

Neural Constraints in Auditory Cortex

Jonathan Z. Simon
Didier A. Depireux
David J. Klein
Shihab A. Shamma

Institute for Systems Research
University of Maryland
College Park

Outline

- **Introduction to Auditory Spectro-Temporal Processing**
- **Stimuli—Dynamic & Broadband: Ripples, Ripple Combinations**
- **Examples & Properties of Spectro-Temporal Response Fields**
- **Constraints on Neural Connectivity**

- **Introduction to Auditory Spectro-Temporal Processing**
- Stimuli—Dynamic & Broadband: Ripples, Ripple Combinations
- Examples & Properties of Spectro-Temporal Response Fields
- Constraints on Neural Connectivity

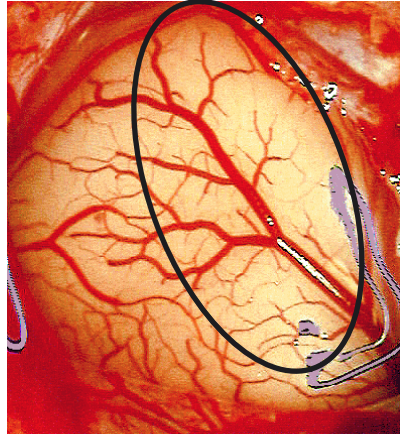
Basics

- **Most important auditory cues are acoustically non-trivial**
 - e.g. speech, speaker ID, emotional content, pitch, timbre, sound location, and many, many others
- **Enormous parallel and serial neural processing in multiple stages** from auditory nerve to cortex
- **Neural code is essentially unknown** for almost all auditory features
 - Especially in cortex
 - Much progress in coding near periphery, especially coding of sound location

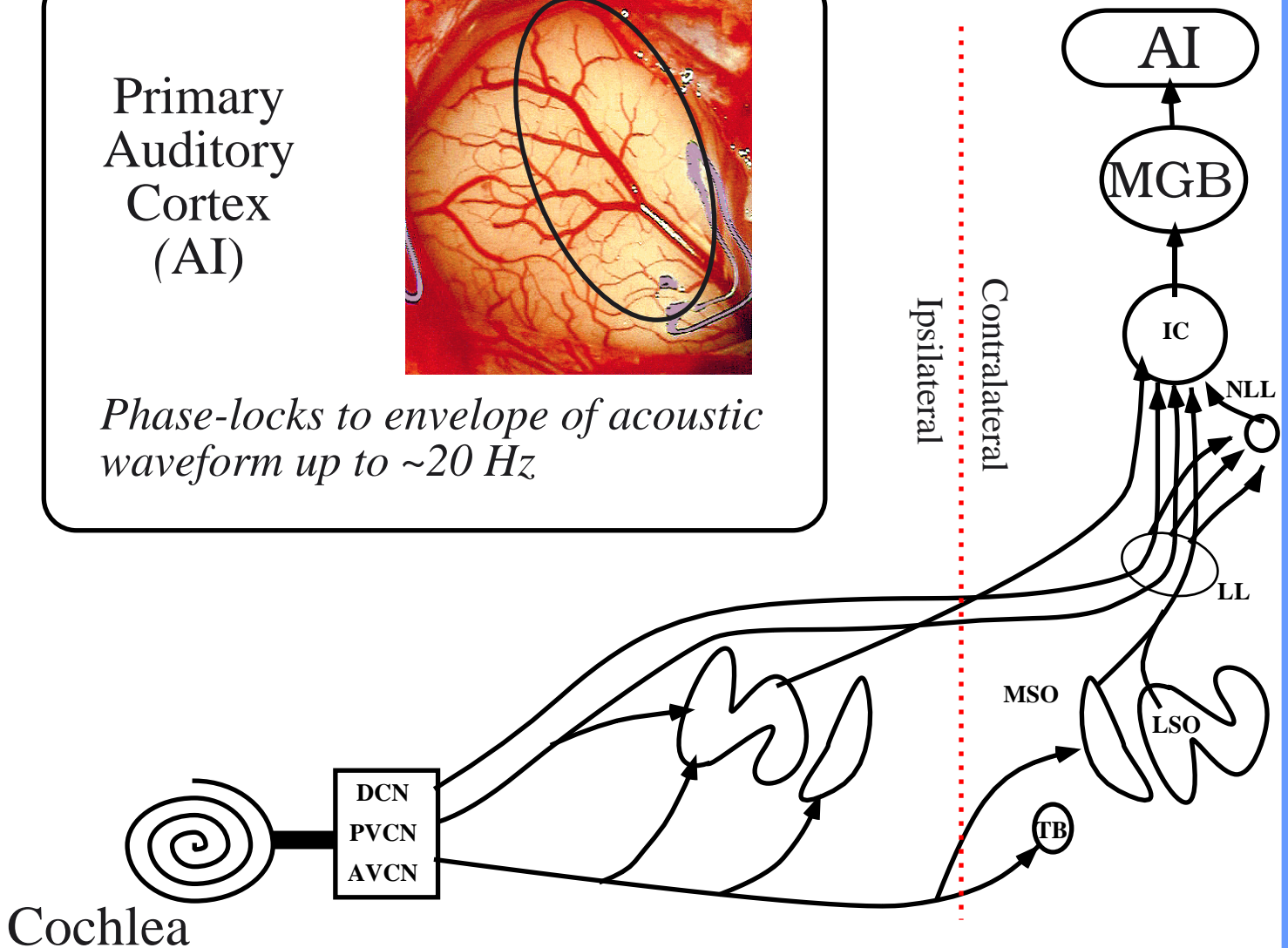
Auditory Pathway

(oversimplified)

Primary
Auditory
Cortex
(AI)



Phase-locks to envelope of acoustic waveform up to ~20 Hz



Linear distance $\sim \log f$

Phase-locks to acoustic waveform itself up to ~2 kHz

Motivation

- **The Quest**

Teasing out “function” of Primary Auditory Cortex (AI)

which sounds/features evoke responses?

$\approx \left\{ \begin{array}{l} \text{how are they encoded into spike trains?} \end{array} \right.$

- **Broadband and dynamic sounds**

- Evoke strong, sustained, dynamic responses in AI
- Many natural sounds, e.g. speech, backgrounds

- **Reasonable quest:** Quantitative measure of how spikes encode sound features

- Quantitative descriptor (and predictor)
- Qualitative descriptor/Visual tool

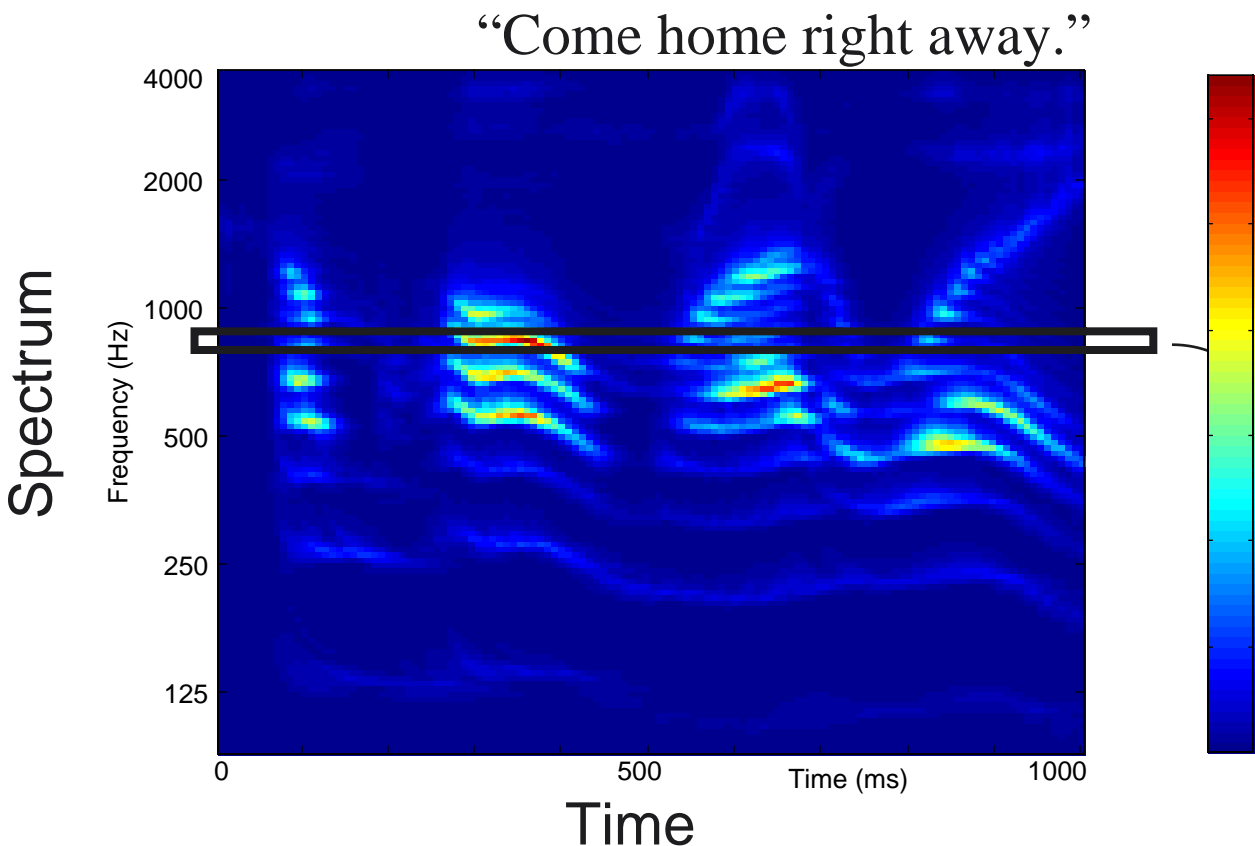
The Path

- **Compromise** from quantitative necessity
 - Restrict broadband and dynamic sounds to mathematically simple subset:
 - **Noise**—strongly modulated in **spectrum** and **time**
 - not a severe compromise
- **Spectro-Temporal Receptive Field (STRF)** succeeds:
 - Quantitative descriptor (and predictor)
 - Qualitative descriptor/Visual Tool
- **Bonus**
 - Constraints on Neural Connectivity

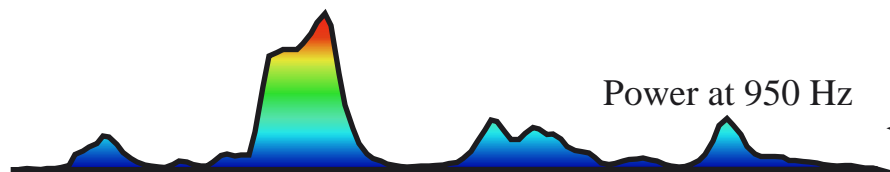
Sound Features

- Spectro-Temporal Features of Any Sound
- Spectral content of sound as a function of time.

Which spectral frequency bands have enhanced power?
Which spectral frequency bands have diminished power?
How do these change as a function of time?



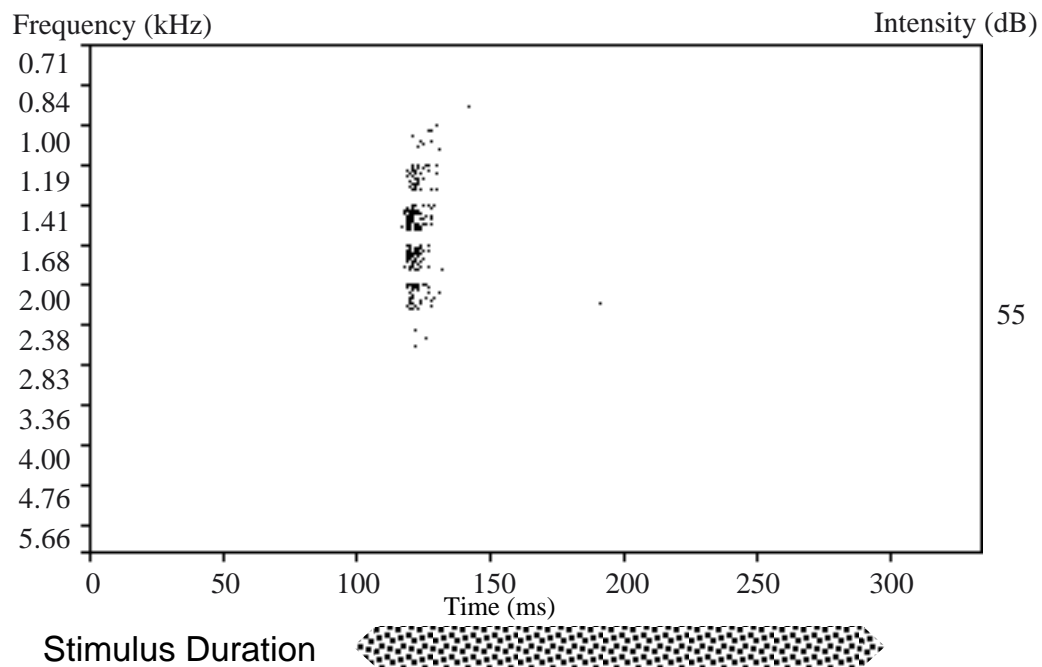
- $\log f \approx$ linear cochlear distance



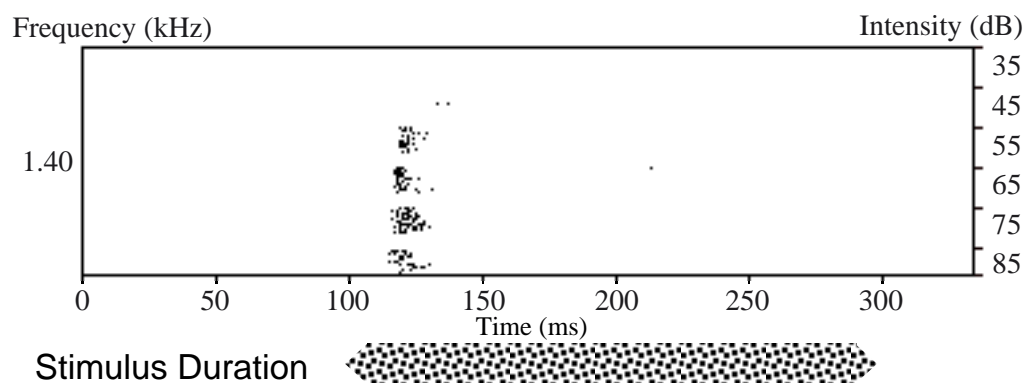
- Characterization from cross-section is limited

Response to Pure Tones

188/14a01.t1-.fea



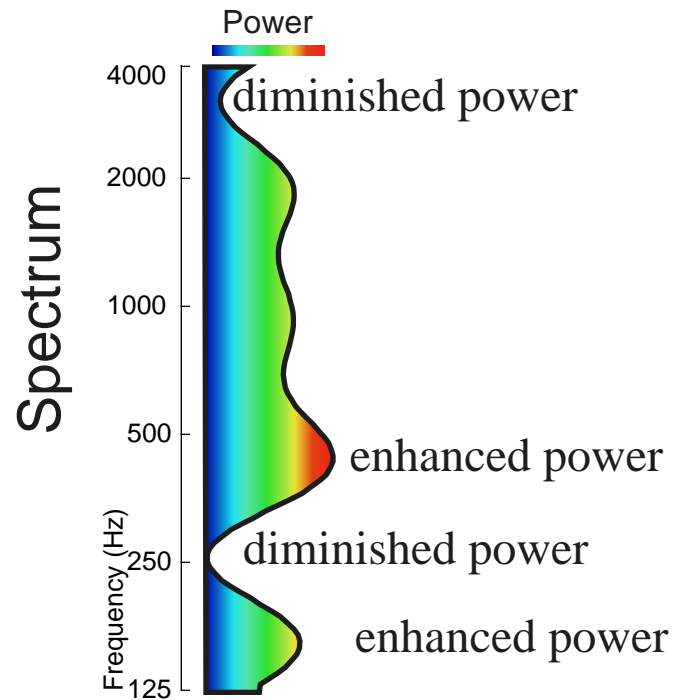
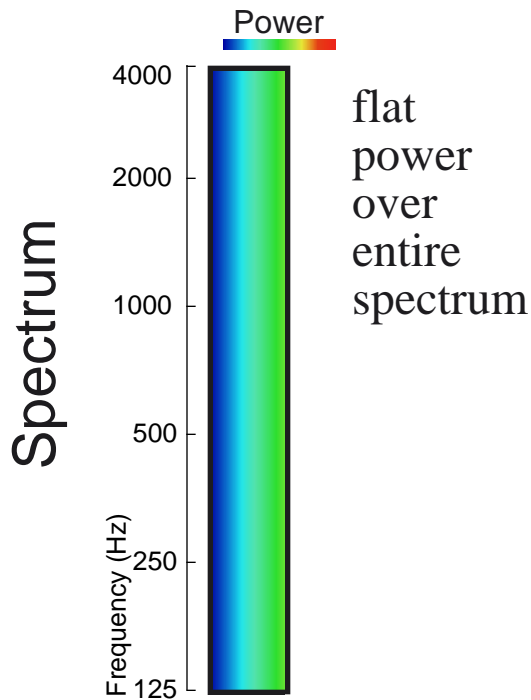
188/14a02.t11.fea



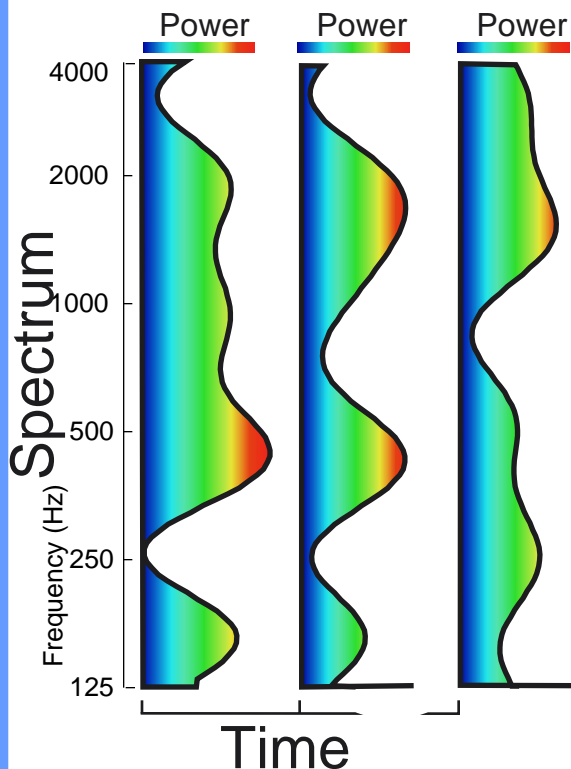
- Introduction to Auditory Spectro-Temporal Processing
- **Stimuli—Dynamic & Broadband: Ripples, Ripple Combinations**
- Examples & Properties of Spectro-Temporal Response Fields
- Constraints on Neural Connectivity

Stimulus Construction

- Pink Noise = flat power density in octaves ($\log f$)
not white
- *Unmodulated noise (flat)*
- *Spectrally modulated noise*

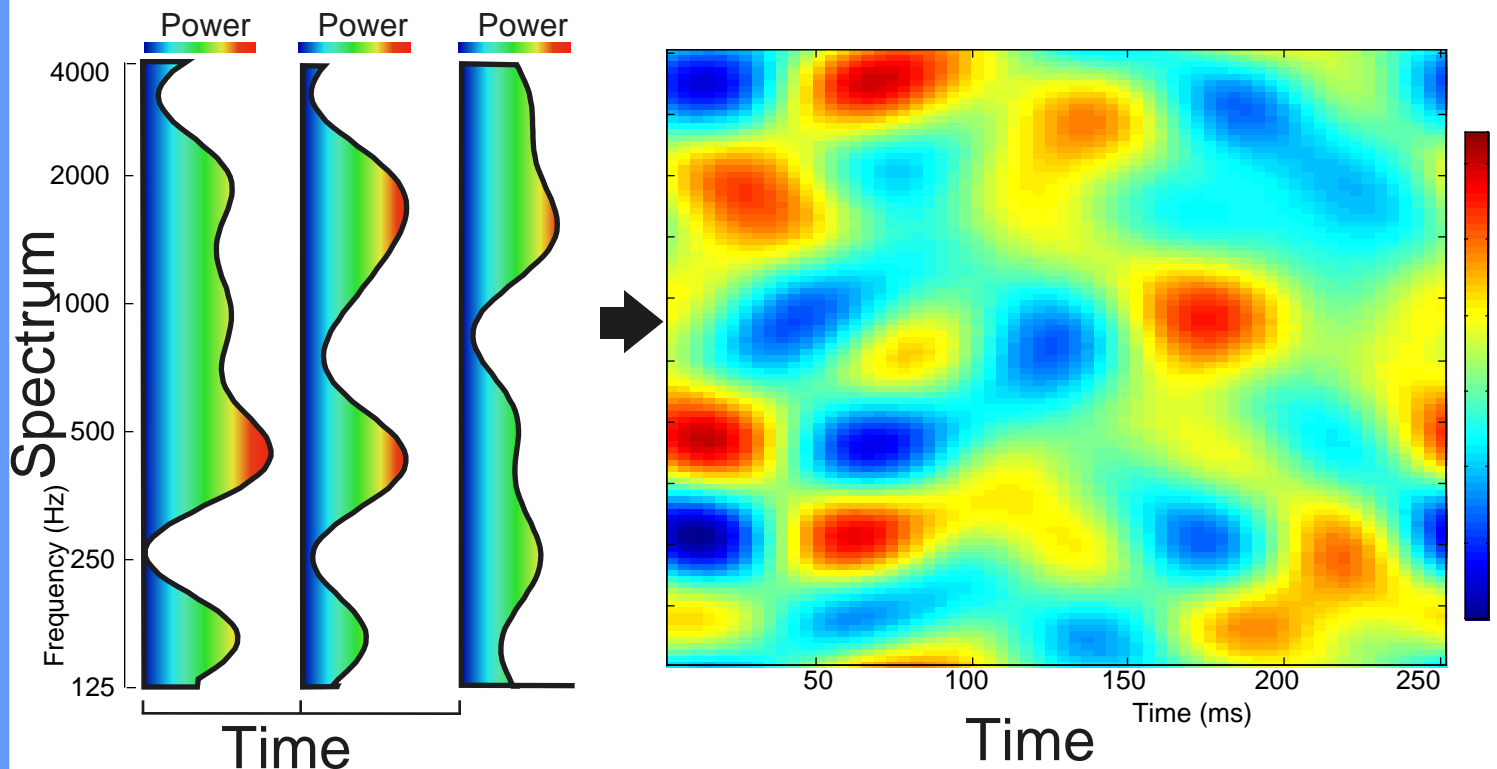


- *Spectro-Temporally modulated noise*



Stimulus Construction

- *Spectro-Temporally modulated noise*



Single Moving Ripple

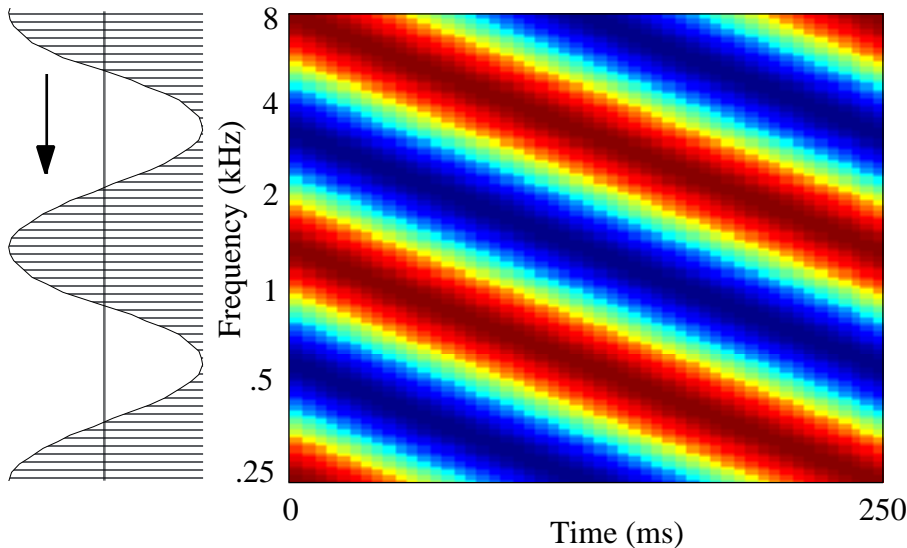
Simplest Dynamic
Stimulus Used

$$S(t,x) = \sin(2\pi w t + 2\pi \Omega x + \phi)$$

$$x = \log_2(f / f_0)$$

w = ripple velocity,
e.g. 4 Hz = 4 cycles/s

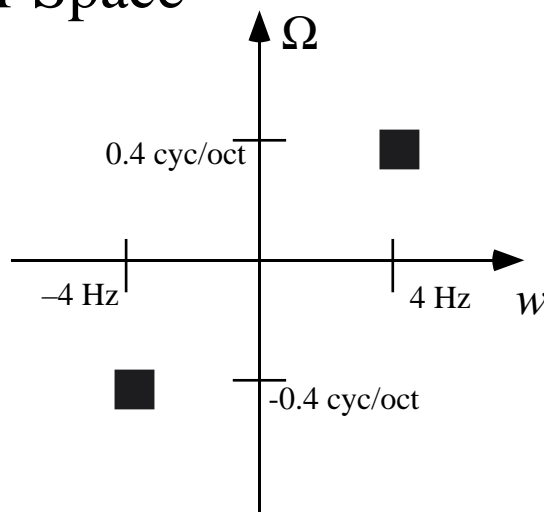
Ω = ripple density,
e.g. 0.4 cycles/octave
= 2 cycles/5 octaves



c.f. visual
contrast gratings

$$\int [.] \exp(\pm 2\pi j \Omega x \pm 2\pi j w t)$$

in Fourier Space



The Fourier transform
of a single moving
sinusoid has support
only on a single point
(and its complex
conjugate).

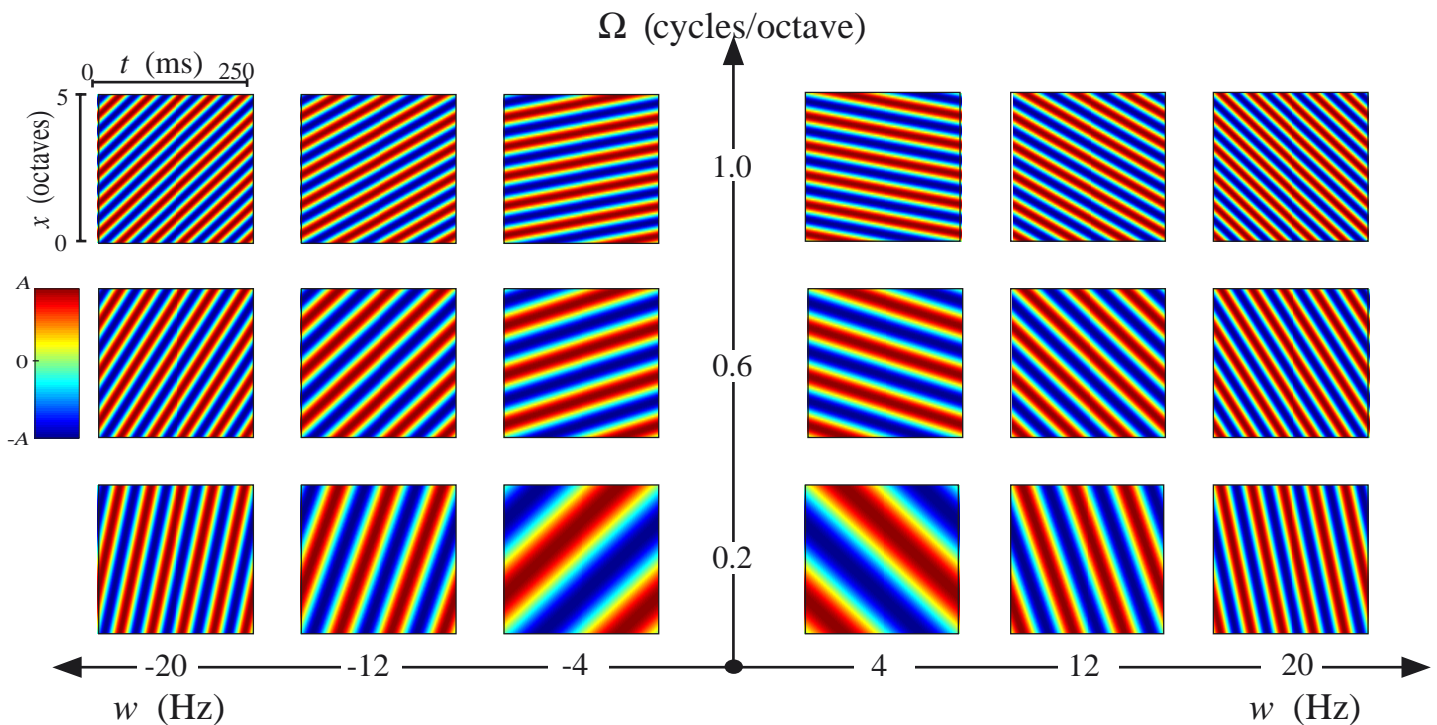
Multiple Individual Ripples

$$S(t,x) = \sin(2\pi w t + 2\pi \Omega x + \phi)$$

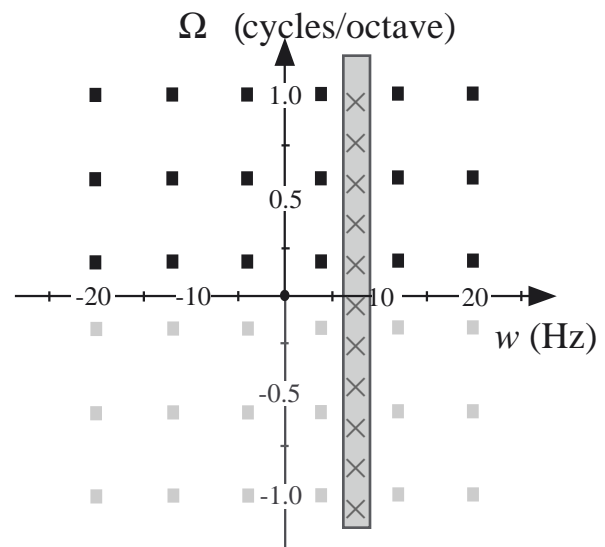
$$x = \log_2(f/f_0)$$

w = ripple velocity (Hz)

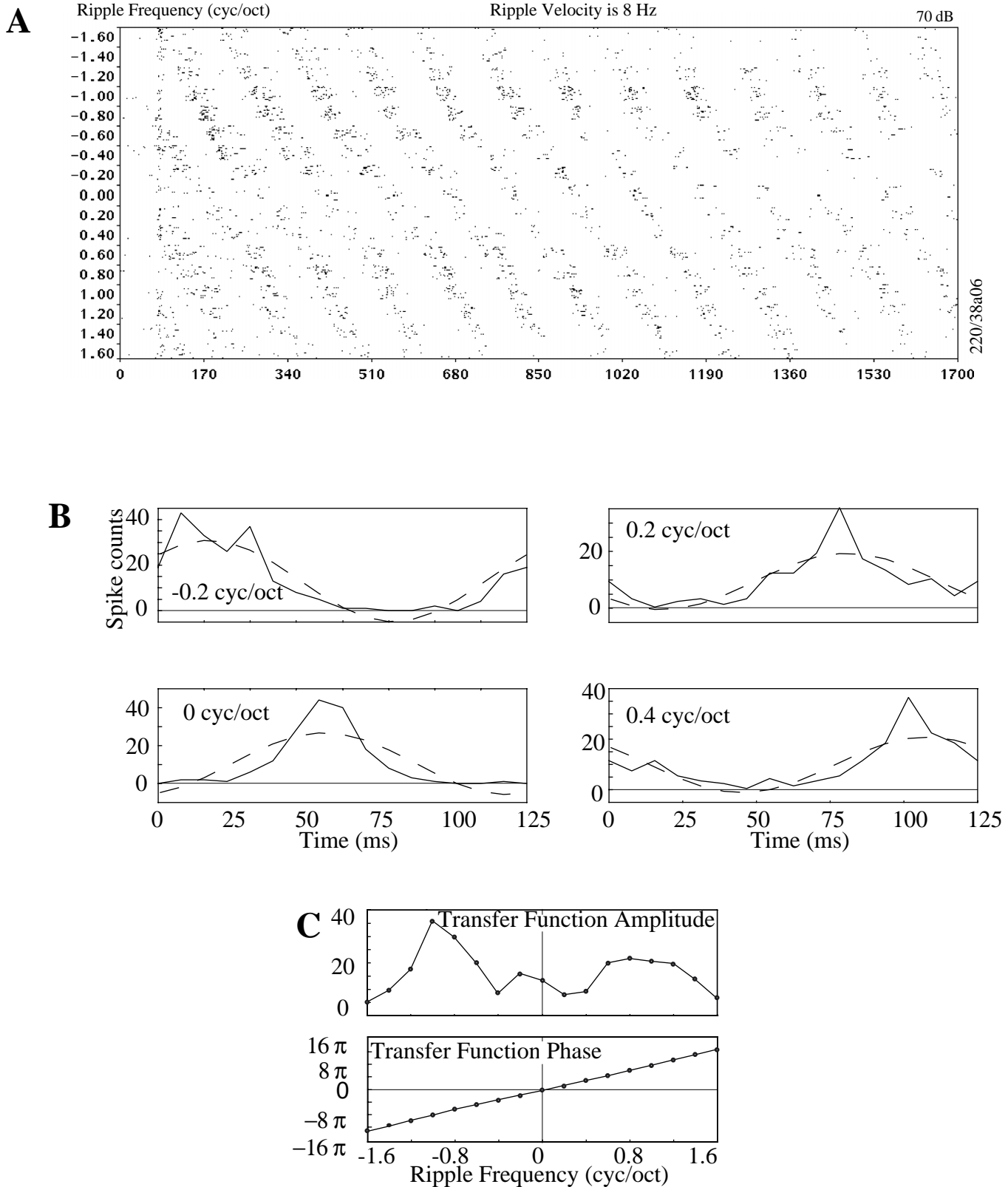
Ω = ripple density (cyc/oct)



The Transfer function can be obtained by measuring the amplitude and phase of the response to each single ripple.

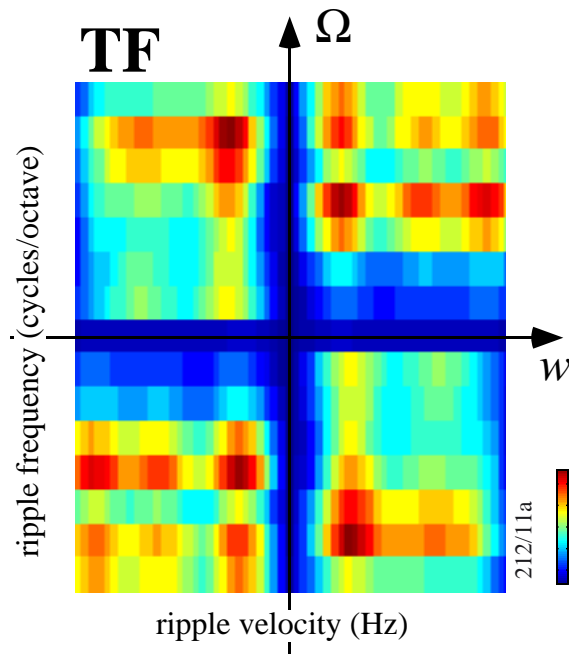


Spike Train Measurements



Spike events in (A) are turned into period histograms in (B).
The amplitudes and phases give the transfer function in (C).

Spectro-Temporal Response Field (STRF)



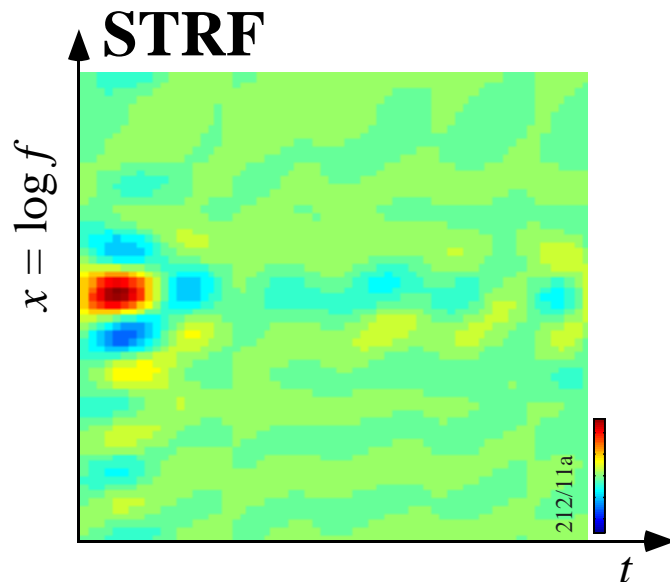
2 Dimensional Transfer Function

- Complex conjugate symmetric
- Spectral range:
~ 0 — ~ 2 cycle/octave
- Temporal range:
~ 2 — ~ 20 Hz

2 Dimensional Inverse
Fourier Transform

$$\int [.] \exp(\pm 2\pi j \Omega x \pm 2\pi j w t)$$

2 Dimensional
Fourier Transform

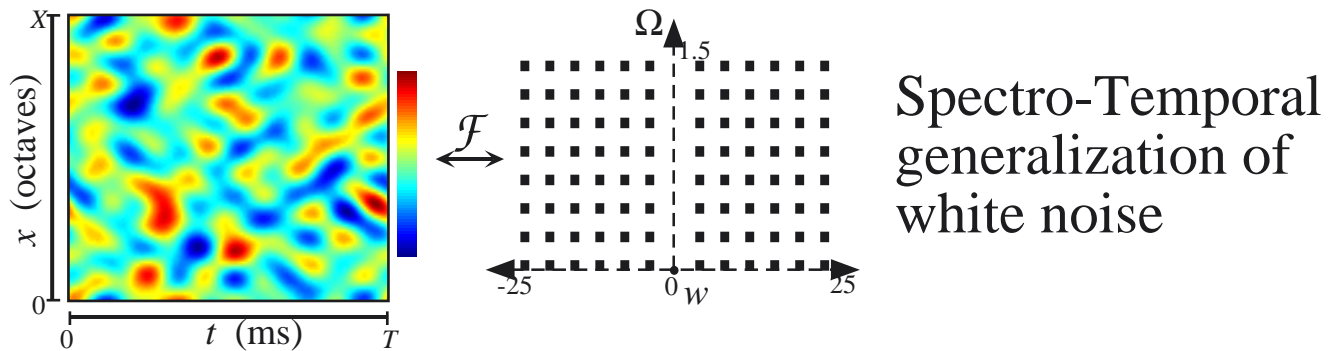


Spectro-Temporal
Response Function
of the same neuron

Spectro-Temporal Noise

To speed up the characterization of a cell's response, we use combinations of ripples of *all* velocities w and densities Ω , with random phases.

$$S^{\text{noise}}(t, x) = \sum_j \sum_k \sin(2\pi w_j t + 2\pi \Omega_k x + \phi_{j,k})$$



$$\text{Cross-Correlation: } C(\tau, x) = \frac{1}{T} \int_0^T S(t, x) R(t - \tau) dt = \frac{1}{T} \sum_k S(t_k - \tau, x)$$

= Spike-Triggered Average

- $C(\tau, x)$ contains cross terms
- Cross terms have random phase and can be attenuated by averaging over multiple, random-phase stimuli S_j

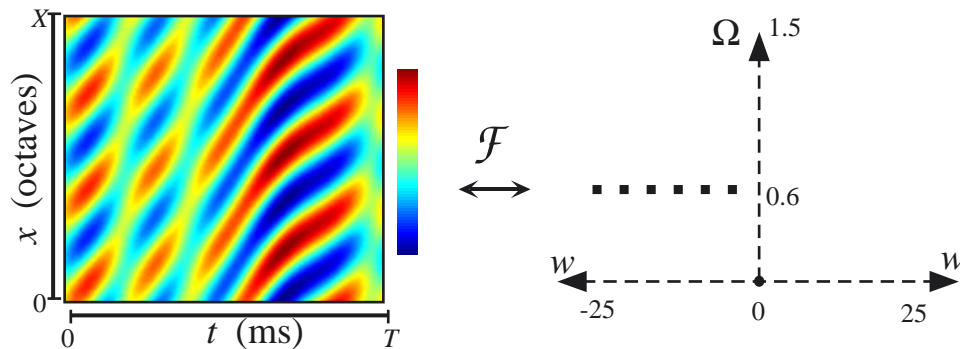
$$\text{STRF}_{\text{est}}(\tau, x) = \frac{1}{m} \sum_{j=1}^m C_j(-\tau, x)$$

- Cross terms give noisy estimates without many random-phase stimuli

Temporally Orthogonal Ripple Combinations (TORCs)

To eliminate interference from cross-terms, we use specific combinations of ripples with differing velocities w and random phases.

$$S^{\text{TORC}}(t, x) = \sum_j \sin(2\pi w_j t + 2\pi \Omega_k x + \phi_{j,k})$$



- Stimuli have unique instances of each ripple velocity.
- Multiple stimuli are still needed to present a complete set of ripples.

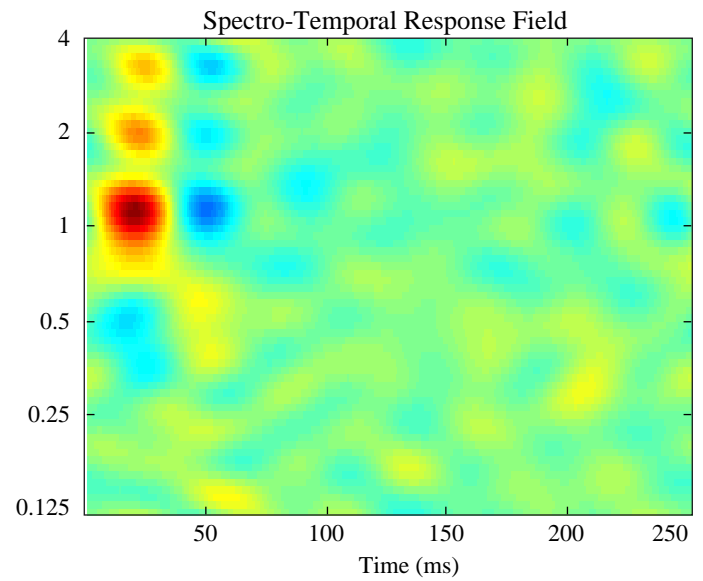
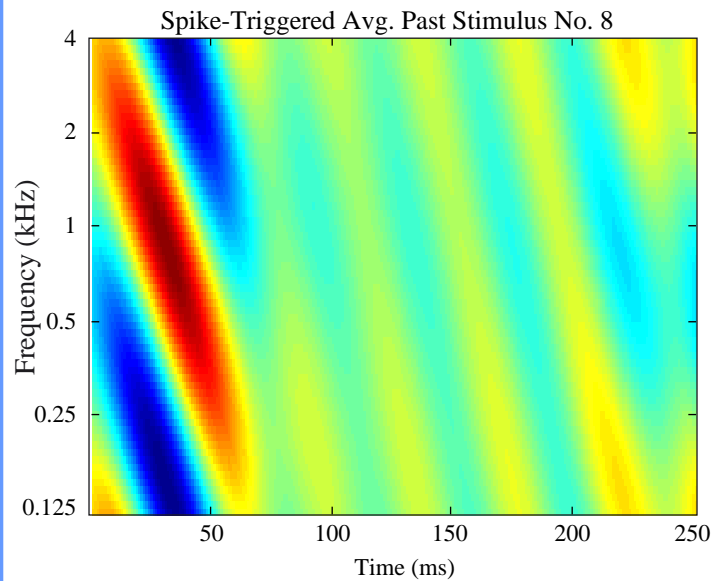
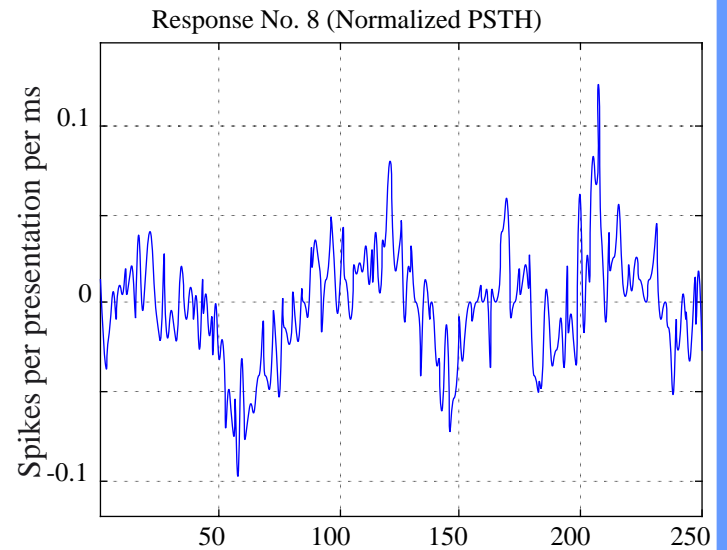
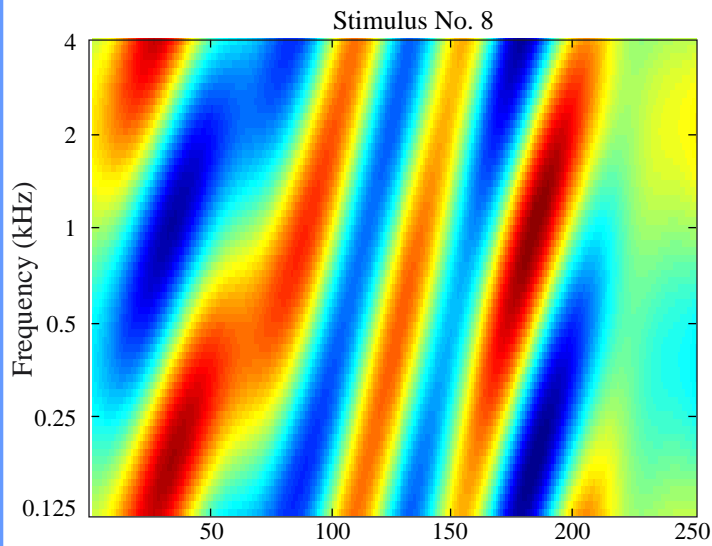
$$\text{Cross-Correlation: } C(\tau, x) = \frac{1}{T} \int_0^T S(t, x) R(t - \tau) dt = \frac{1}{T} \sum_k S(t_k - \tau, x)$$

= Spike-Triggered Average

- $C(\tau, x)$ contains no cross terms

$$\text{STRF}_{\text{est}}(\tau, x) = \sum_{j=1}^m C_j(-\tau, x)$$

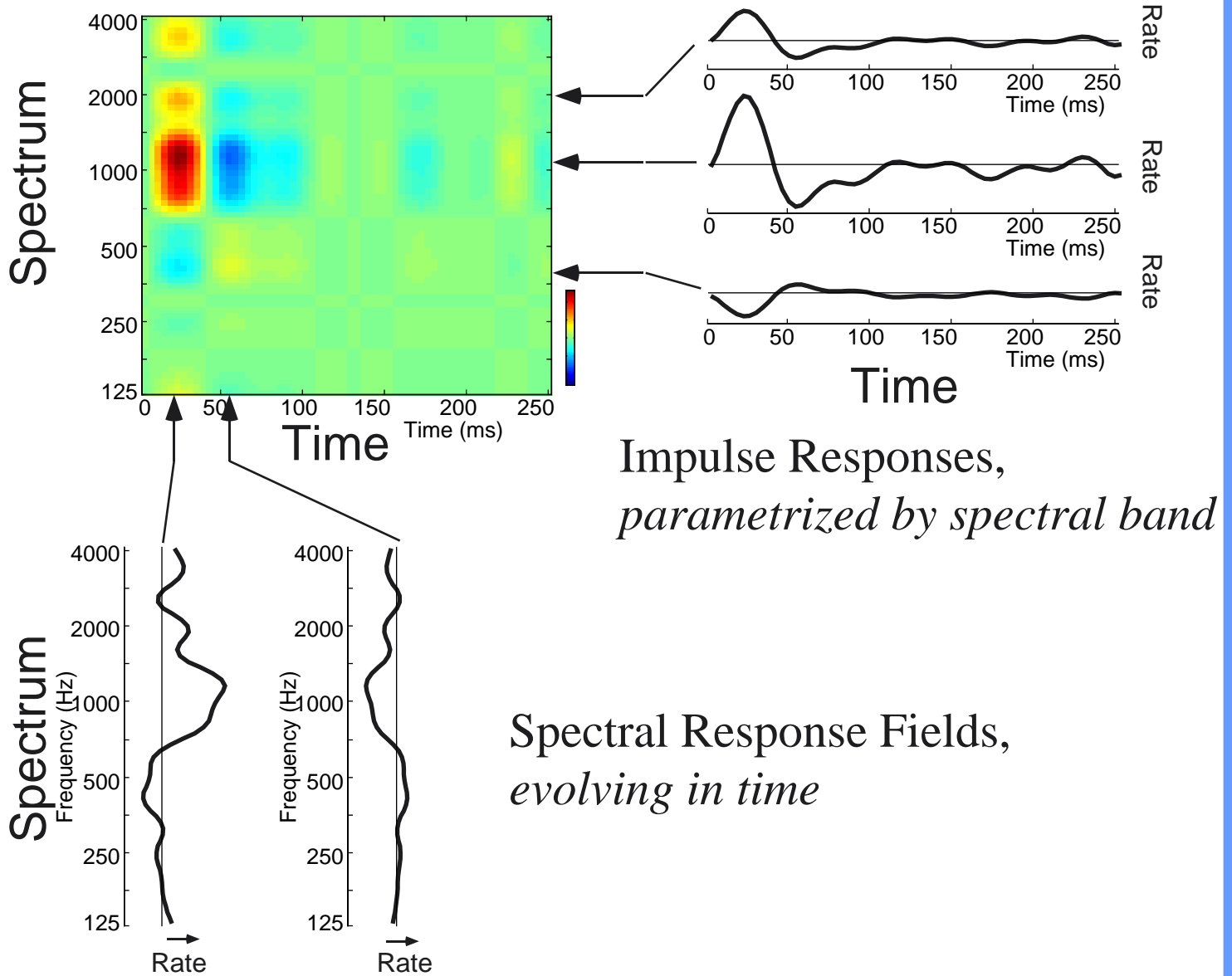
Spike Averaged Data



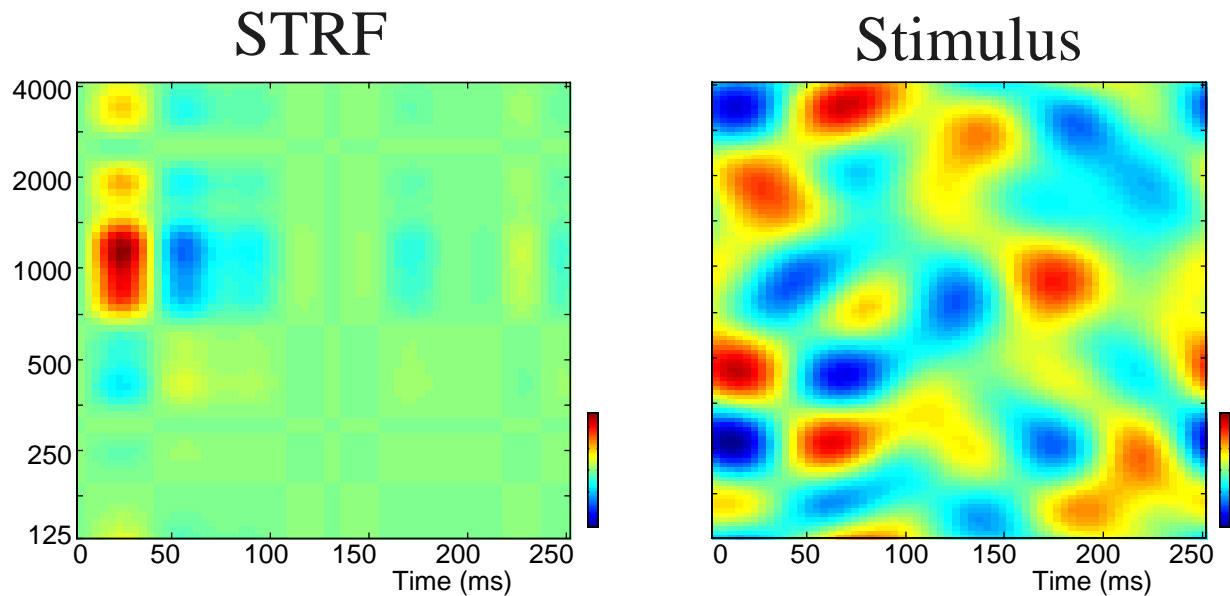
- Introduction to Auditory Spectro-Temporal Processing
- Stimuli—Dynamic & Broadband: Ripples, Ripple Combinations
- **Examples & Properties of Spectro-Temporal Response Fields**
- Constraints on Neural Connectivity

Interpreting STRFs

Cross-section interpretations



Interpreting STRFs



Stimulus Effect on Rate

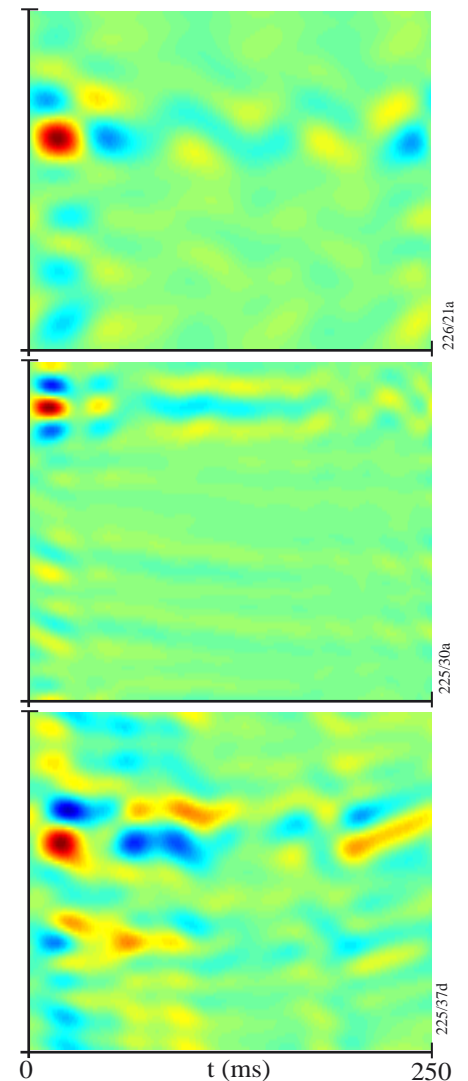
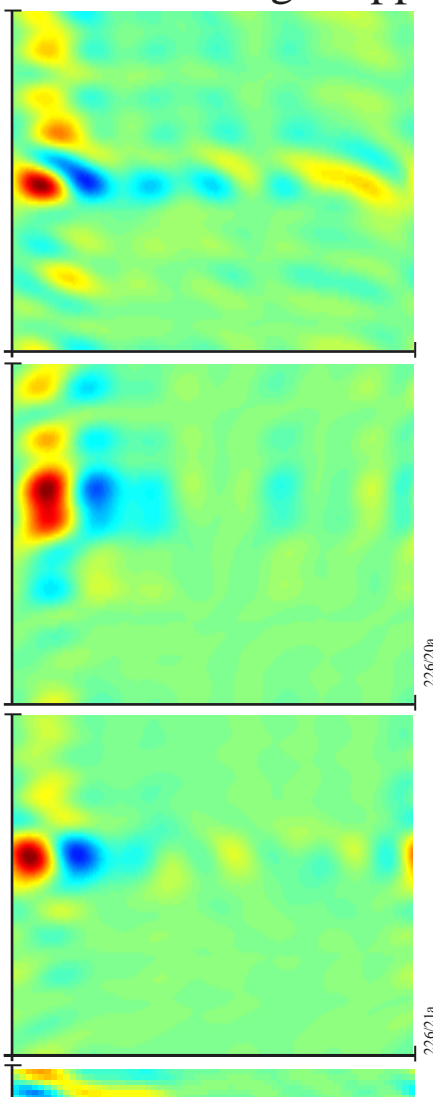
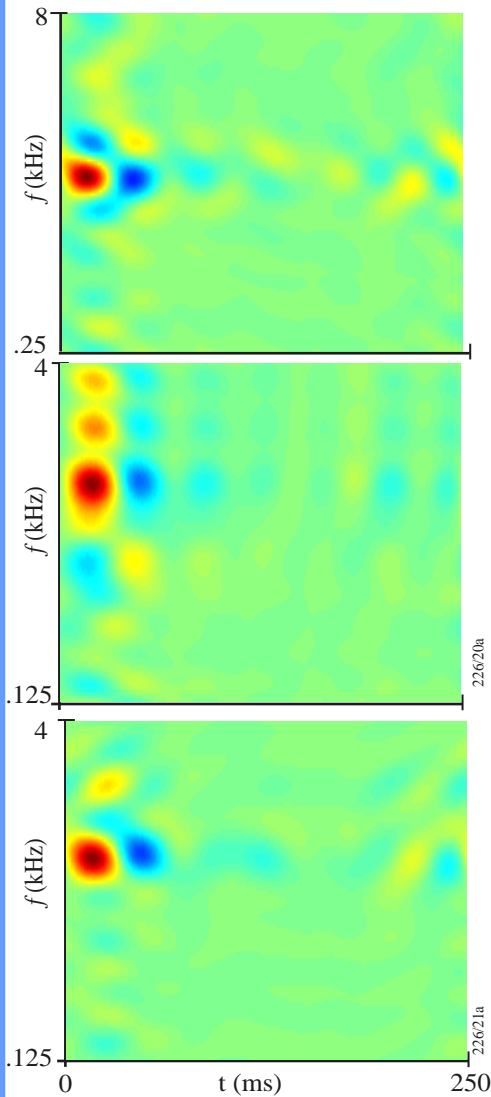
STRF region	Stimulus Power	Spike rate contribution
Excitatory ●	Enhanced ●	Faster ⌋⌋⌋⌋⌋
Inhibitory ●	Enhanced ●	Slower ⌋ ⌋
Excitatory ●	Diminished ●	Slower ⌋ ⌋
Inhibitory ●	Diminished ●	Faster (!) ⌋ ⌋⌋⌋⌋

STRFs Compared

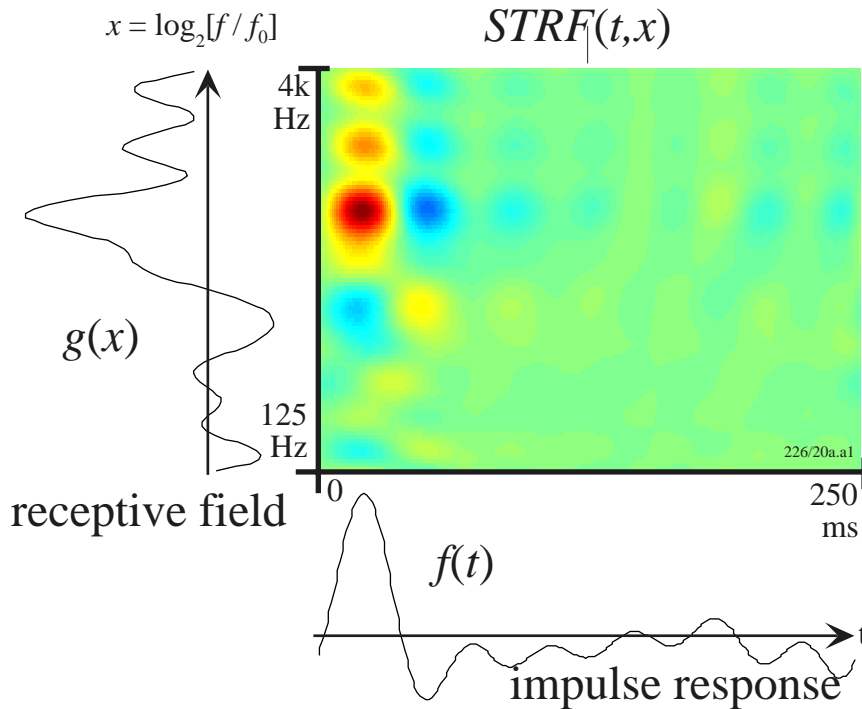
STRF from TORCs

STRF from single ripples

STRF from Spectro-Temporal Noise



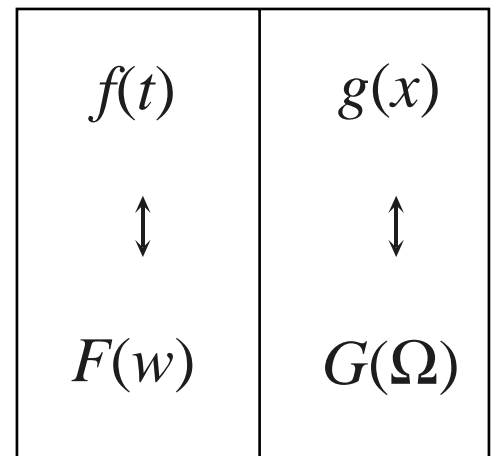
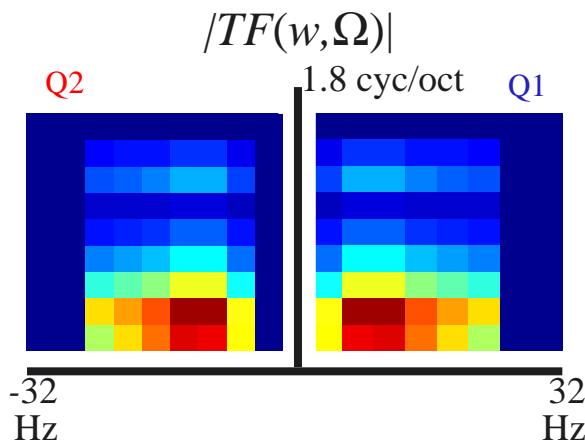
Full Separability



The STRF is a simple product of a single spectral response function with a single temporal response function.

$$STRF(t, x) = f(t) g(x)$$

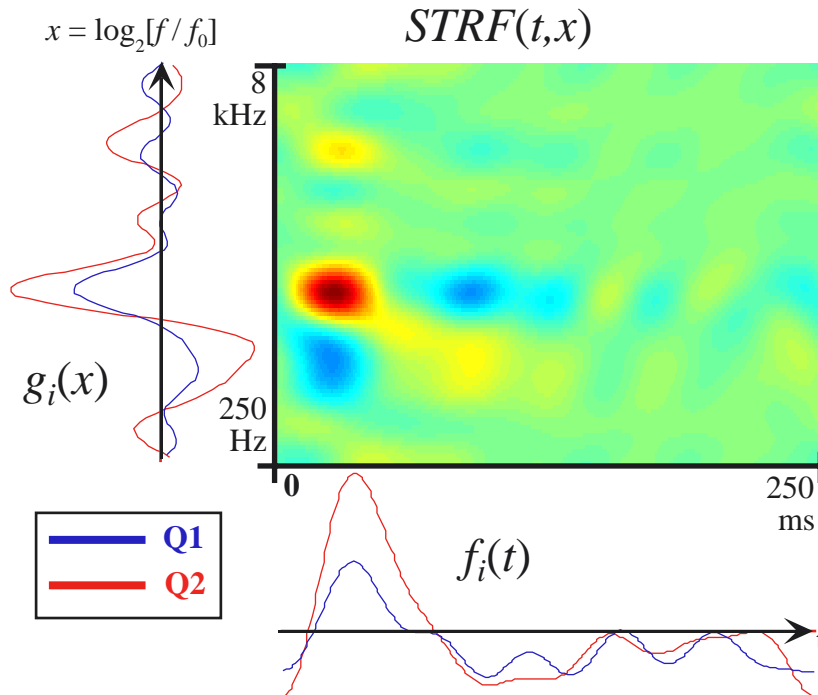
$$|\mathcal{F}\{ \} | \updownarrow$$



$$TF(w, \Omega) = F(w) G(\Omega)$$

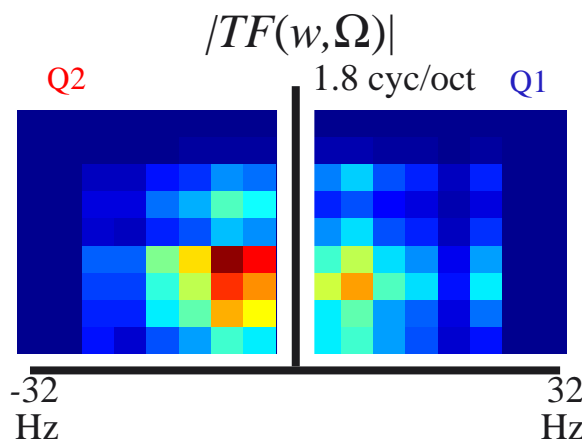
Therefore the TF is also a simple product

Quadrant Separability



The STRF is not separable, but each quadrant of the transfer function is, i.e., there are different spectral and temporal responses for upwards and downwards frequency modulation.

$$|\mathcal{F}\{\cdot\}| \updownarrow$$



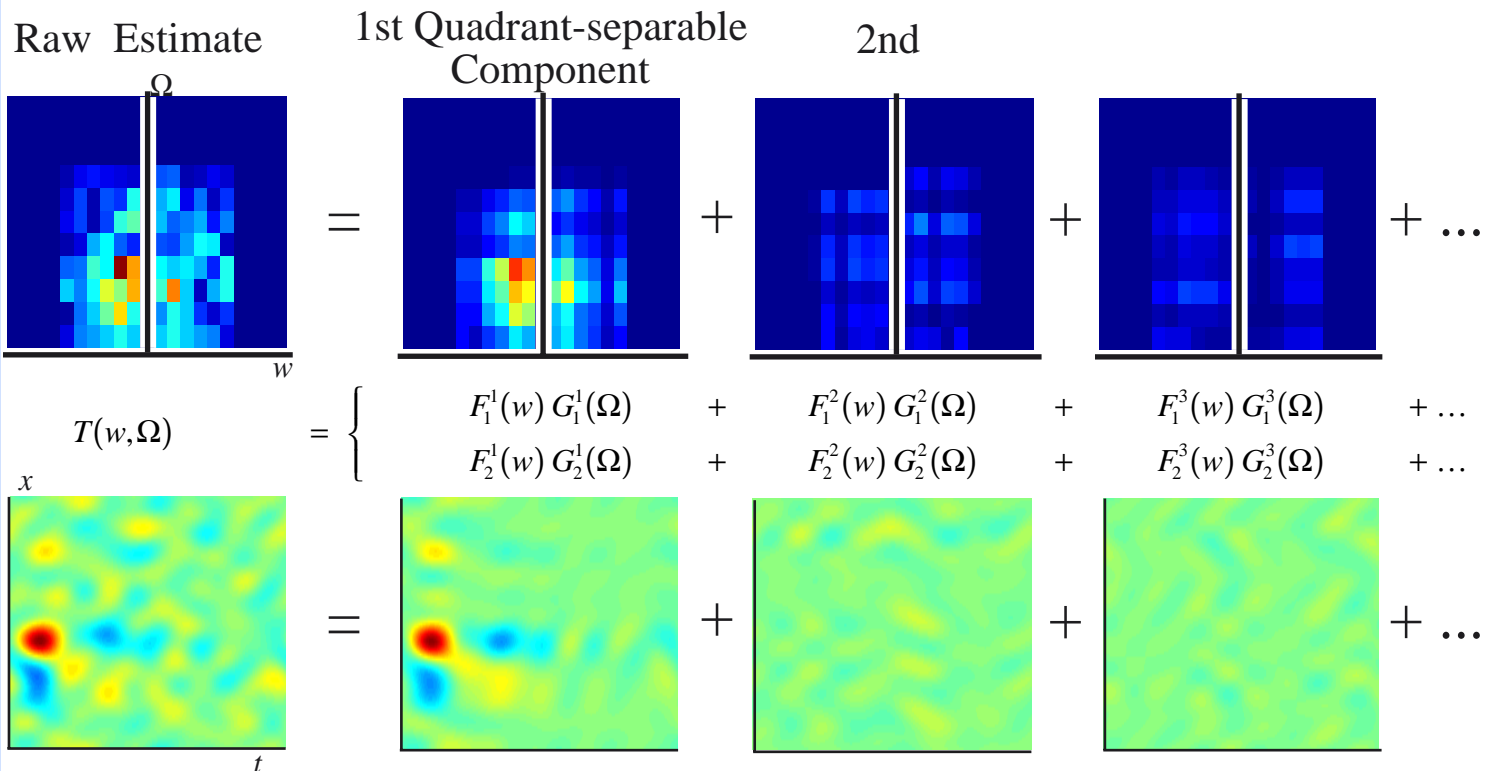
$f_i(t)$	$g_i(x)$
\updownarrow	\updownarrow
$F_i(w)$	$G_i(\Omega)$

$$T(w, \Omega) = \begin{cases} F_1(w) G_1(\Omega) & w > 0, \Omega > 0 \\ F_2(w) G_2(\Omega) & w < 0, \Omega > 0 \end{cases}$$

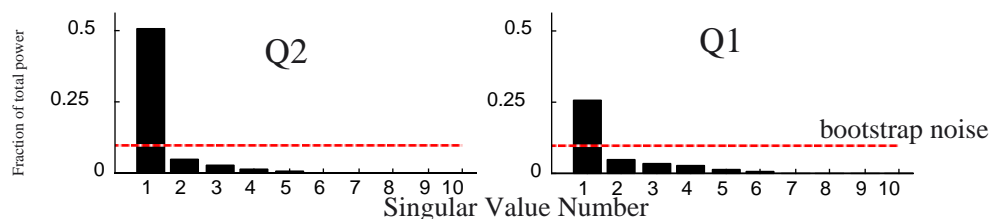
$$\text{for } \Omega > 0: T(w, \Omega) = T^*(-w, -\Omega)$$

Measuring Separability with SVD

- Singular Value Decomposition (SVD) can be used to estimate the separability of a Transfer Function (possibly corrupted by noise). It decomposes the Transfer Function into a sum of Quadrant Separable Transfer Functions, ordered by their power.
- Large jumps in the singular values separate signal from noise (& straddle bootstrap estimate of noise).



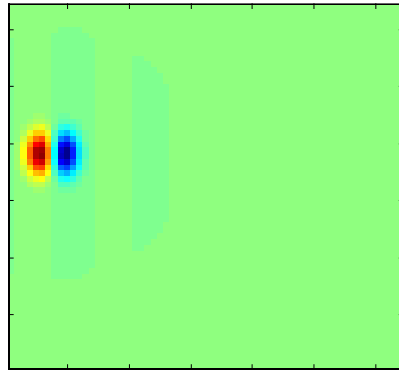
All units measured in AI are quadrant separable (or fully separable).



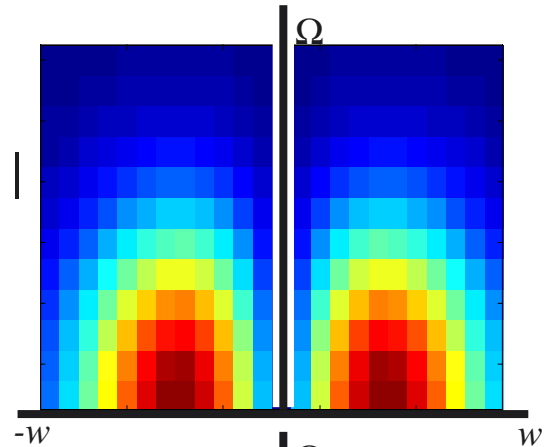
- Introduction to Auditory Spectro-Temporal Processing
- Stimuli—Dynamic & Broadband: Ripples, Ripple Combinations
- Examples & Properties of Spectro-Temporal Response Fields
- **Constraints on Neural Connectivity**

Separability Examples

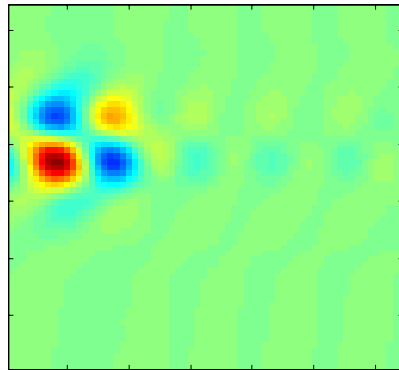
Fully
Separable



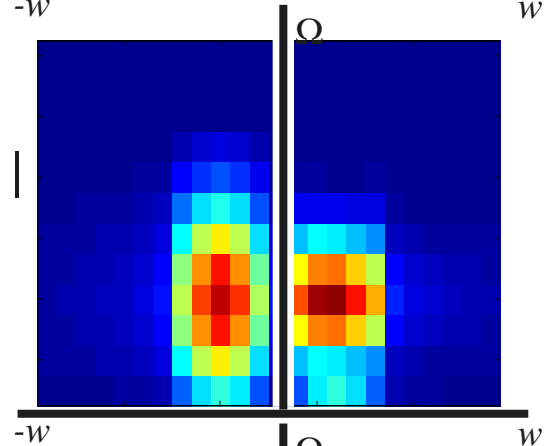
$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow



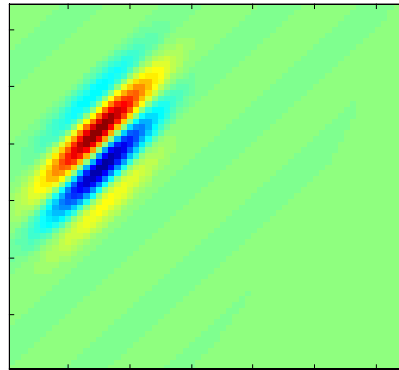
Quadrant
Separable



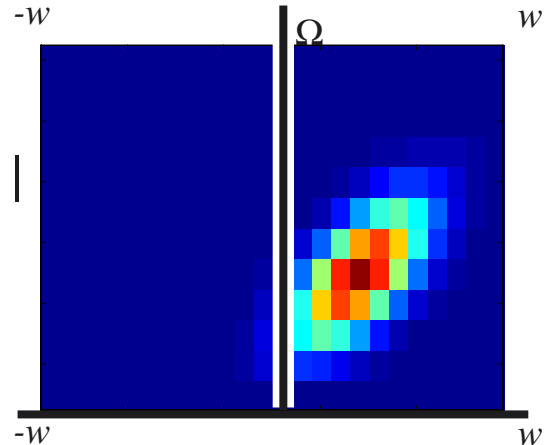
$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow



Velocity
Selective
is
Inseparable



$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow

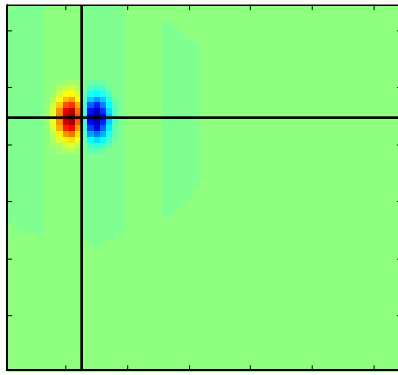


Quadrant
separability is
incompatible
with velocity
selectivity.

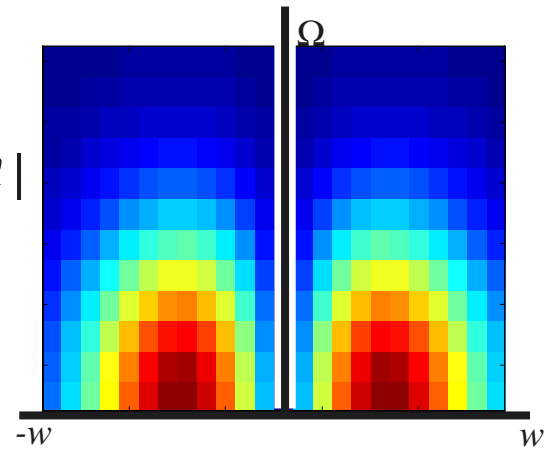
Simulation

Separability Counterexample

Fully
Separable
Input

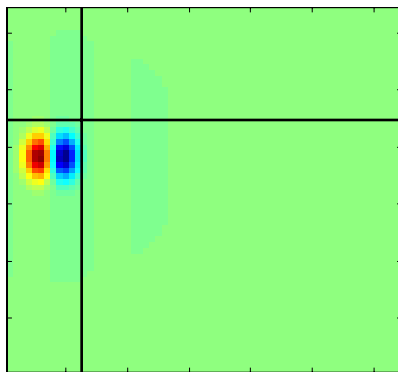


$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow

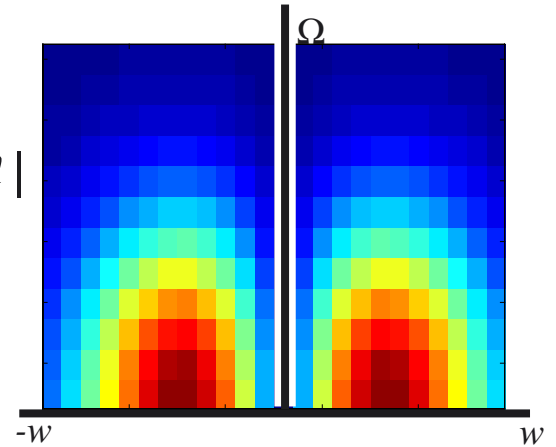


+

Fully
Separable
(displaced)
Input

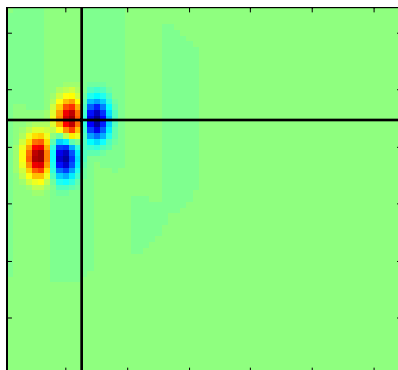


$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow

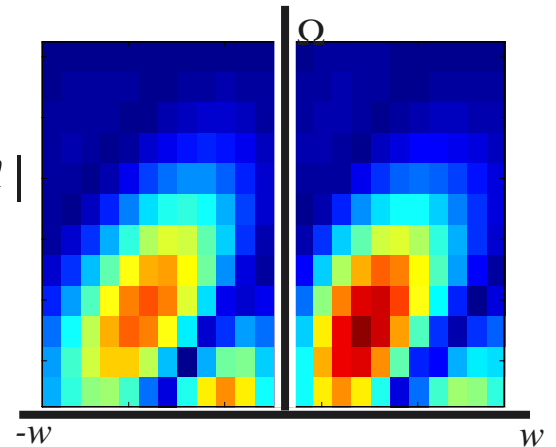


=

Sum of two
Fully
Separable
Inputs is
Inseparable



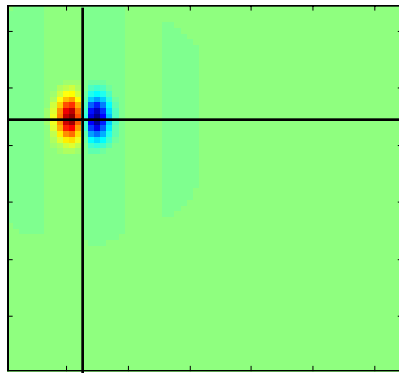
$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow



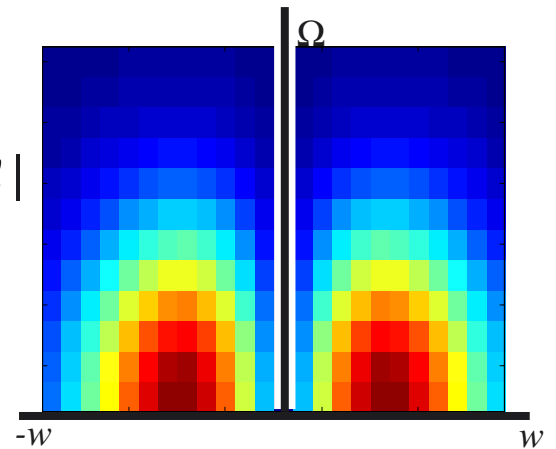
Naive sum of two fully separable
input STRFs is inseparable.

Separability Example

Fully
Separable
Input

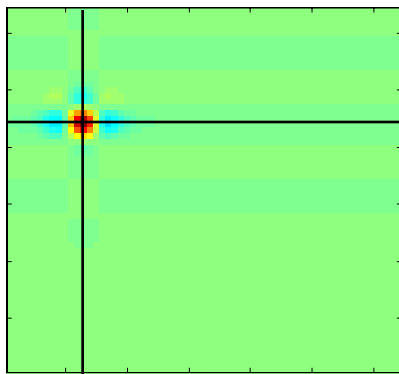


$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow

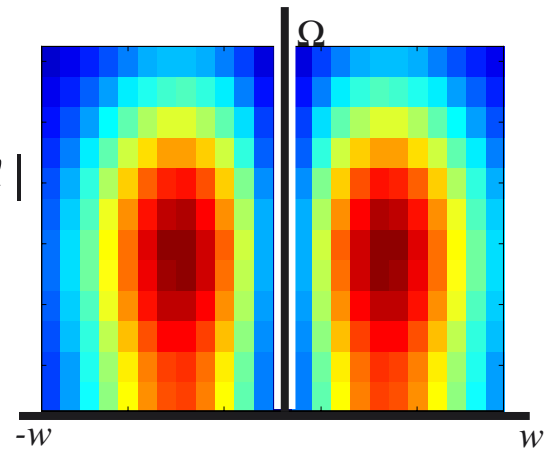


+

Same Fully
Separable
but Lagged
(& shifted
spectrally)
Input

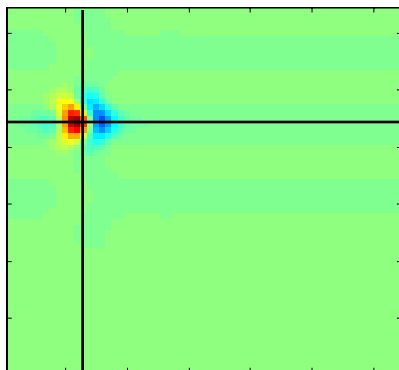


$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow

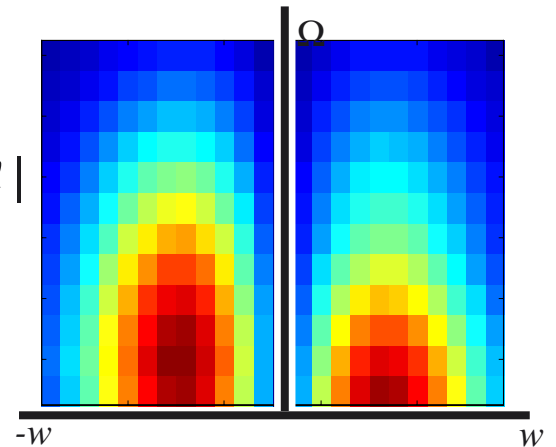


=

Sum of
Non-Lagged
and Lagged
Inputs is
Separable



$|\mathcal{F}\{\cdot\}|$
 \longleftrightarrow



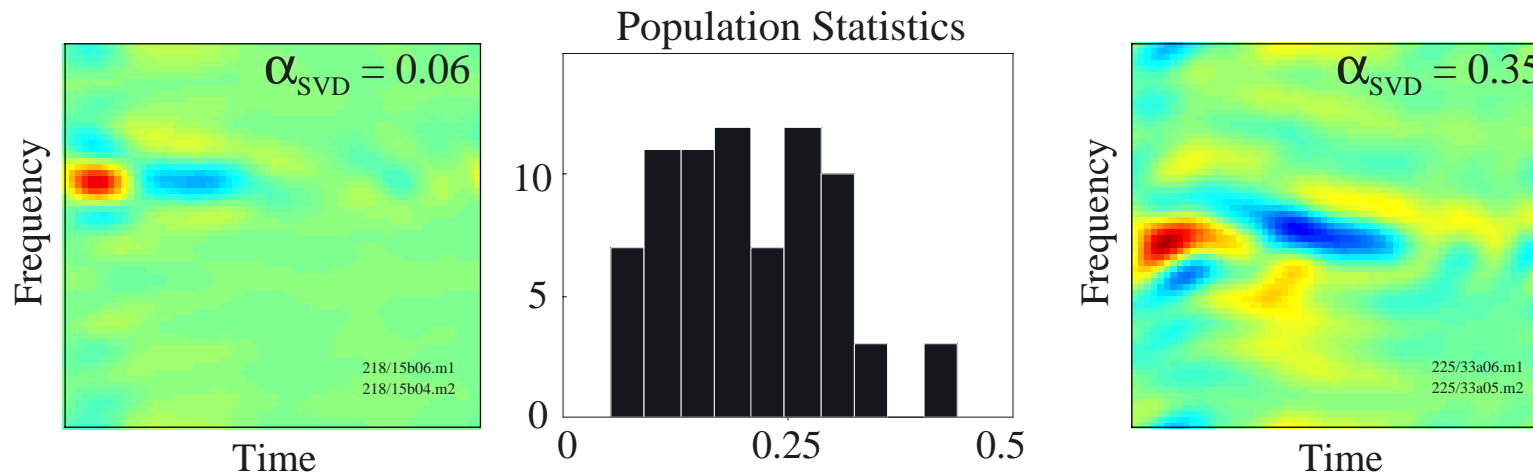
Sum of two fully separable input STRFs is separable if the temporal processing is in quadrature.

Measure of Separability

- SVD supplies a natural measure of separability, α_{SVD}

$$\alpha_{\text{SVD}} = \left(1 - \frac{\lambda_1^2}{\sum_i \lambda_i^2} \right)$$

- $\alpha_{\text{SVD}} \approx 0$ is fully separable
- $\alpha_{\text{SVD}} > 0.3$ is strongly inseparable



Symmetry by Power

- α_d : Power asymmetry breaks full separability, producing quadrant separability

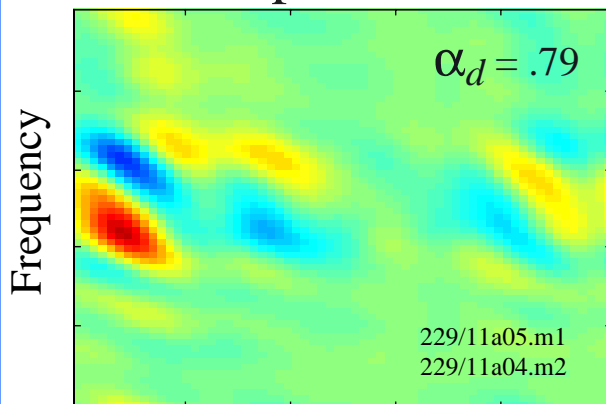
$$\alpha_d = (P_1 - P_2)/(P_1 + P_2)$$

$$P_1 = (\text{Power in quadrant 1}) = (\lambda_1)^2$$

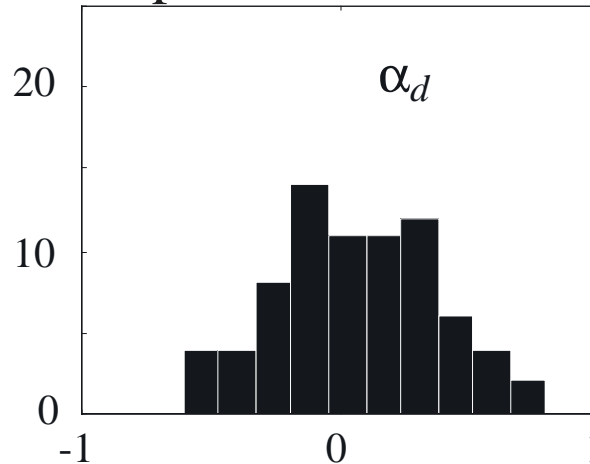
$$P_2 = (\text{Power in quadrant 2}) = (\lambda_2)^2$$

- $\alpha_d \approx 0$ is symmetric in power
- $|\alpha_d| > 0.3$ is quite asymmetric in power—strongly inseparable

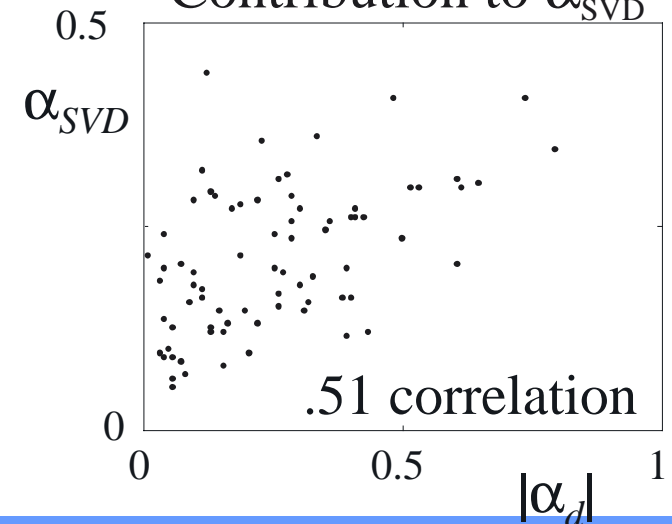
Example STRF



Population Statistics



Contribution to α_{SVD}



Spectral Symmetry

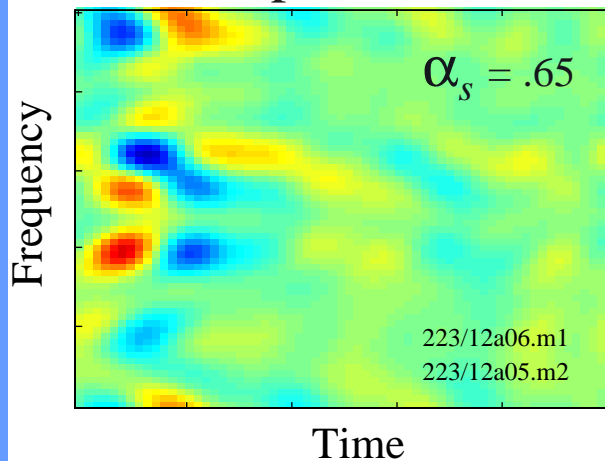
- α_s : Asymmetry between spectral cross-sections $G_i(\Omega)$:

$$\alpha_s = 1 - \frac{\left| \sum_{\Omega > 0} G_1(\Omega) G_2^*(\Omega) \right|}{\sqrt{\sum_{\Omega > 0} |G_1(\Omega)|^2 |G_2(\Omega)|^2}}$$

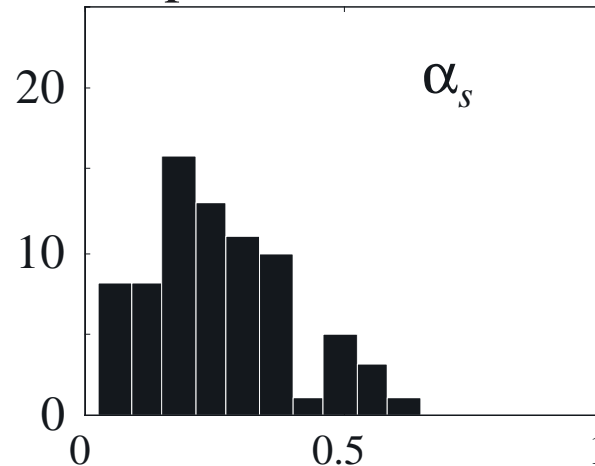
where the quantity inside the big absolute value bars is the (complex) correlation between $G_1(\Omega)$ and $G_2(\Omega)$

- $\alpha_s \approx 0$ is spectrally symmetric
- $\alpha_s > 0.3$ is spectrally asymmetric—strongly inseparable

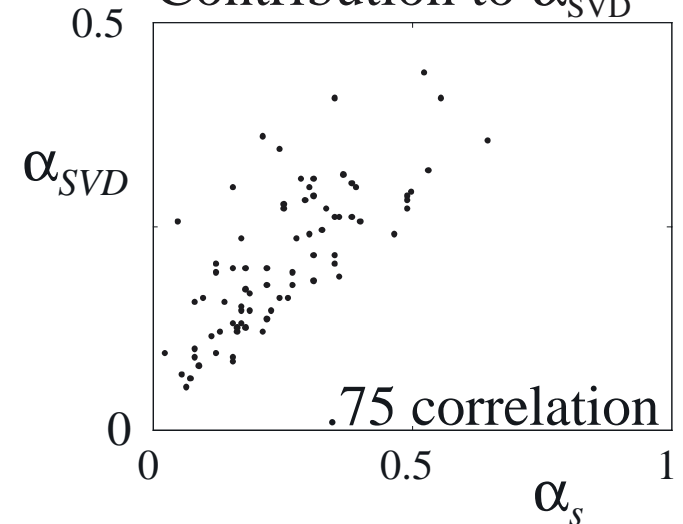
Example STRF



Population Statistics



Contribution to α_{SVD}



Temporal Symmetry

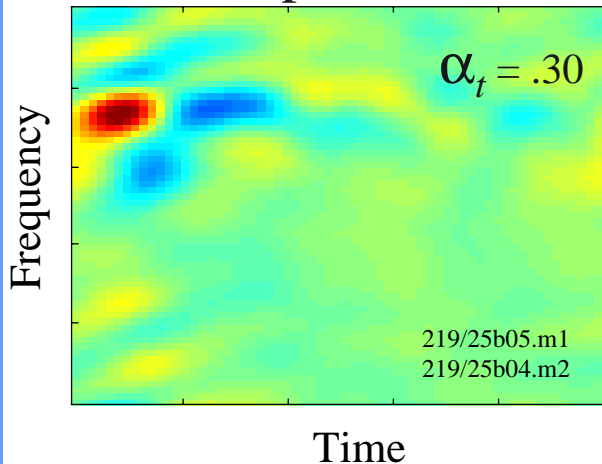
- α_t : Asymmetry between temporal cross-sections $F_i(w)$:

$$\alpha_t = 1 - \left| \frac{\sum_{w>0} F_1(w) F_2(-w)}{\sqrt{\sum_{w>0} |F_1(w)|^2 |F_2(-w)|^2}} \right|$$

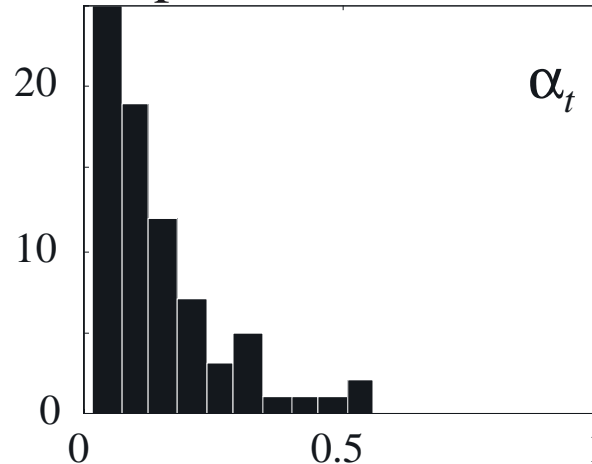
where the quantity inside the big absolute value bars is the (complex) correlation between $F_1(w)$ and $F_2^*(-w)$

- $\alpha_t \approx 0$ is temporally symmetric
- $\alpha_t > 0.3$ is temporally asymmetric—strongly inseparable

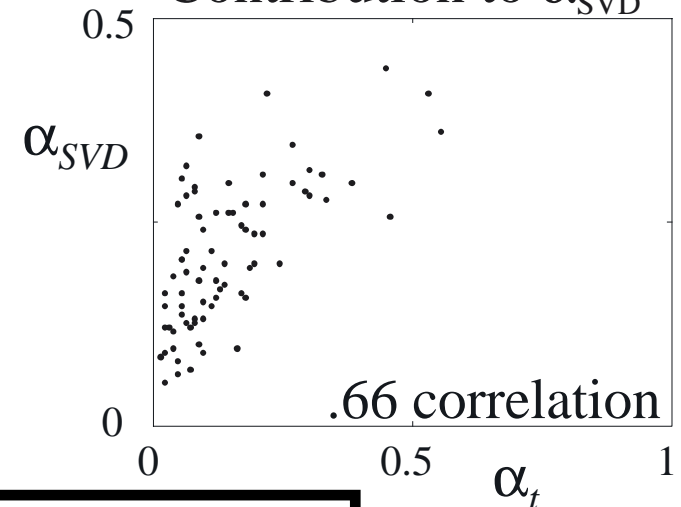
Example STRF



Population Statistics



Contribution to α_{SVD}

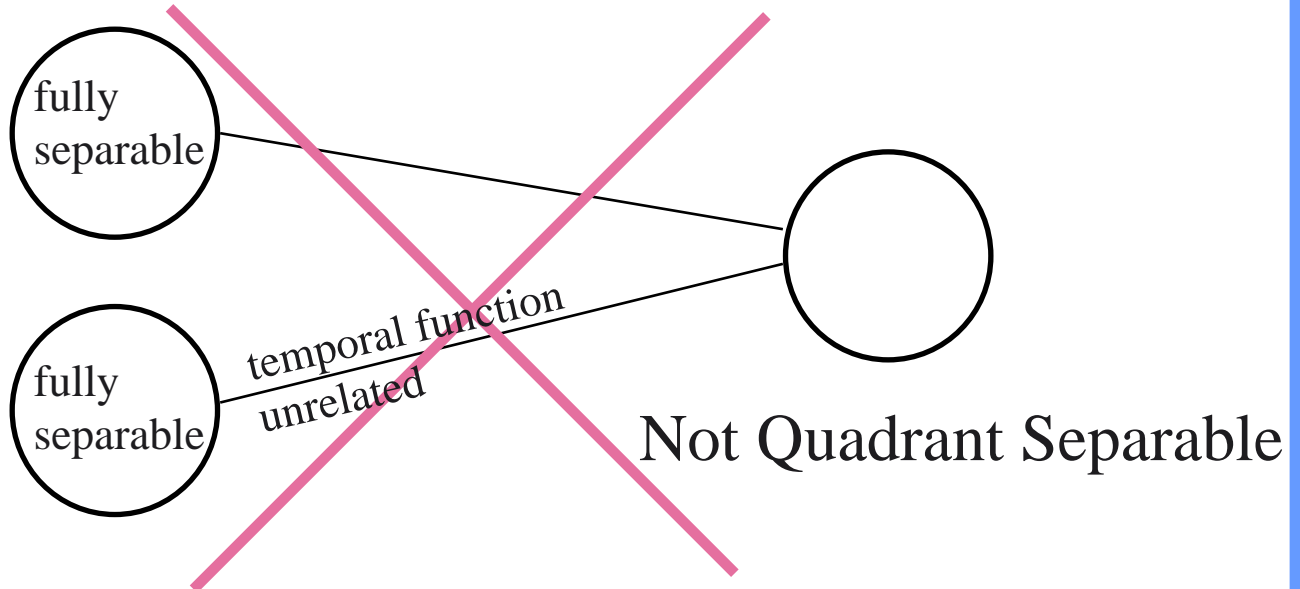


Distribution is strongly skewed toward temporal symmetry.

Neural Connectivity Constraints

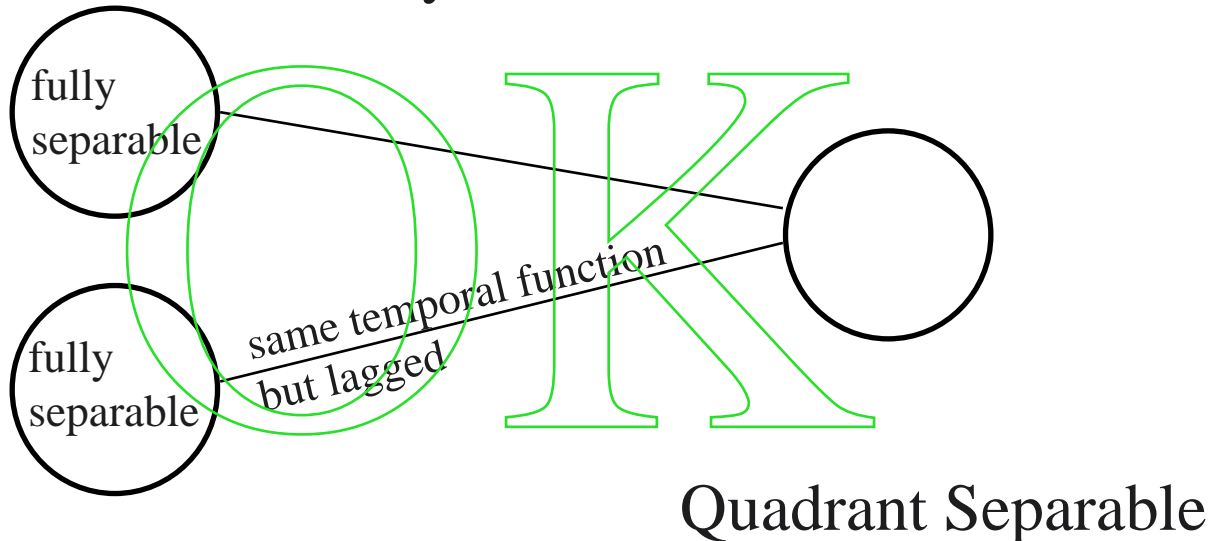
Input to AI =
Medial Geniculate Body

AI



Input to AI =
Medial Geniculate Body

AI



Summary

- **The function of AI**

To encode spectro-temporal features of sounds
spectrally: to ~ 1 cycles/octave
temporally: ~ 2 to ~ 20 Hz (in ferret)

plus encoding other sound features not addressed here

- **Spectro-Temporal Response Field (STRF)**

- **Descriptor** of response to broadband dynamic stimuli
- **Predictor** of spike train for stimuli of dynamic, spectral modulations of noise
 - STRFs agree despite measurement method
 - Linear processing conveys most of the information
- **Visual Tool** conveys spectro-temporal regions of excitation and inhibition

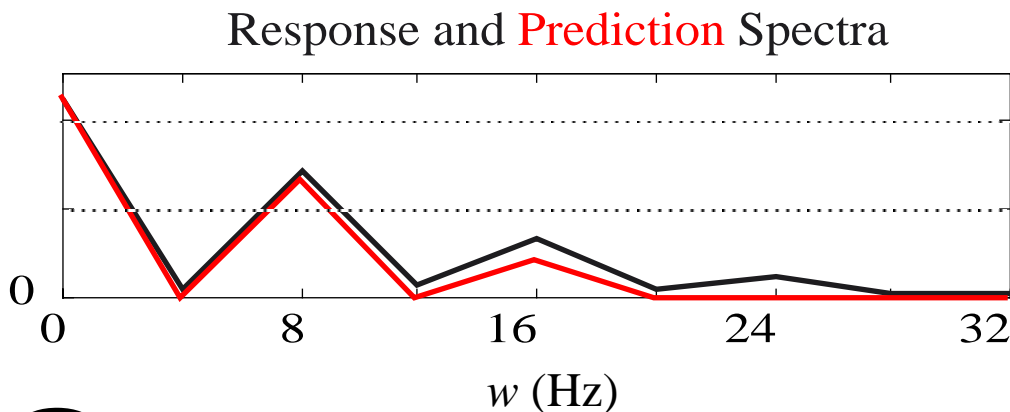
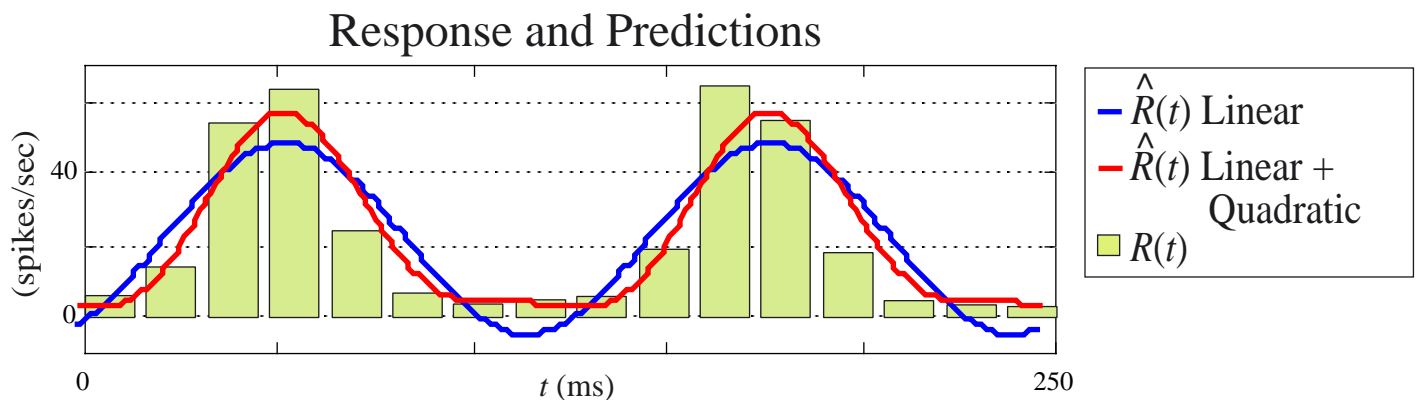
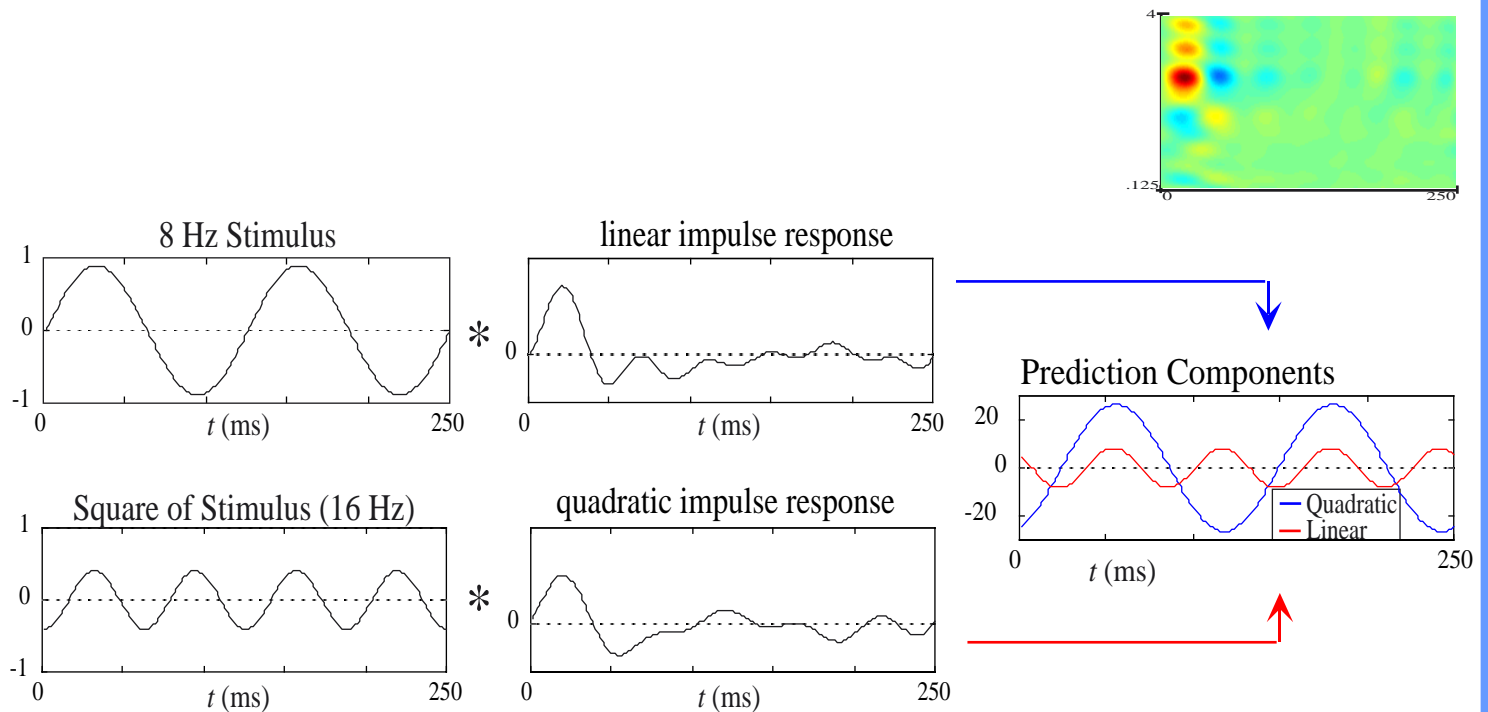
- **Constraints of Quadrant Separability**

- Limits possible network dynamics

- Introduction to Auditory Spectro-Temporal Processing
- Stimuli—Dynamic & Broadband: Ripples, Ripple Combinations
- Examples & Properties of Spectro-Temporal Response Fields
- Constraints on Neural Connectivity
- MagnetoEncephaloGraphy (MEG)
- Predicting Responses to Novel Stimuli
- **Non-Linearities**

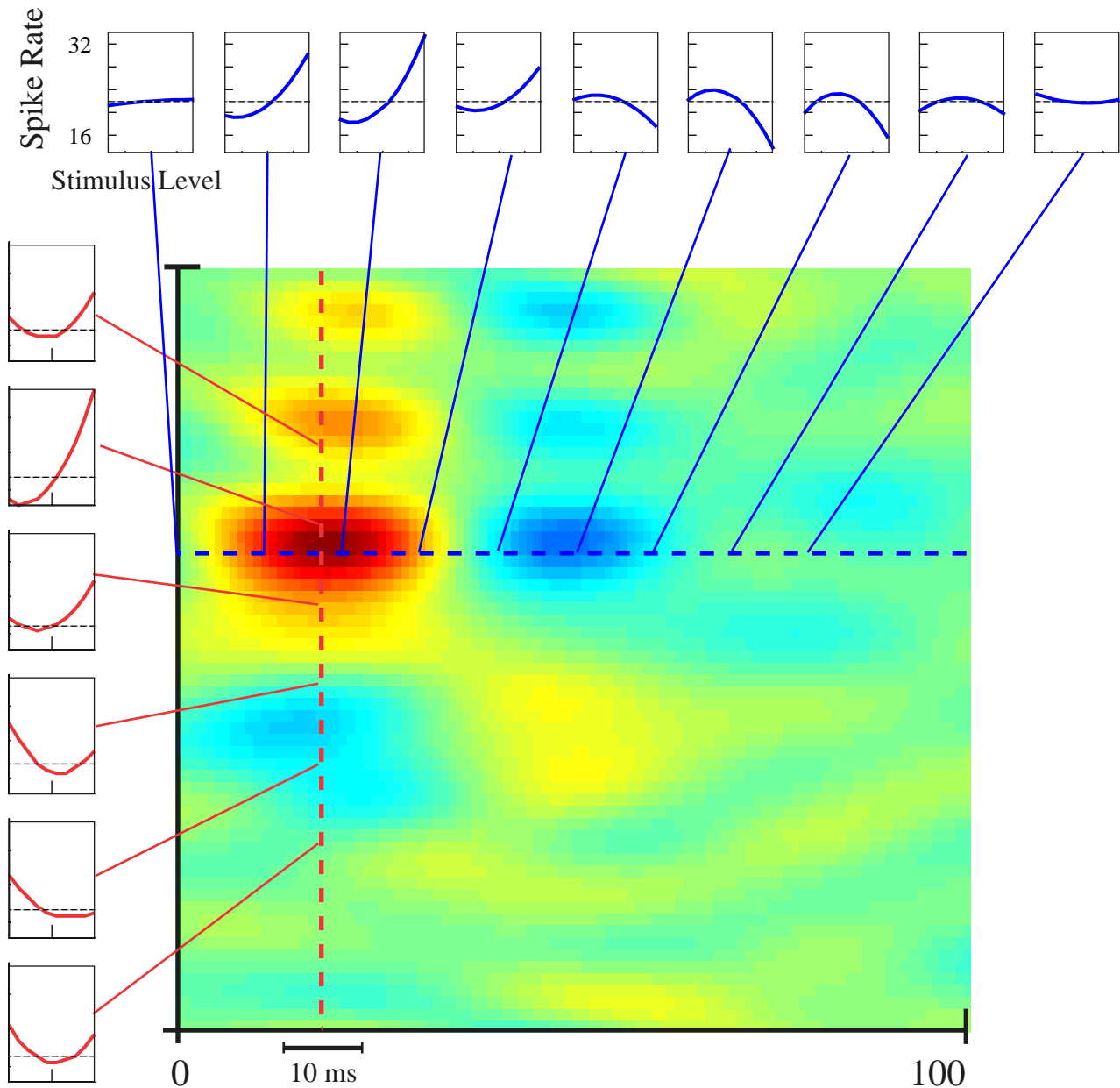
Non-Linearity—Predictions

- Preliminary results indicate that the non-linear predictions fit the responses more accurately than the linear predictions, although the differences between the two are typically subtle.



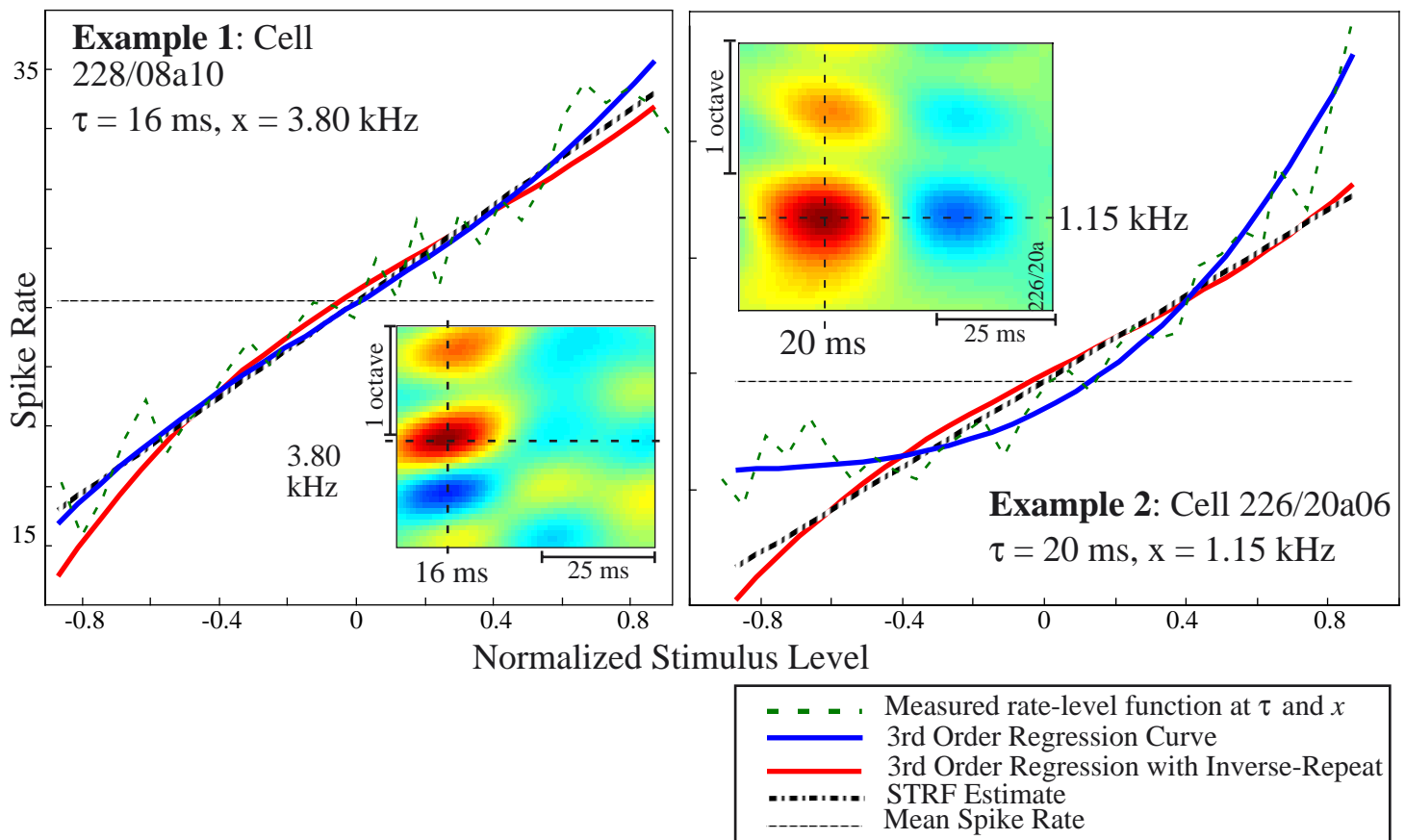
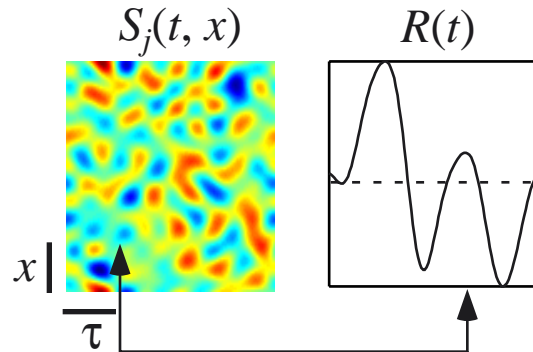
Spectro-Temporal Rate-Level Functions

Rate-level functions change with τ and x .



Non-Linearity—Theory

- The value of the STRF at each point (τ, x) is the slope of a linear rate-level function: $R_{\tau,x}(t) = [\text{STRF}(\tau, x)] \cdot S(t-\tau, x)$.
- Polynomial rate-level curves measured at every (τ, x) improve the description. These are potentially non-linear functions.



- Using cubic polynomials, we have shown that either the non-linearities are absent, or they are dominantly second order.
- Subtraction of the response to the inverted envelope gives a nearly linear polynomial fit. This would be expected, for example, from a purely even order (e.g., rectifying non-linearity).