langle A_j\rangle}{dr}\right|_{r=0} < 0$$

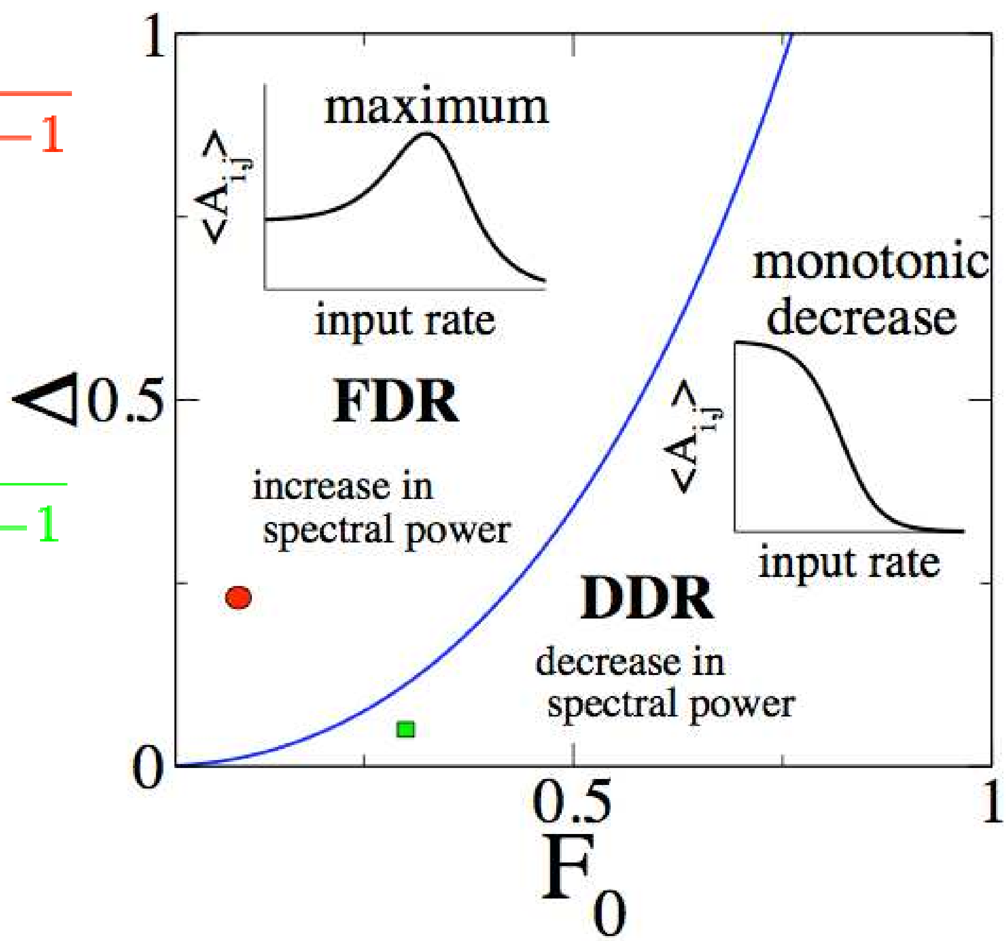


Distinction between different regimes

When does facilitation dominate? And when depression?

$$\Delta > \frac{F_0^2 \tau_D}{\tau_F - F_0[\tau_F^{-1} + \tau_D^{-1}]^{-1}}$$

$$\Delta < \frac{F_0^2 \tau_D}{\tau_F - F_0[\tau_F^{-1} + \tau_D^{-1}]^{-1}}$$



Power spectra

Summed spike trains with dynamic amplitudes $A_{i,j}$: general expression for the power spectrum

$$S_{xx} \;=\; \left\langle A_{i,j} \right\rangle^2 S_0 + r \left\langle \sum_{l=-\infty}^{\infty} (A_{k,j} A_{k+l,j} - \left\langle A_{k,j} \right\rangle \left\langle A_{k+l,j} \right\rangle) e^{2\pi i f (t_{k+l,j} - t_{k,j})} \right\rangle$$

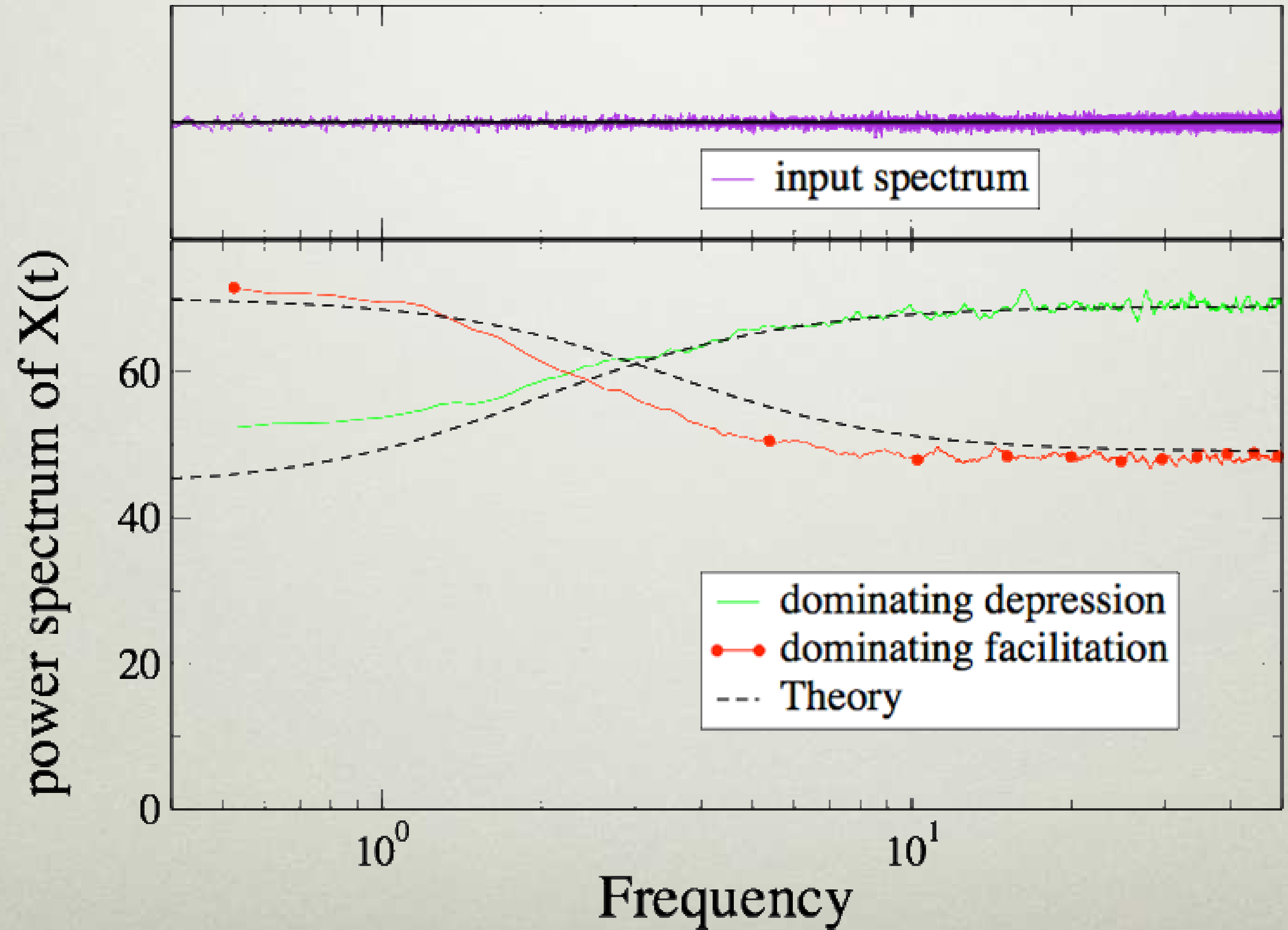
For Poisson input with a weak rate

$$S_{XX} \approx rN \left\langle A_{i,j}^2 \right\rangle + 2r^2 N \left\langle A_{i,j} \right\rangle \left[\frac{\Delta \tau_F}{1 + (2\pi f \tau_F)^2} - \frac{F_0^2 \tau_D}{1 + (2\pi f \tau_D)^2} - \frac{\Delta F_0 \tilde{\tau}}{1 + (2\pi f \tilde{\tau})^2} \right]$$

Neglecting the multiplicative nature of the conductance noise:

$$S_{VV} = \frac{\left[g_0 \tau \tau_{eff} (\langle V \rangle - V_e) \right]^2}{(1 + (2\pi f \tau)^2)(1 + (2\pi f \tau_{eff})^2)} \frac{S_{XX}(f)}{N^2},$$

Power spectra

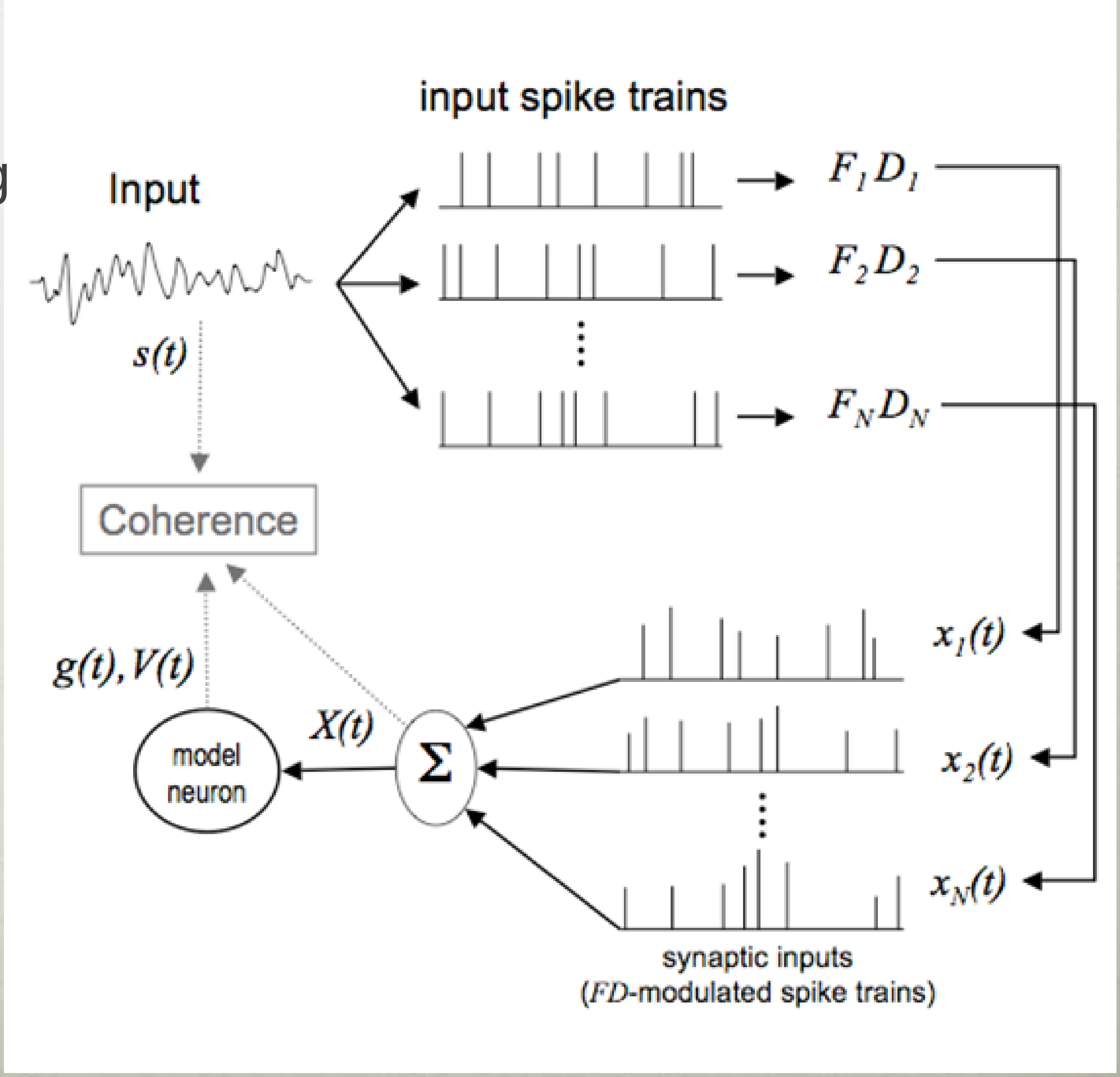


Signal transmission

Model with rate modulation

Modulation of the input firing rate by a band-limited Gaussian white noise (0-100Hz)

$$R(t) = r \cdot [1 + \varepsilon s(t)]$$



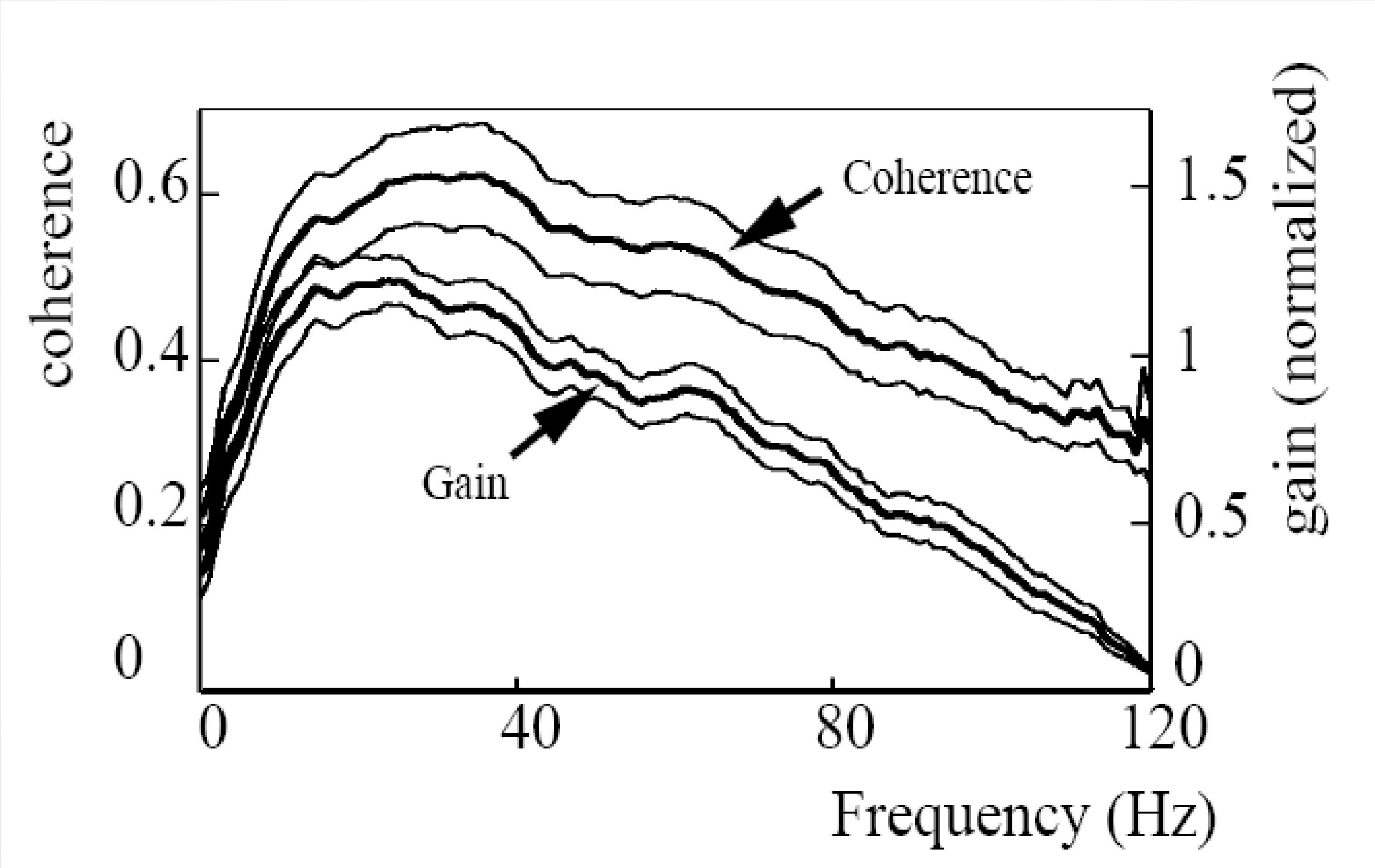
0 < COHERENCE < 1

$$C_{ZR} = \frac{|S_{ZR}(f)|^2}{S_{ZZ}(f)S_{RR}(f)}$$

Input=electrical stimulus Output= ELL spikes

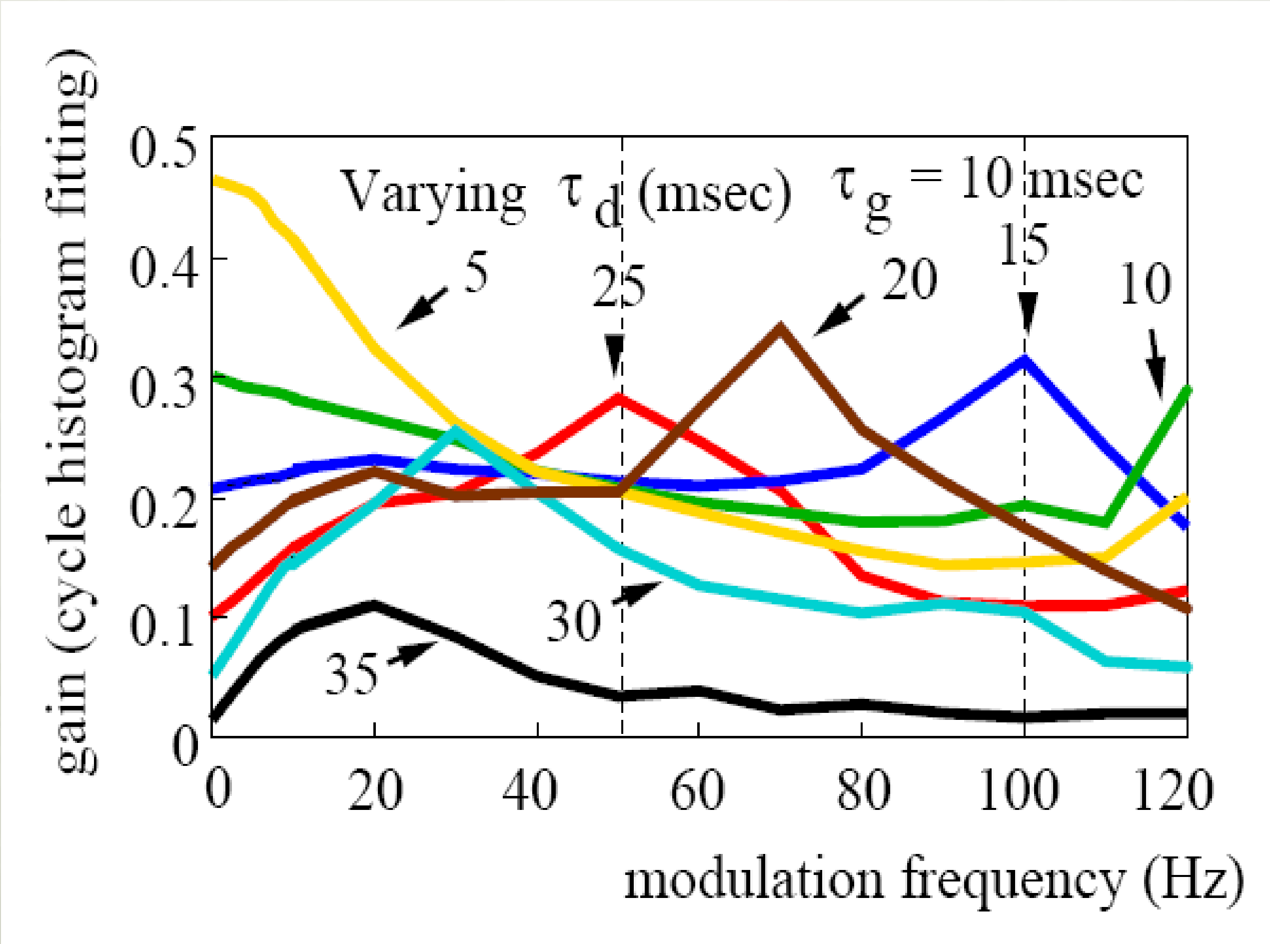
How can one infer receptor-to-ELL plasticity?

$C_1 = C_2\ C_3$



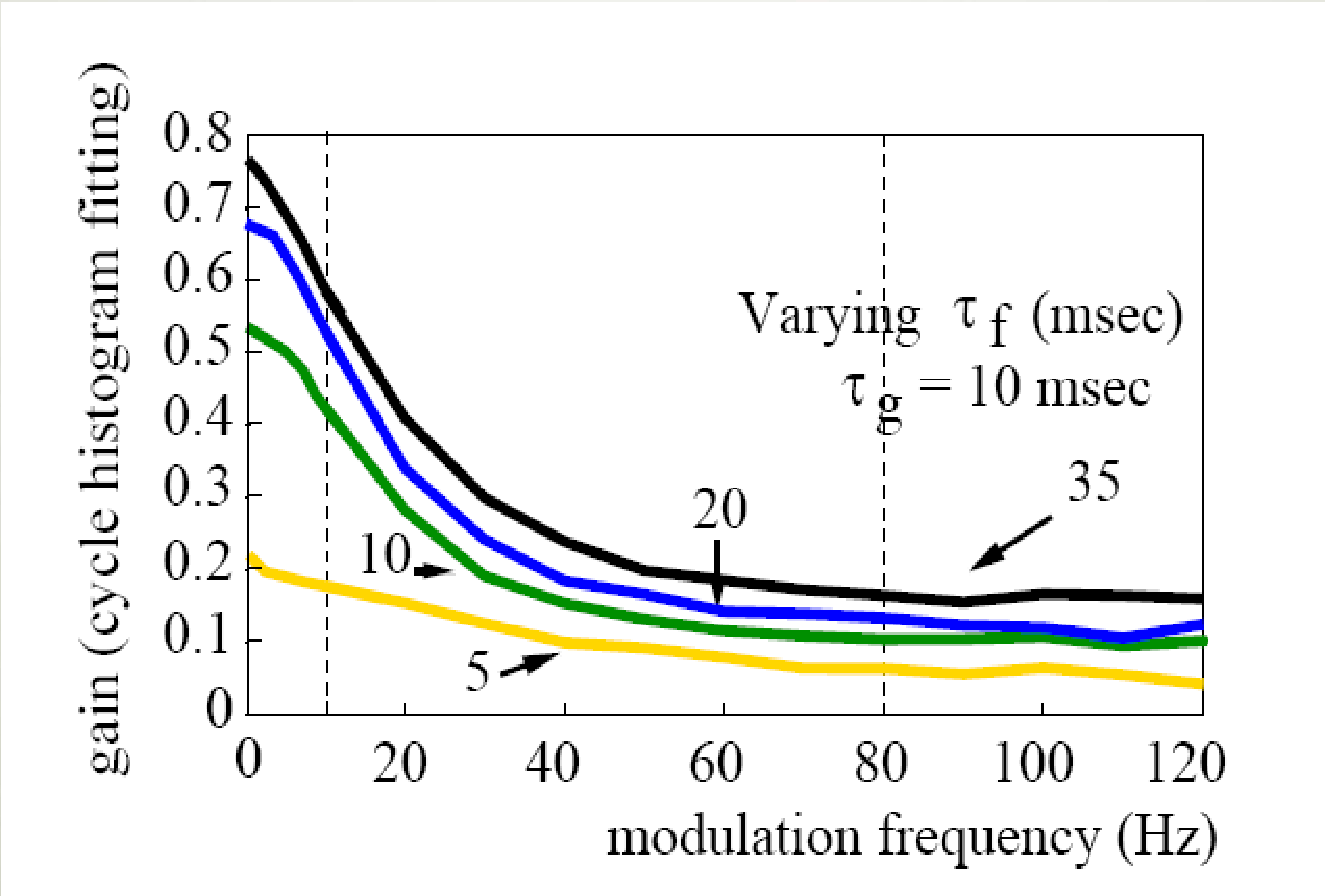
Chacron et al., Nat. Neurosci. 2005

Depression alone

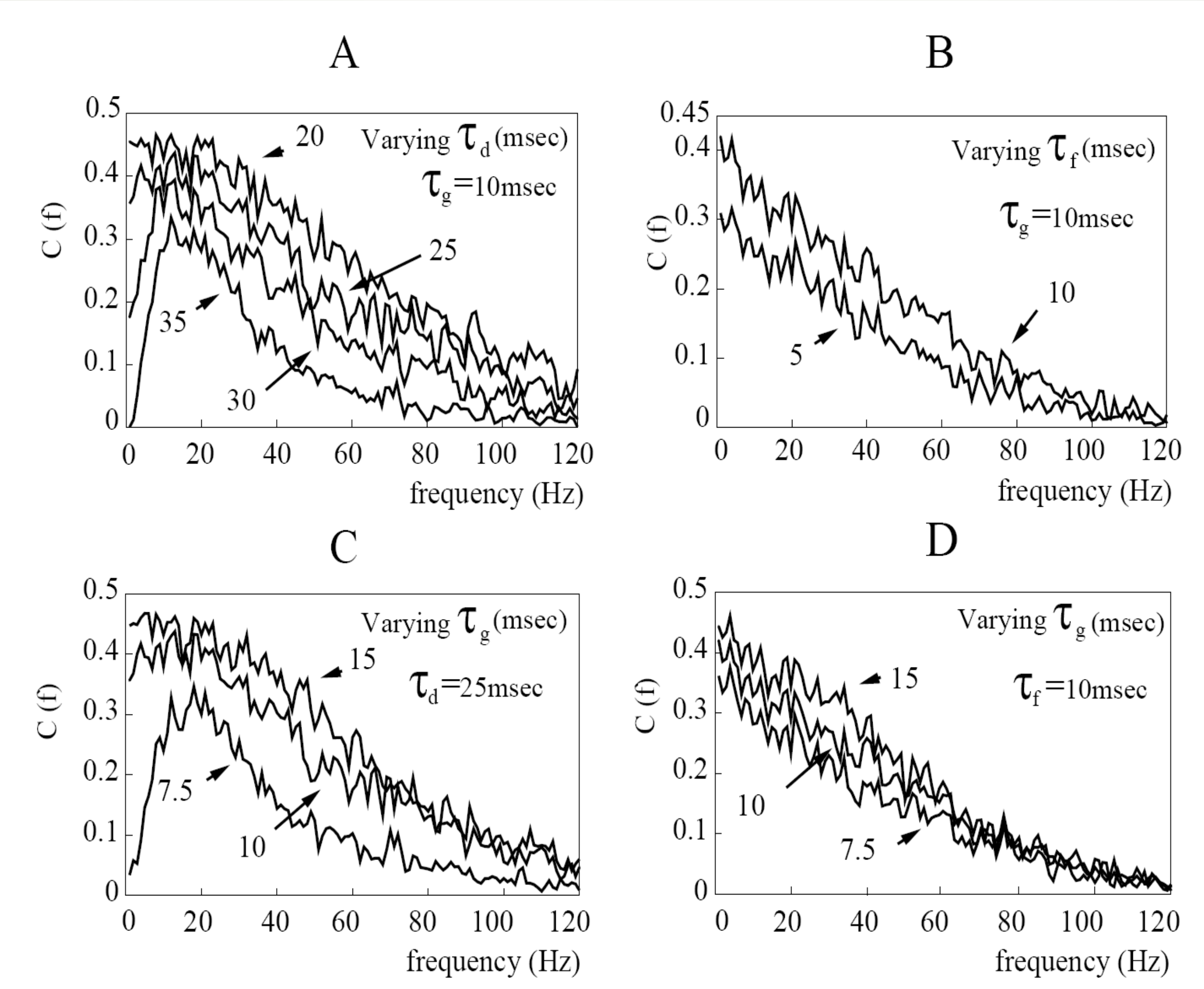


Szalisznyo, Longtin, Maler, Biosystems 2008

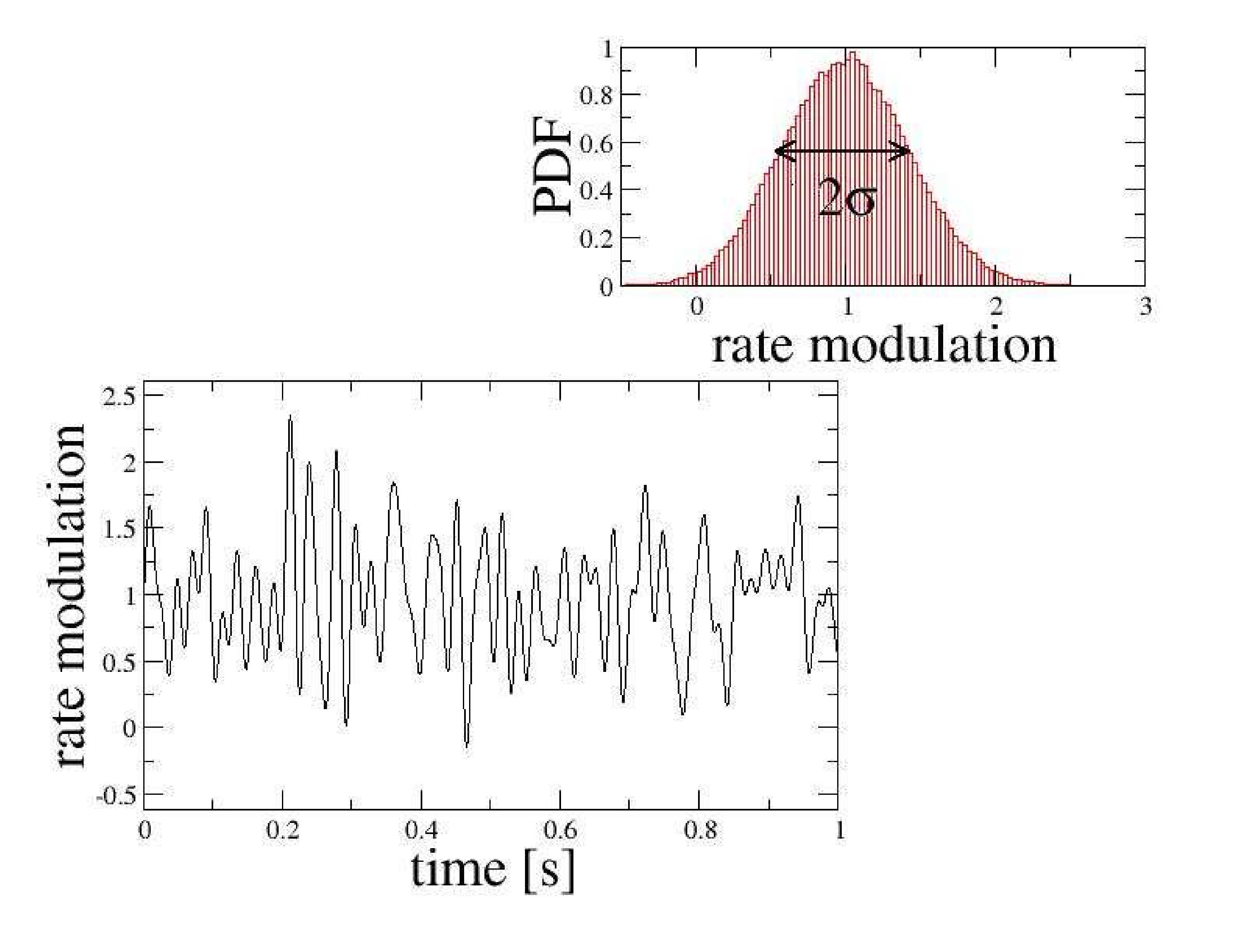
Facilitation alone



Prediction that D dominates, mixed AMPA+NMDA

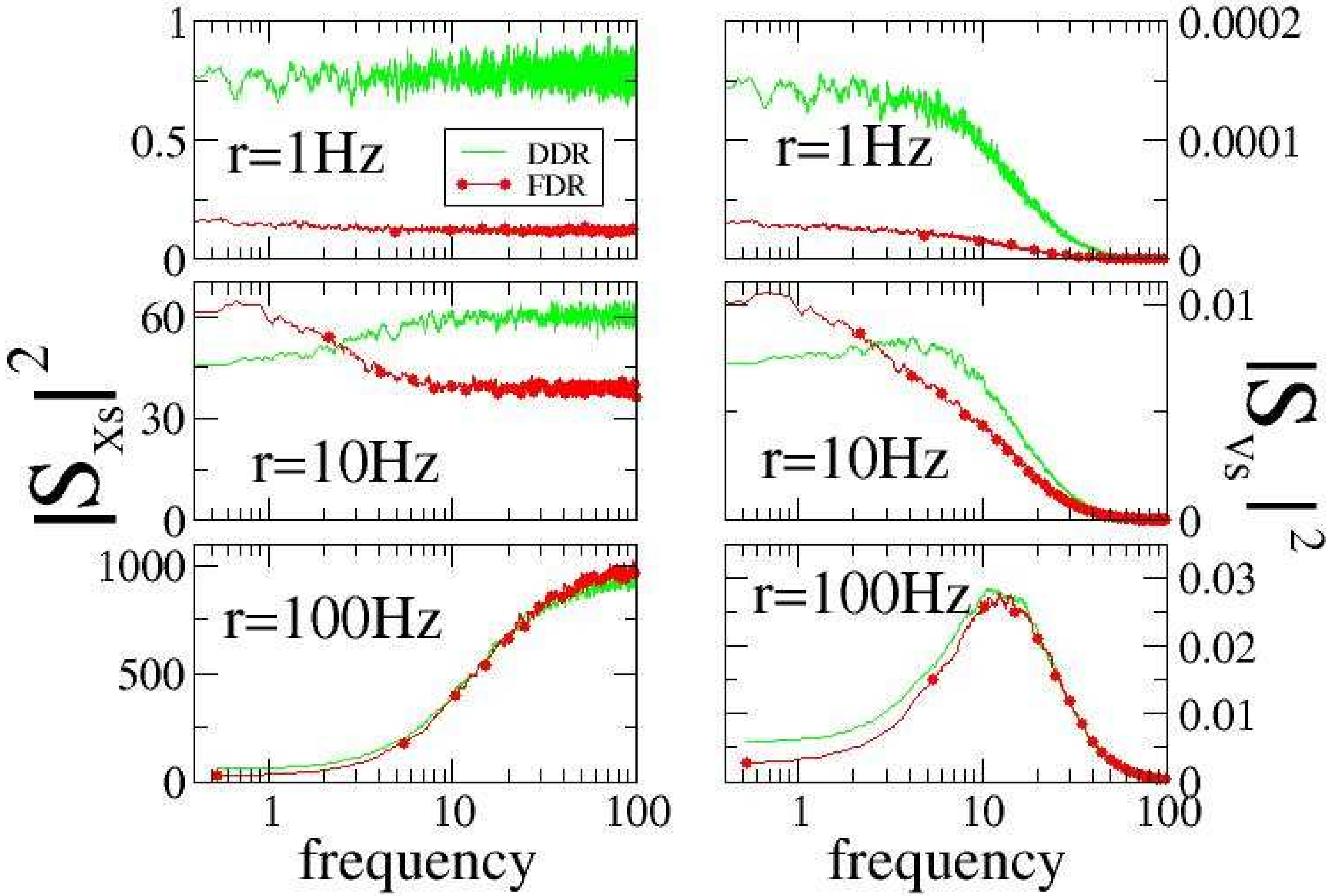


Band-limited noise stimulus (0-100Hz)



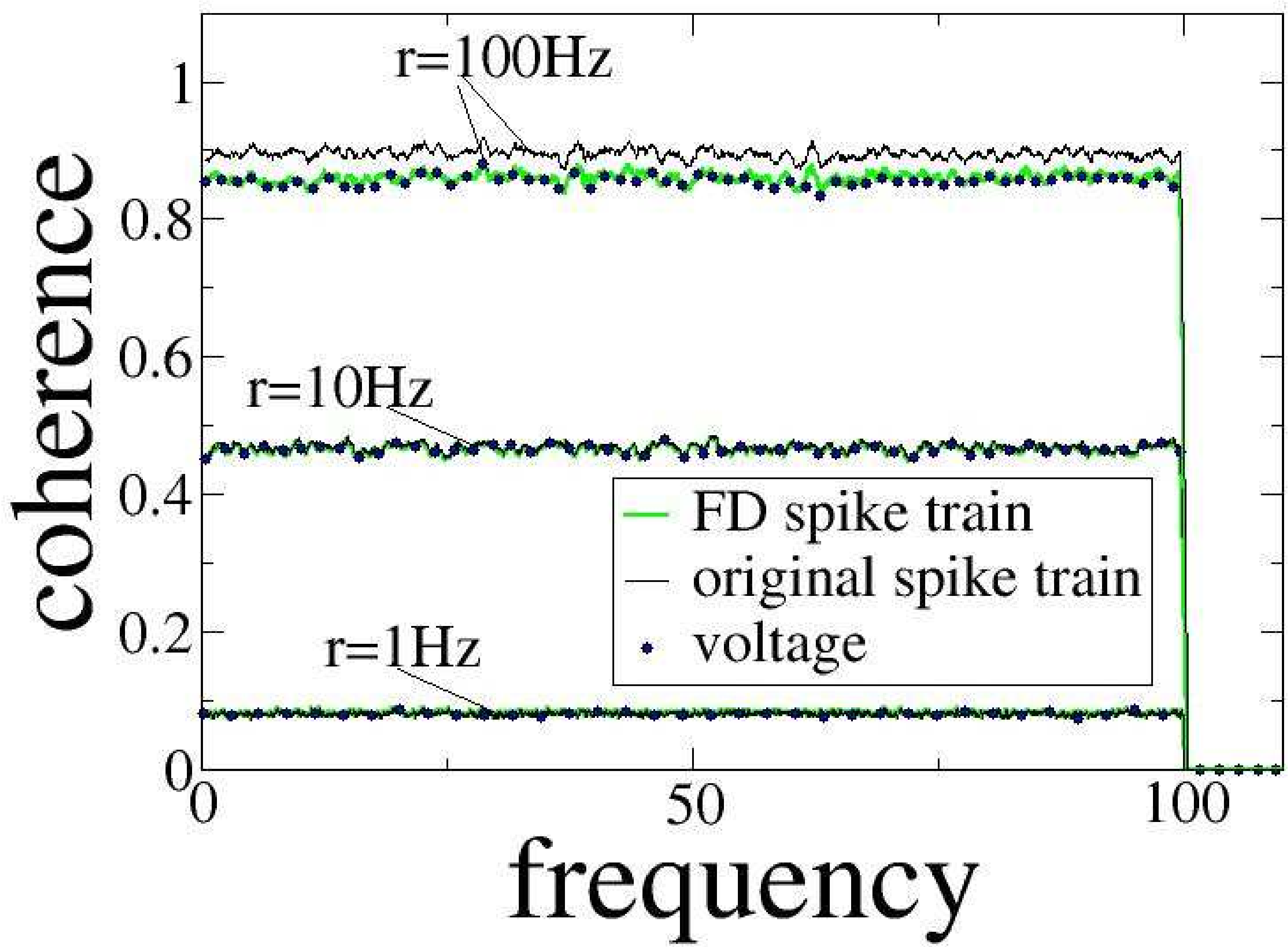
$$\sigma = 0.42$$

Cross-spectra



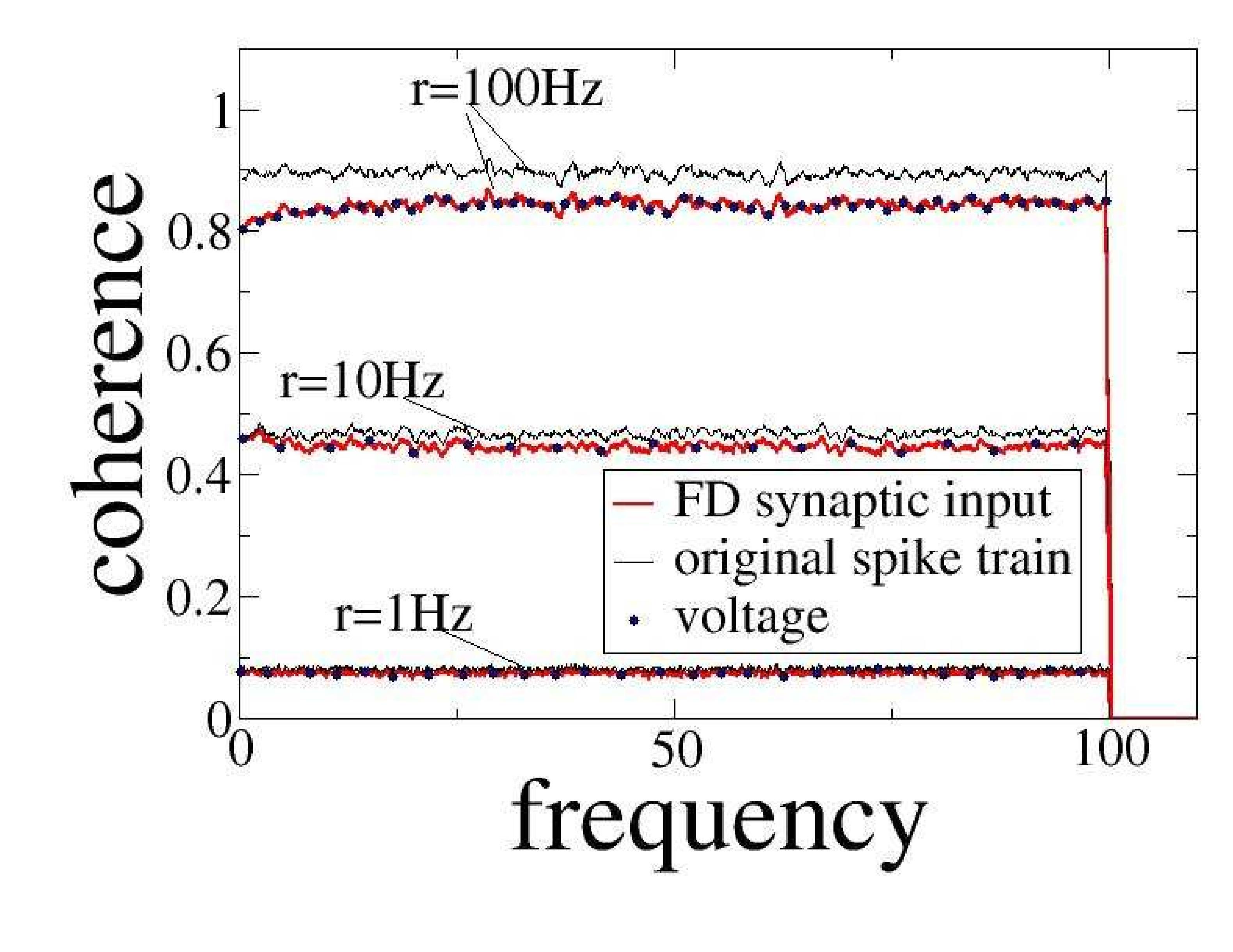
Coherence function DDR

$$C_{ZR} = \frac{|S_{ZR}(f)|^2}{S_{ZZ}(f)S_{RR}(f)}$$

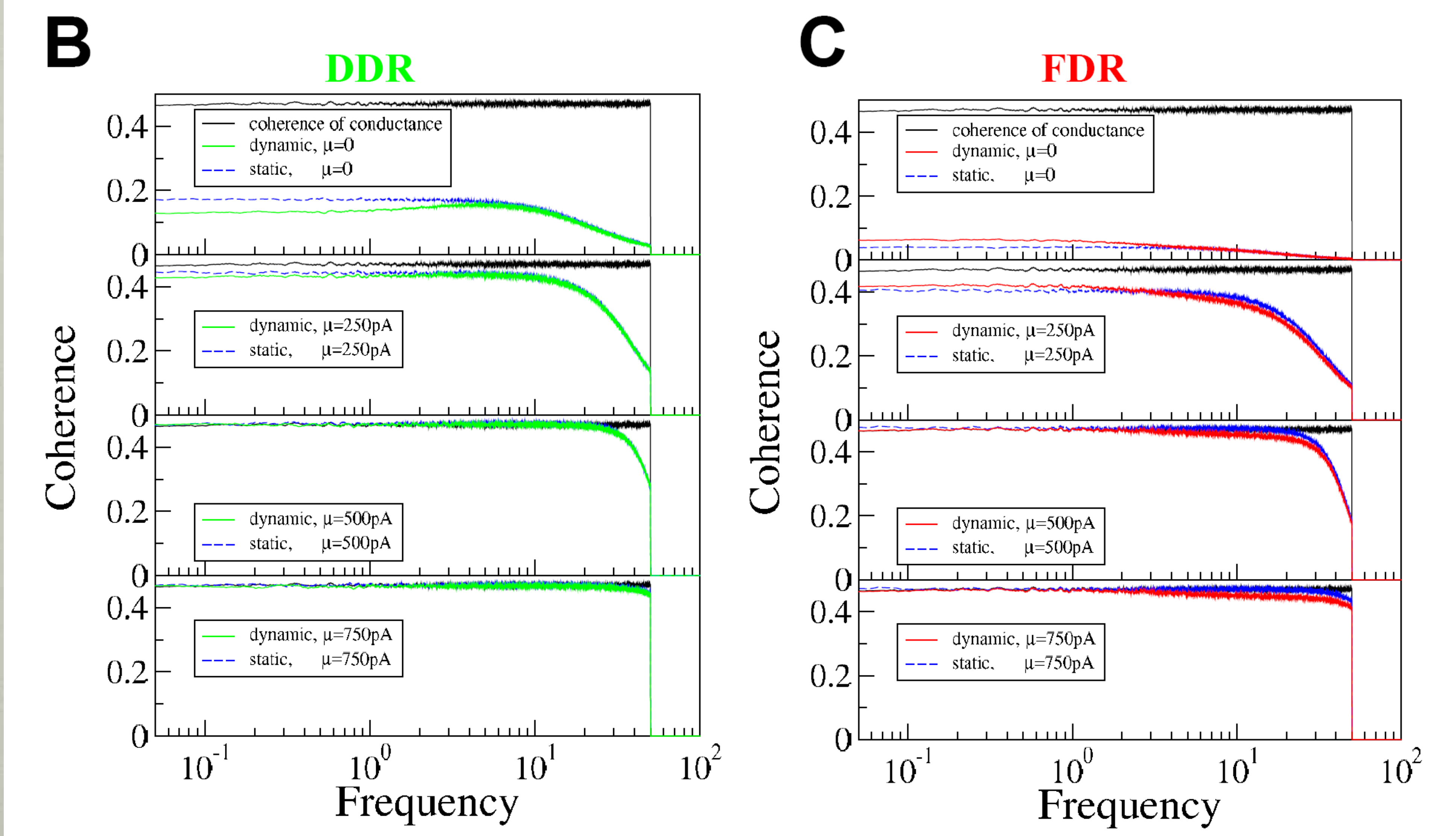


Coherence function FDR

$$C_{ZR} = \frac{|S_{ZR}(f)|^2}{S_{ZZ}(f)S_{RR}(f)}$$



Input: Poisson rate modulation
Output: LIF spikes



Summary

- Analytical results for the spontaneous case permit distinction between different regimes (FDR & DDR)
- Synaptic input and subthreshold membrane voltage show a flat coherence with rate modulation for both FDR and DDR
  -> **broadband coding**
- Information transmission about a stationary rate modulation is always reduced by dynamic synapses
- Coherence can be controlled by LIF mean rate

Chaos

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