Estimating transient phase-amplitude coupling using local mutual information

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Outline

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Intro to theory

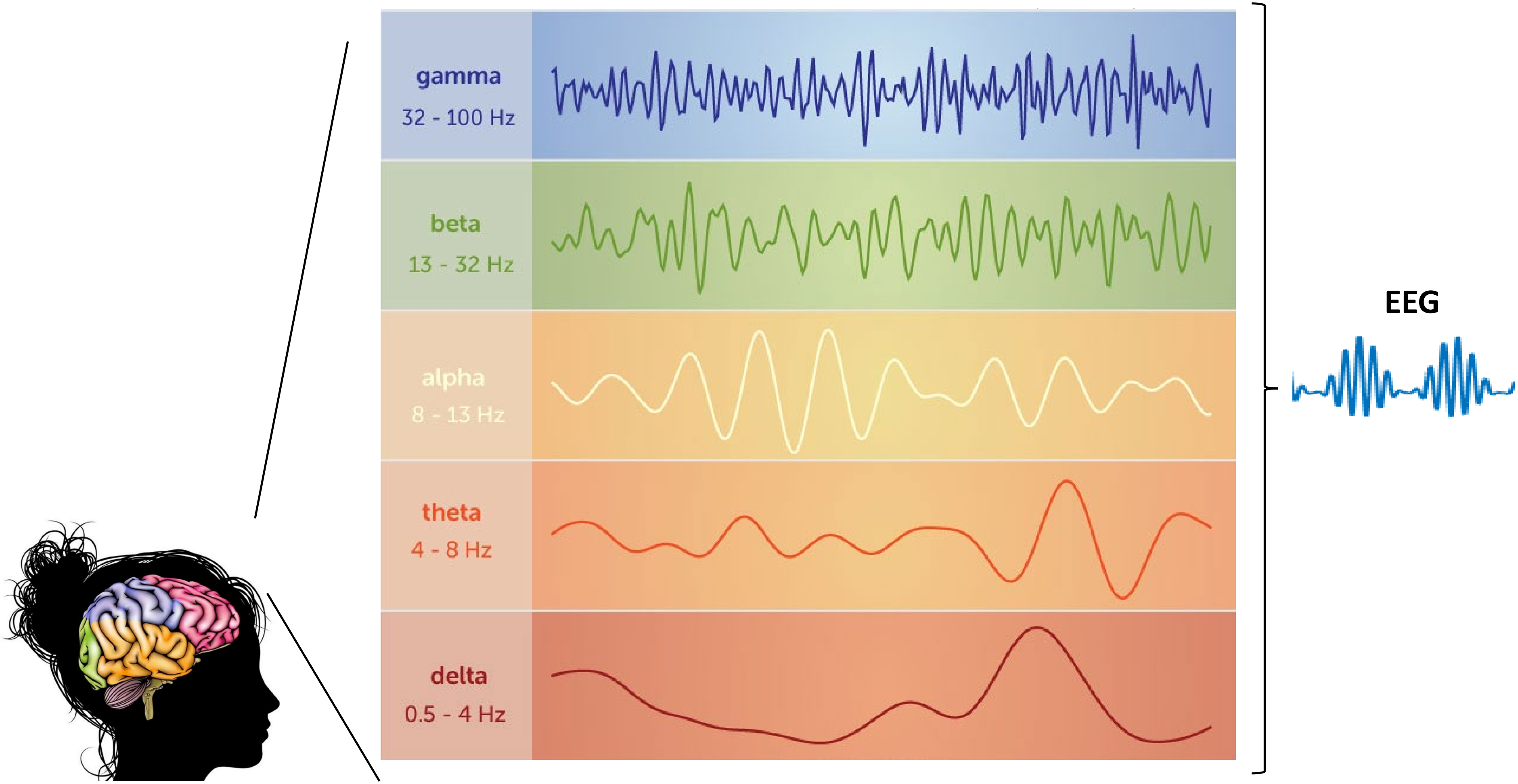
- Intro to Phase-Amplitude Coupling (PAC)
- Local (pointwise) Information Theory Measures
- Estimating PAC with Local Mutual Information

Results

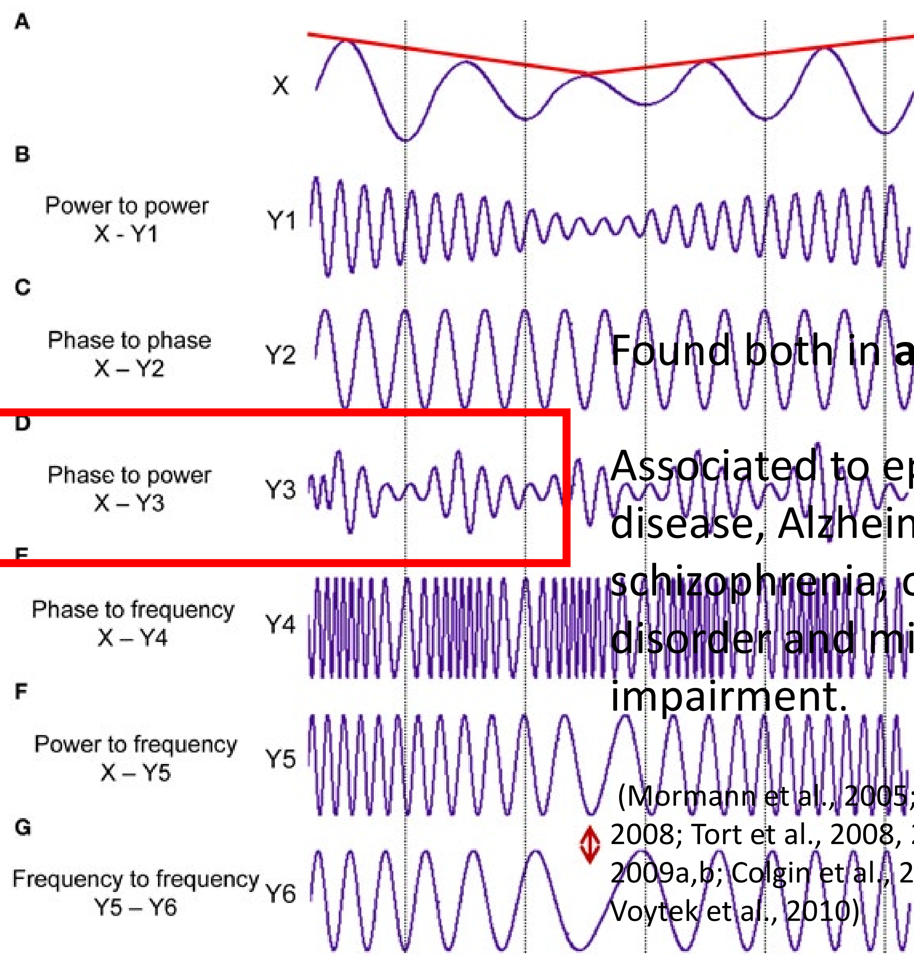
- Simulations
- ECoG data analysis

Demo

Brain oscillations



Cross-Frequency Coupling



Found both in **animals** and **humans**

Associated to epilepsy, Parkinson's disease, Alzheimer's disease, schizophrenia, obsessive-compulsive disorder and mild cognitive impairment.

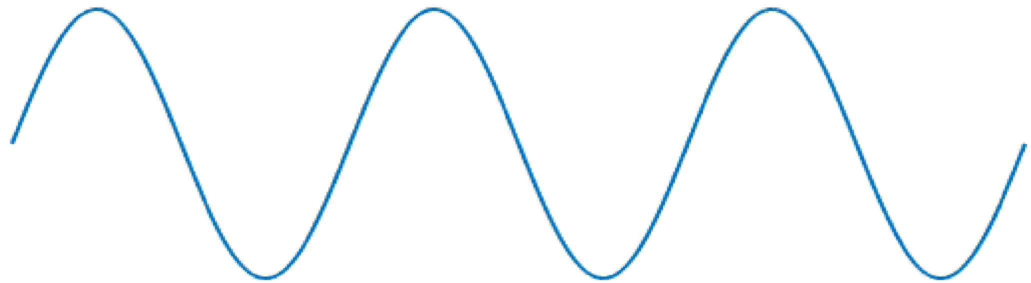
(Mormann et al., 2005; Cohen, 2008; Osipova et al., 2008; Tort et al., 2008, 2009, 2010; Cohen et al., 2009a,b; Colgin et al., 2009; Axmacher et al., 2010a,b; Voytek et al., 2010)

Jirsa and Muller, 2013

Amplitude Modulation Fundamentals

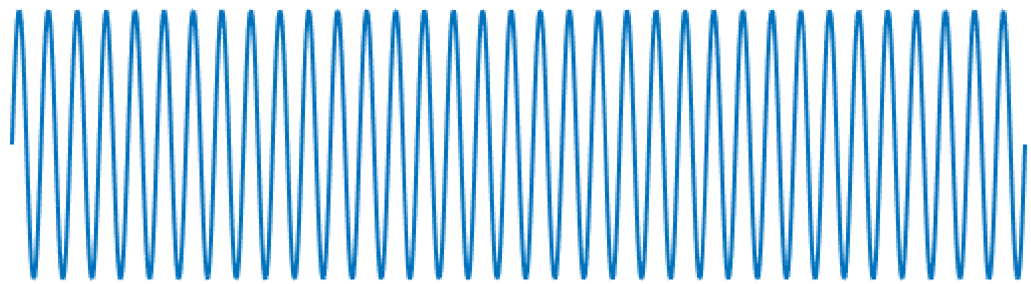
Modulator

$$v_{\mathrm{mod}} = V_{\mathrm{mod}} \sin\left(2\pi f_{\mathrm{mod}} t\right)$$



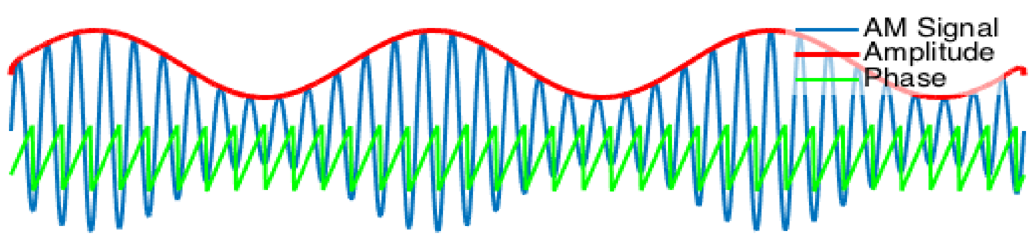
Carrier

$$v_{carr} = V_{carr} \sin\left(2\pi f_{carr} t\right)$$



AM Signal

$$v_{AM} = V_{carr} \sin\left(2\pi f_{carr} t\right) + \left[V_{\mathrm{mod}} \sin\left(2\pi f_{\mathrm{mod}} t\right)\right] \sin\left(2\pi f_{carr} t\right)$$



Instantaneous Phase and Amplitude

$$S_t = s_{m_t} e^{i\phi_t}$$

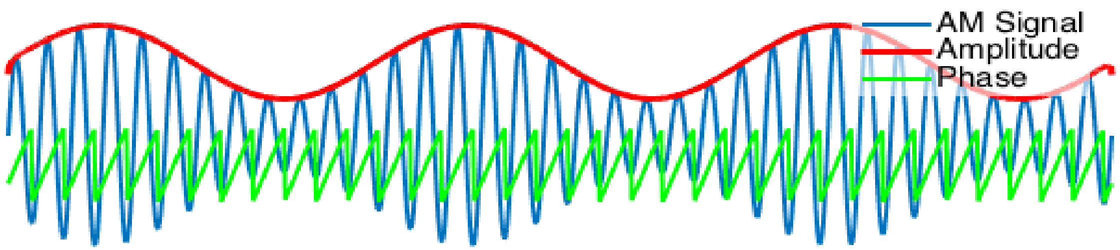
By mean of the ***Hilbert transform*** a signal can be expressed as its **analytic signal**

$$s_{m_t} = |S_t|$$

Instantaneous amplitude (or the envelope)

$$\phi_t = arg[S_t]$$

Instantaneous phase.



$abs(hilbert(S_t))$

$angle(hilbert(S_t))$

Computing PAC

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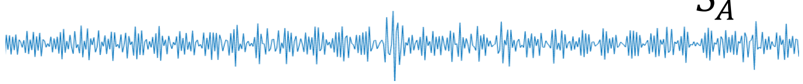
Electrophysiological signal

Band-pass Filter

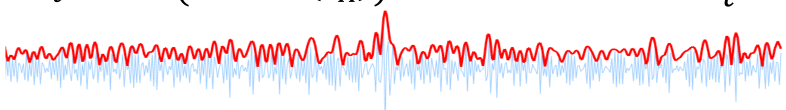
High frequency band f_{Amp} (e.g: 30-50Hz)



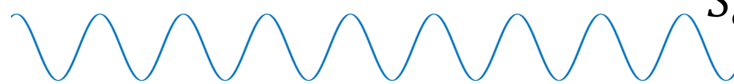
S_A

$$A_t = abs(hilbert(S_A))$$

A_t



Low frequency band f_{phase} (e.g: 5-12Hz)



S_ϕ

$$A_t = angle\left(hilbert(S_\phi)\right)$$

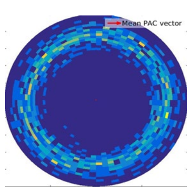
ϕ_t

Mean Vector Length

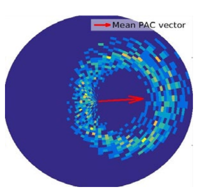
Canolty et al. 2006

- Composite vectors $z_t = A_t e^{i\phi_t}$
- Mean vector length

$$MVLmi = \left| \frac{1}{N} \sum_{t=1}^{T} z_t \right|$$



No Coupling



Coupling

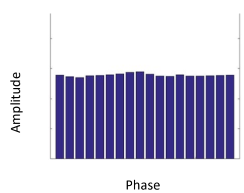
Kullback-Leibler Modulation Index

Tort et al, 2010

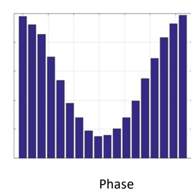
$$P(j) = \frac{\langle A_{f_A} \rangle \phi_{f_p}(j)}{\sum_{k=1}^{N} \langle A_{f_A} \rangle \phi_{f_p}(k)}$$

$$MI = \frac{D_{KL}(P,U)}{\log N}$$

Compute the Kullback-Leibler with a uniform distribution



No Coupling



Coupling

GLM Measure

Penny et al. 2008

$$A_t = X\beta + e$$

$$X = \begin{vmatrix} cos\phi_1 & sin\phi_1 & 1 \\ \vdots & \vdots & \vdots \\ cos\phi_{max} & cos\phi_{max} & 1 \end{vmatrix}$$

Use the explained variance as an index of PAC

ERPAC

Voytek et al. 2013

Time resolved PAC by applying ***GLM Measure*** for each latency in event related data

Information Theory Definitions

Given the measurements x and y of the RV X and Y

Mutual Information: average reduction in uncertainty about X given the knowledge of the value of Y

$$I(X,Y) = -\sum p(x,y)\log_2 \frac{p(x|y)}{p(x)}$$

$$I(X,Y) = H(X) - H(X|Y)$$

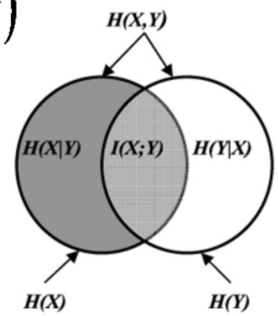


Figure from Goncalvez and Macrini 2011

The mutual information is a measure of dependency (**both linear and nonlinear**) between the two random variables *X* and *Y*

KSG Mutual Information Estimator

(Ksrakov, Stogbauer and Grassberger)

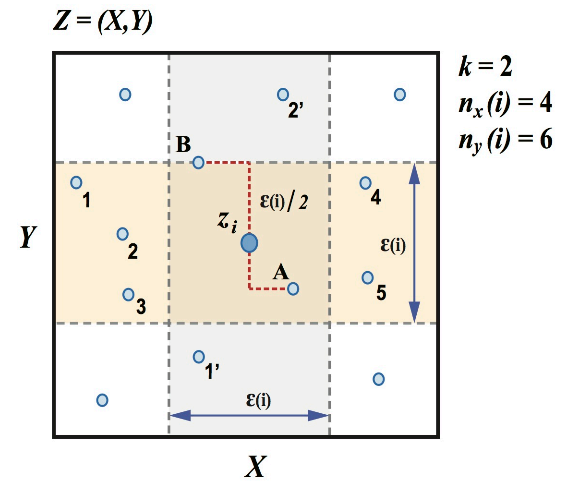
- Extension of Kozachenko-Leonenko estimator of Entropy
- Non-parametric estimator
- Data efficient
- Minimal bias

Assume the joint space $Z = (X, Y)$

Determining *k*-nearest neighbors for each z_i

$$\|z - z'\| = max\{\|x - x'\|, \|y - y'\|\}$$

- Find K-nearest neighbor of z_i (a distance $\frac{\varepsilon}{2}$)
- Count the number of points $n_x(i)$ and $n_y(i)$ in the marginal space within a row (and column) of width ε



Estimate Mutual Information

$$I(X,Y) = \psi(k) - \langle \psi(n_x + 1) + \psi(n_y + 1) \rangle + \psi(N)$$

Kraskov et al. 2004

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Estimating local Mutual Information

Lizier et al. 2008, considered the estimation of Local MI from the KSG estimator

Estimate Mutual Information

Kraskov et al. 2004

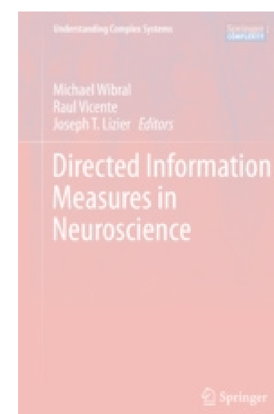
$$I(X,Y)=\psi(k)-\langle\psi(n_x+1)+\psi(n_y+1)\rangle+\psi(N)$$

Unrolling expectation

Estimating Local Mutual Information

$$i(x,y)=\psi(k)-\psi(n_x+1)-\psi(n_y+1)+\psi(N)$$

Lizier, J. T. Directed Information Measures in Neuroscience. Springer, 2014



Goal:
Estimating PAC using local Mutual Information

Instantaneous MIPAC

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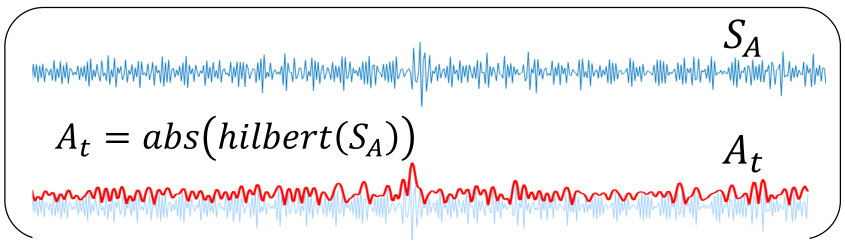
Data model:

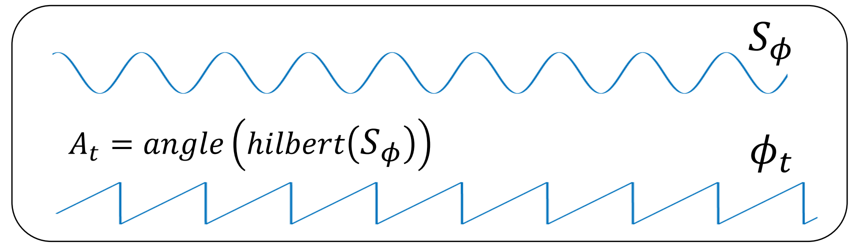
Continuous data $(1 \times N_{lat})$

High frequency band f_{Amp} (e.g: 30-50Hz)

Band-pass Filter



Low frequency band f_{phase} (e.g: 5-12Hz)



Assume the joint space $Z = (A_t, \phi_t$Ě

$$\|z - z'\| = max\{\boxed{\|\phi - \phi'\|}, \boxed{\|A - A'\|}\}$$

Circular norm (Berens, 2009) Euclidean norm

$$i(x,y) = \psi(k) - \psi(n_x + 1) - \psi(n_y + 1) + \psi(N)$$

Inst. MIPAC

% Single trials or continuous

Δ_{var} = Inf ; % Initialize Percentage variance reduction
c = 1;

while $\Delta_{var\_threshold} < \Delta_{var}$

Estimate $i(A_t, \phi_t)$ for ***k=c*** ;

Compute Δ_{var} ;

c = c+1 ;

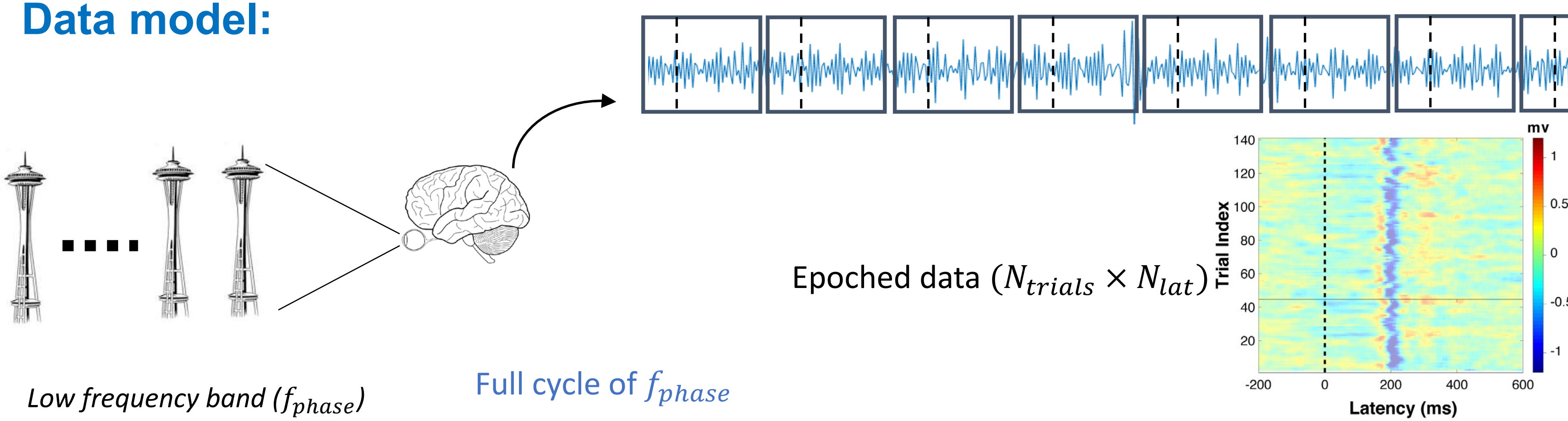
End

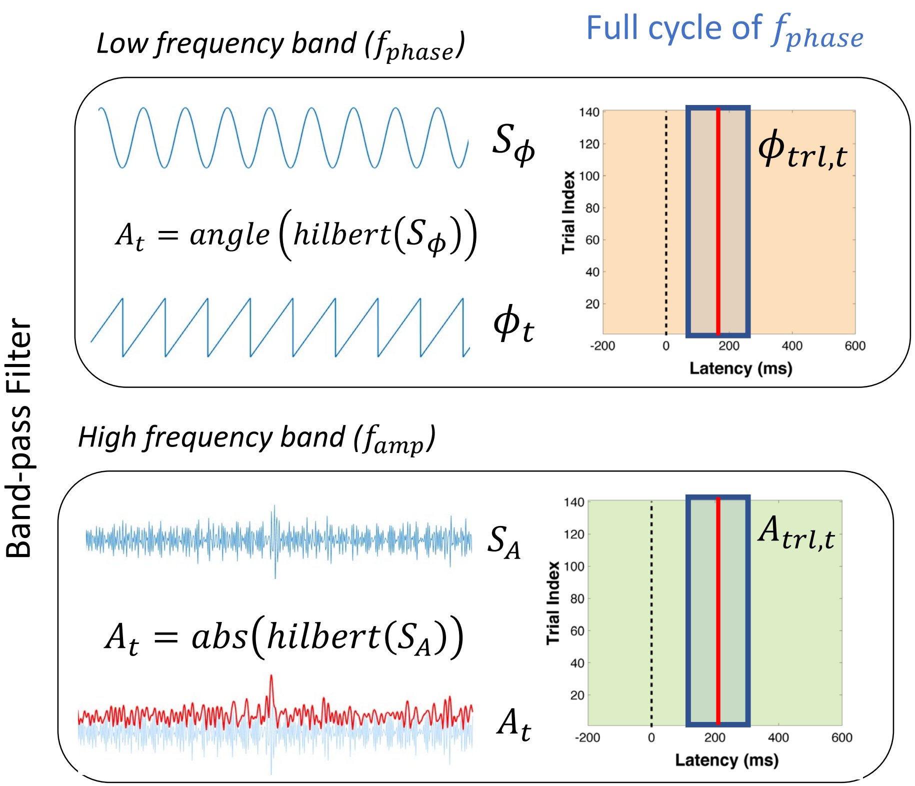
MIPAC = Low-pass filter $i(A_t, \phi_t)$ at f_{phase} ;

Martinez-Cancino et al 2018 (under review in Neuroimage)

Event-related MIPAC

Data model:





Event Related MIPAC (cyclostationary)

% Epoched data

for $t = 1: N_{lat}$

  Δ_{var} = Inf ; % Initialize Percentage variance reduction

  c = 1;

  while $\Delta_{var\_threshold} < \Delta_{var}$

    Estimate $i\left(A_{trl,t}(:,t), \phi_{trl,t}(:,t)\right)$ for ***k=c*** ;

    (Neighbors are count in a latency window)

    Compute Δ_{var} ;

    c = c+1;

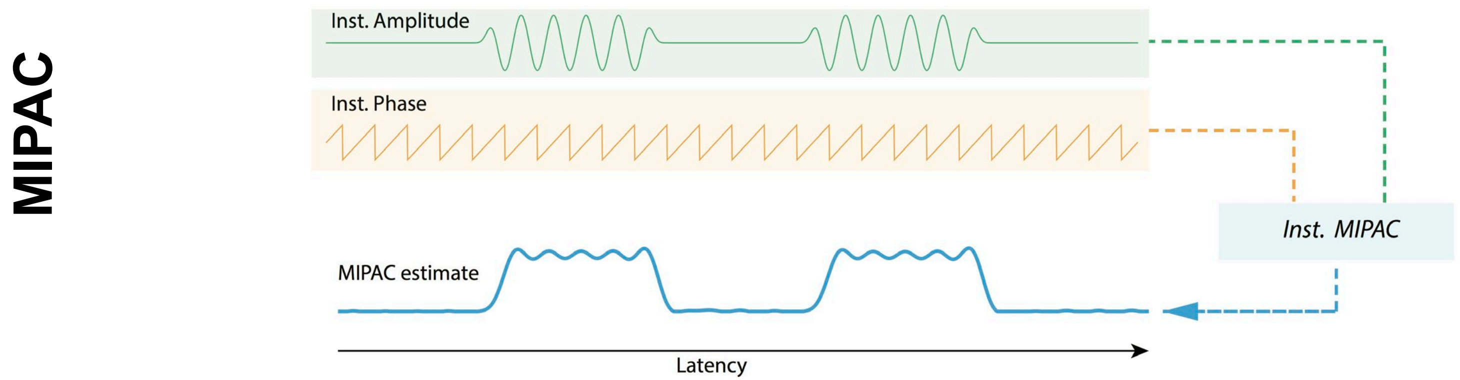
  end

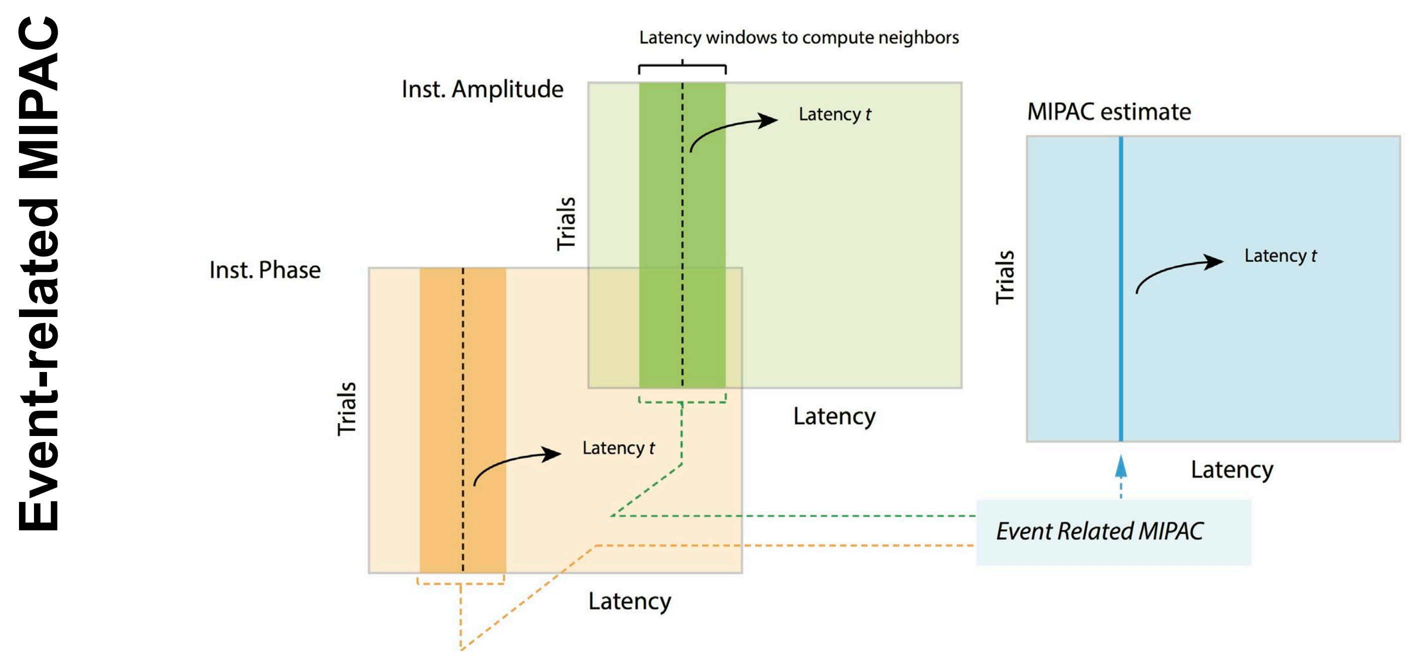
end

MIPAC = Low-pass filter $i\left(A_{trl,t}, \phi_{trl,t}\right)$ at f_{phase}.

Martinez-Cancino et al 2018 (under review in Neuroimage)

Inst. MIPAC and Event-related MIPAC





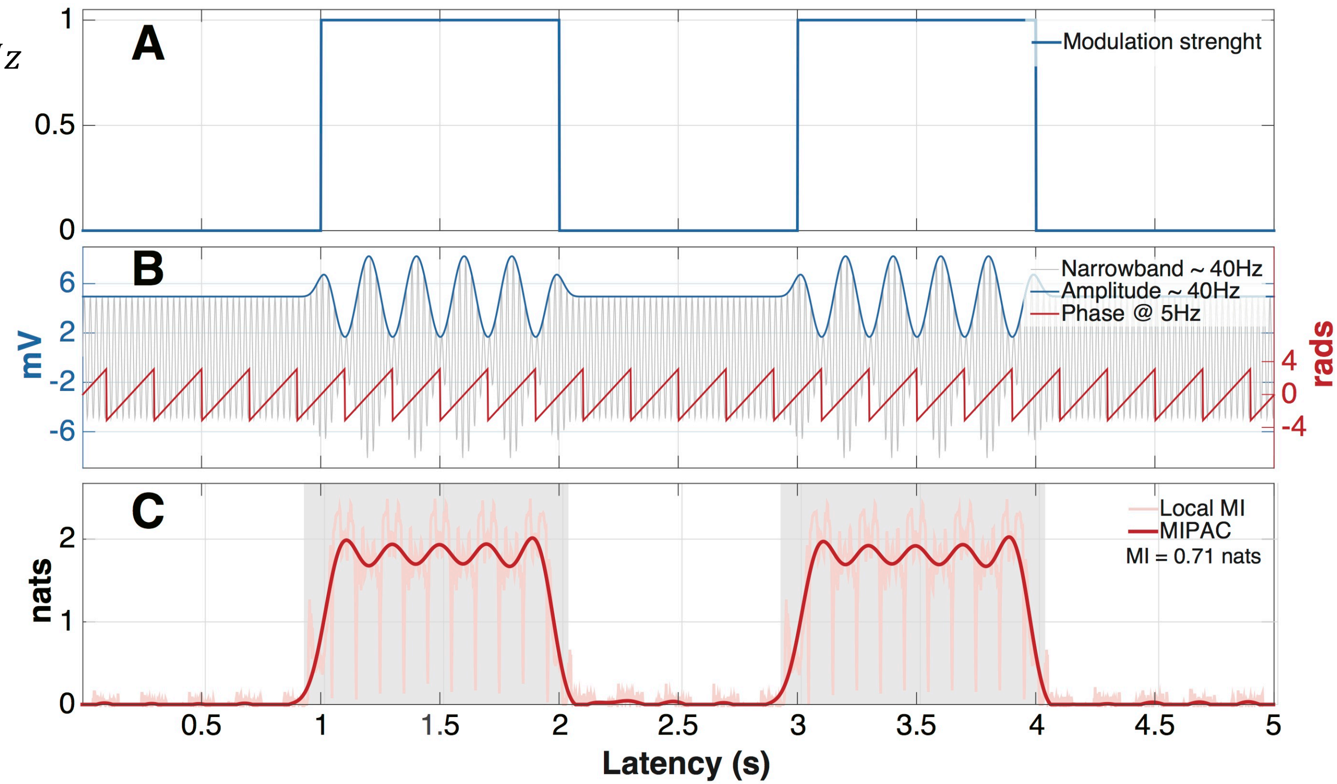
MIPAC Simulations

Simulation 1.1: Instantaneous MIPAC

$f_{mod} = 5Hz$

$f_{carr} = 40Hz$

$S_{rate} = 500Hz$



(A) Block-shaped waveform modulation strength.
(B) Simulated signal
(C) Estimated MIPAC (red), and local MI (light red)

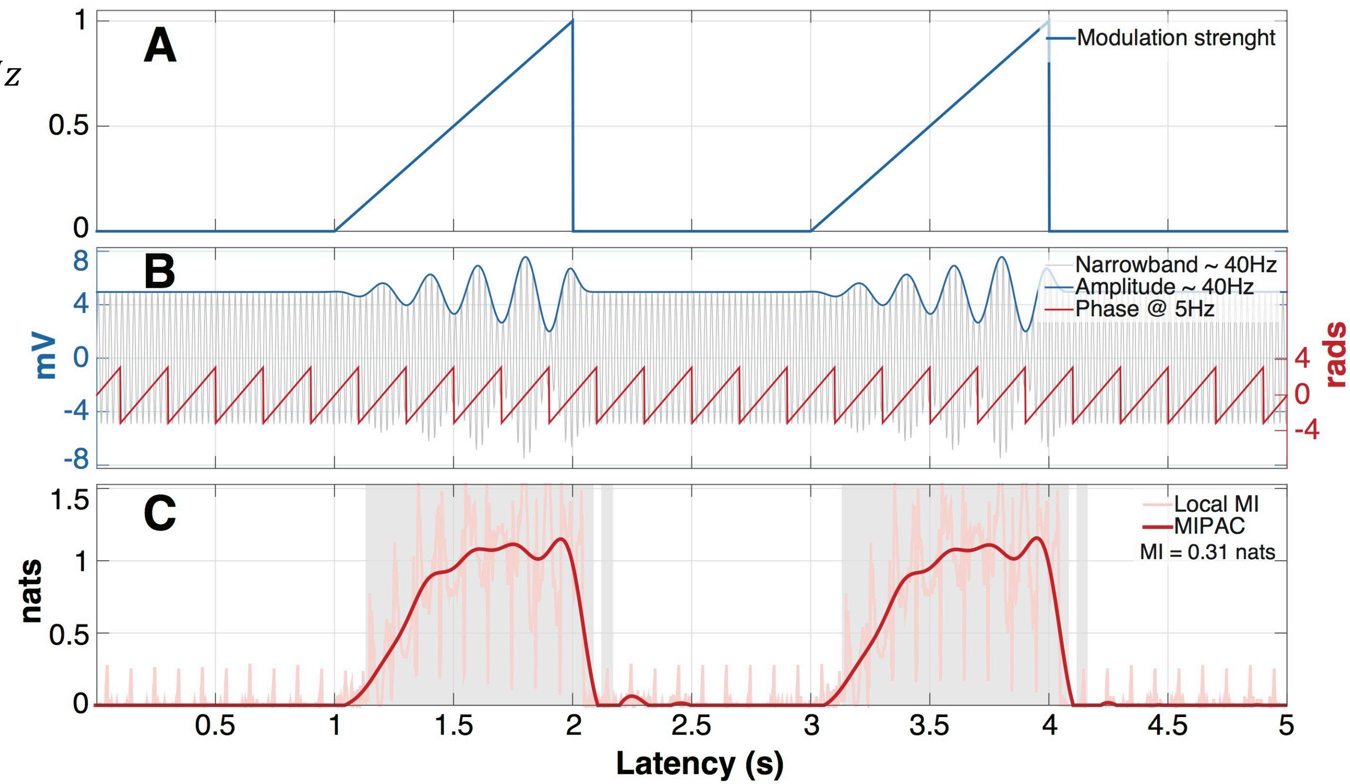
Martinez-Cancino et al 2018 (under review in Neuroimage)

Simulation 1.2: Instantaneous MIPAC

$f_{mod} = 5Hz$

$f_{carr} = 40Hz$

$S_{rate} = 500Hz$



(A) Saw-tooth shape waveform modulation strength.
(B) Simulated signal
(C) Estimated MIPAC (red), and local MI (light red)

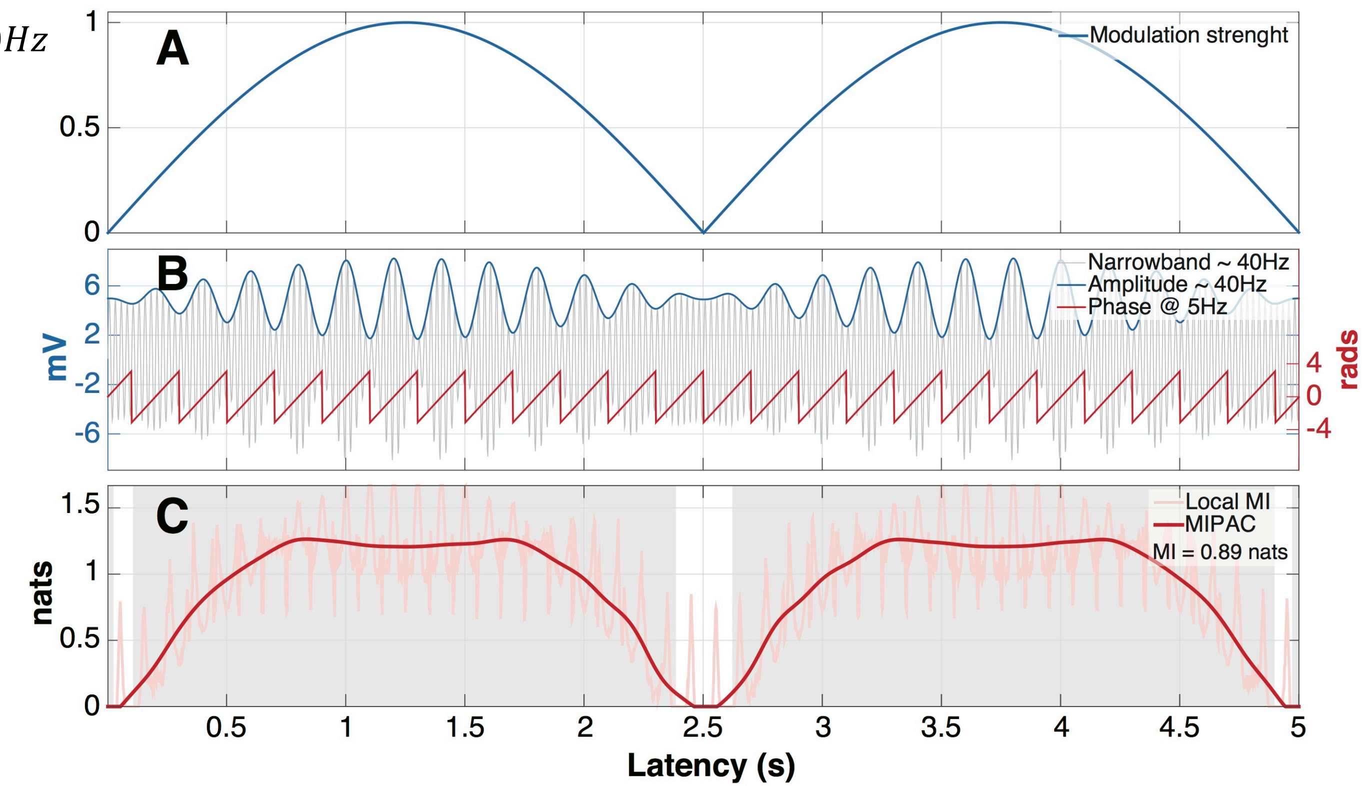
Martinez-Cancino et al 2018 (under review in Neuroimage)

Simulation 1.3: Instantaneous MIPAC

$f_{mod} = 5Hz$

$f_{carr} = 40Hz$

$S_{rate} = 500Hz$



(A) Absolute value of a sinusoid used as modulation strength.

(B) Simulated signal

(C) Estimated MIPAC (red), and local MI (light red)

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Simulation 2: Instantaneous MIPAC Noise Added

$f_{carr} = 40Hz$Ě $\quad Srate = 500Hz \quad f_{mod} = 5Hz \quad SNR = 10$

MIPAC from a simulated Phase-Amplitude-Modulated signal with noise added. MIPAC was estimated from the same signals generated the previous simulations, but with a SNR= 10. Estimated MIPAC (red), and local MI (light red).

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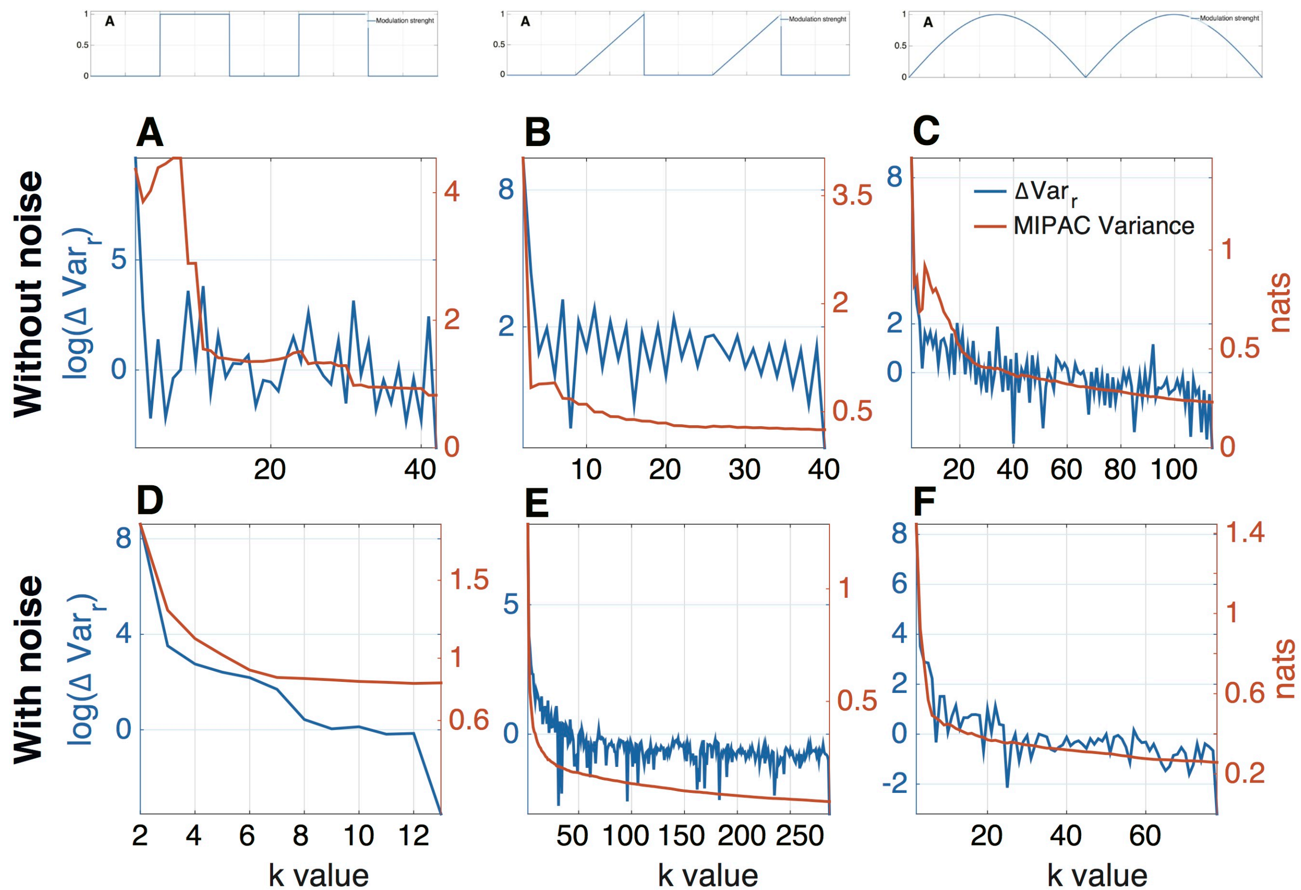
MIPAC convergence



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Simulation 3: Event-related MIPAC

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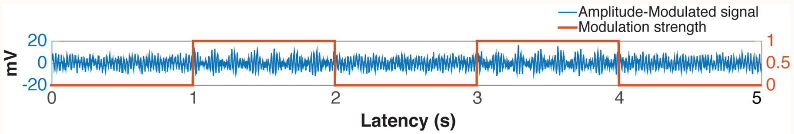
ER PAC data simulation



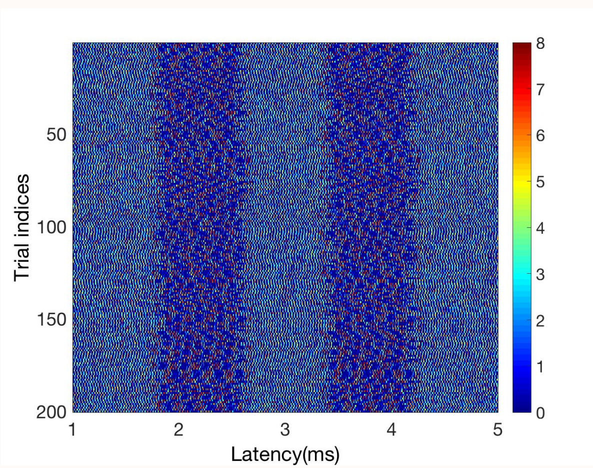
$f_{mod} = 5Hz$

$f_{carr} = 40Hz$

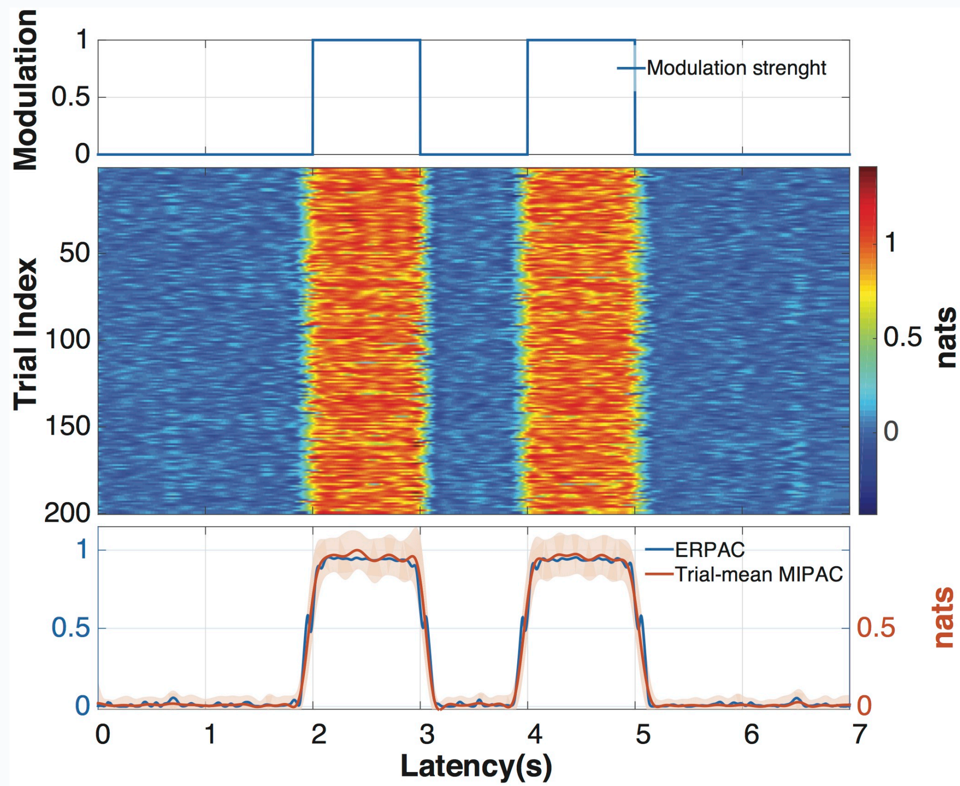
$S_{rate} = 500Hz \qquad SNR = 10$

x200

Each trial was shifted 1-100 pts



Event related MIPAC and ERPAC (*Voytek et al, 2013*) were used to estimate PAC



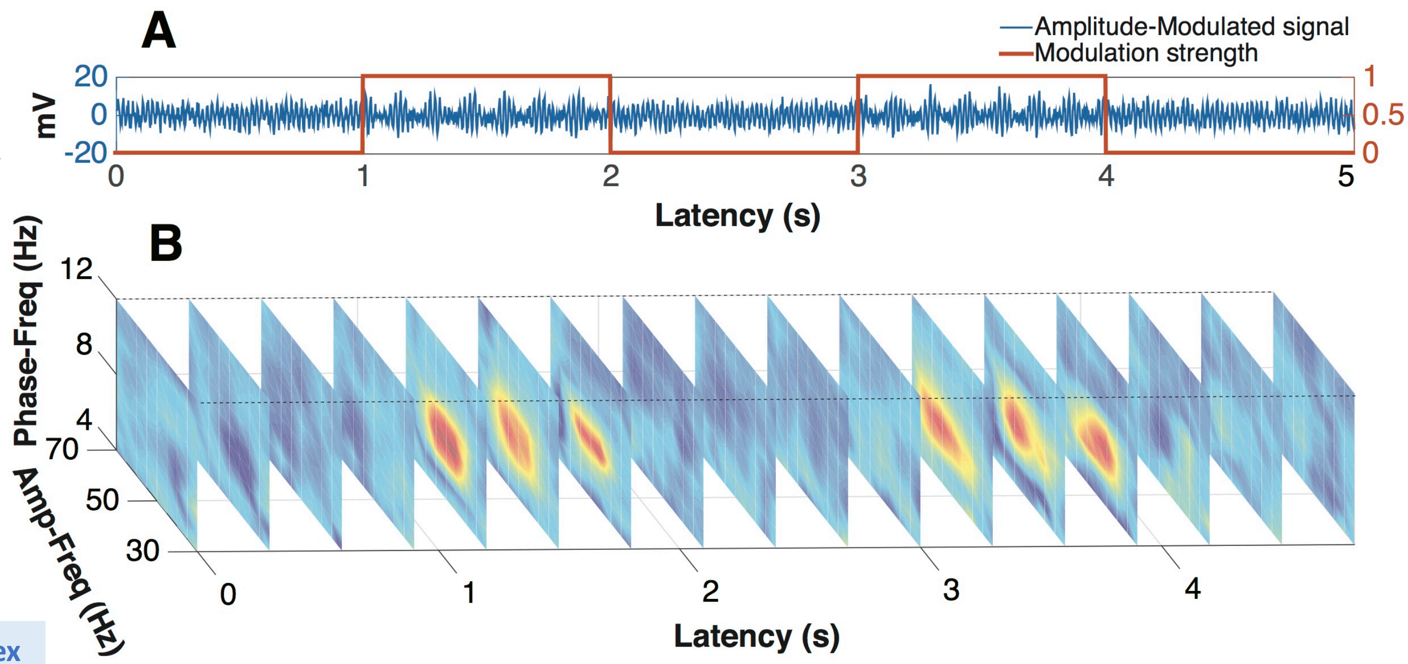
Martinez-Cancino et al 2018 (under review in Neuroimage)

Simulation 4: MIPAC & MImi

$f_{mod} = 7Hz$

$f_{carr} = 50Hz$

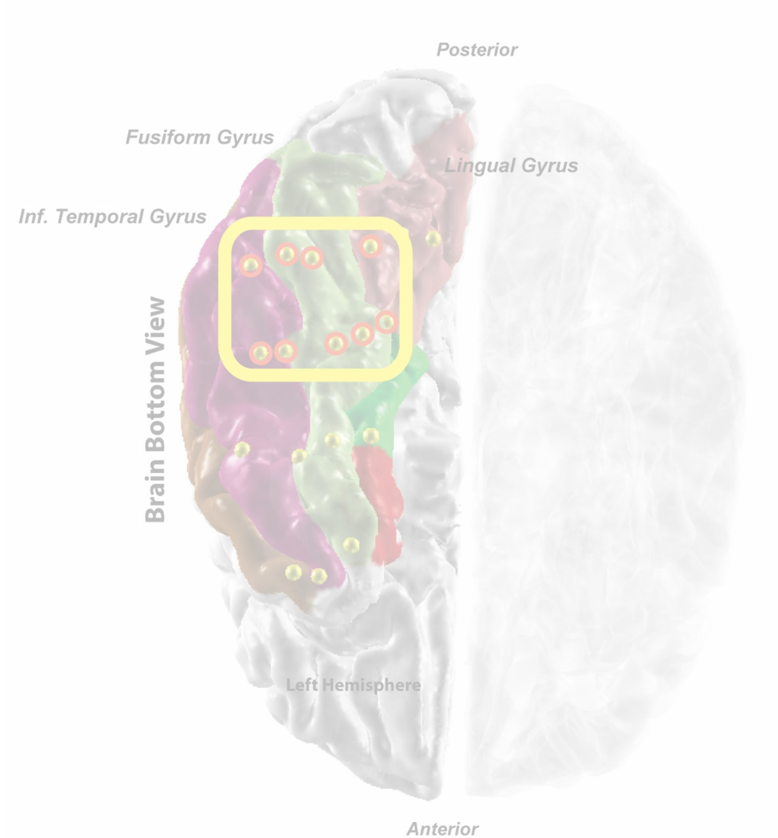
$S_{rate} = 500Hz$



Grand Mean

MI modulation index

Martinez-Cancino et al 2018 (under review in Neuroimage)

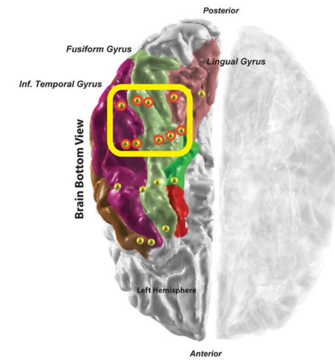


MIPAC application to real data

ECoG Data

Subject

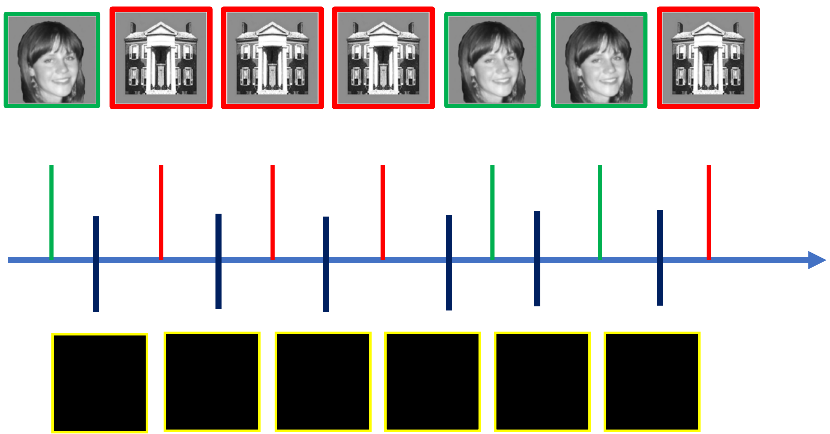
- Clinical monitoring and localization of seizure foci
- 1 subject (mv)
- ECoG channels in: Inf. Temp. Gyrus
  Lingual Gyrus
  Fusiform Gyrus



Experimental design

- Images of Houses and Faces were presented randomly
- 3 runs 100 presentations each (50 H / 50F)

400 ms



400 ms

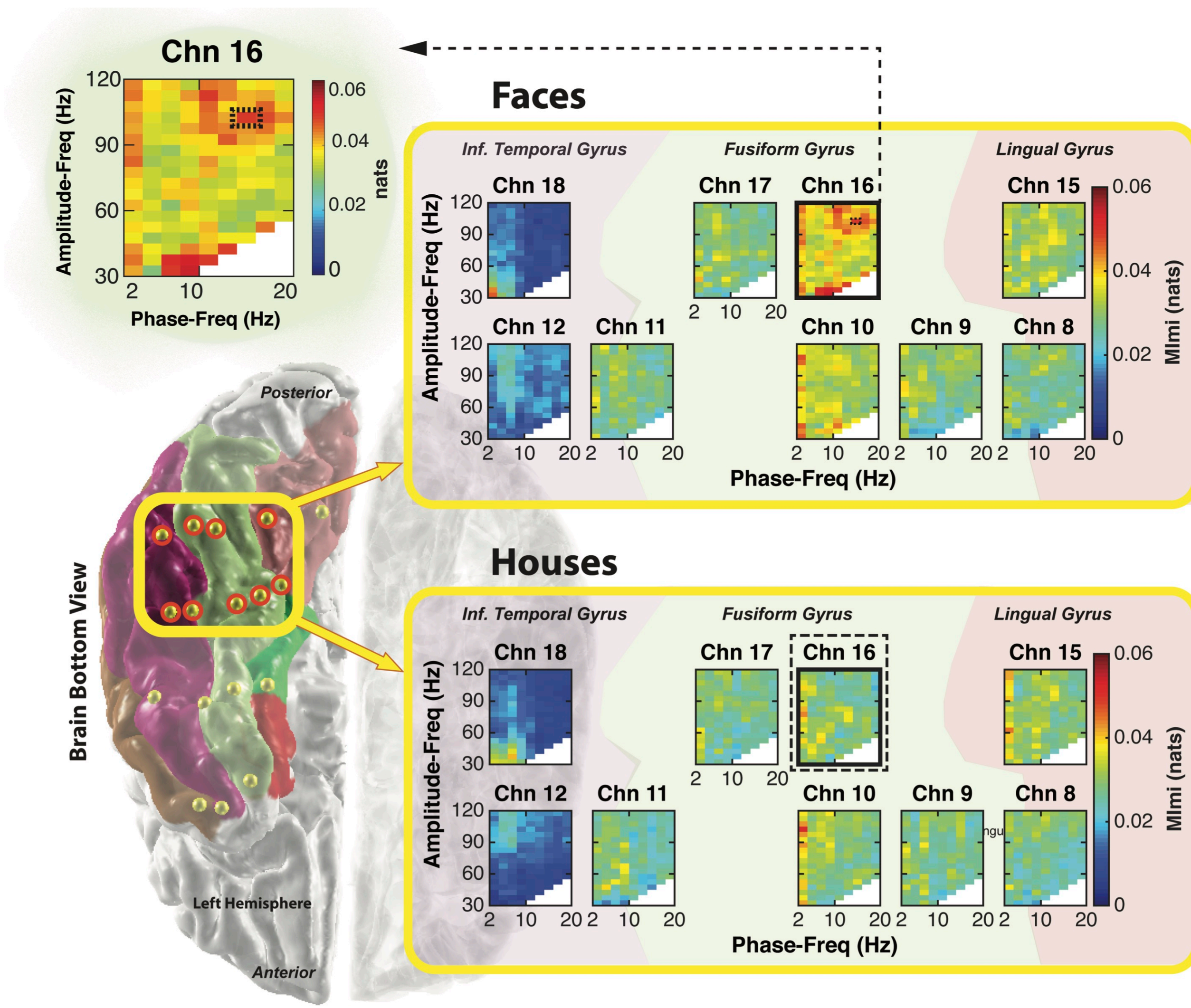
Preprocessing

Performed in EEGLAB ***(Delorme and Makeig, 2004)***

1. Artifact removal
2. CAR
3. Resampling to 512Hz
4. Line noise removal ~(60, 120) Hz
   Hamming-windowed FIR notch filter
5. Extract epochs time-locked to stimulus presentations [-400,800] *ms*

Original publication:
The physiology of perception in human temporal llobe is specialized for contextual novelty
Kai J. Miller, Dora Hermes, Nathan Witthoft, Rajesh P. N. Rao, Jeffrey G. Ojemann

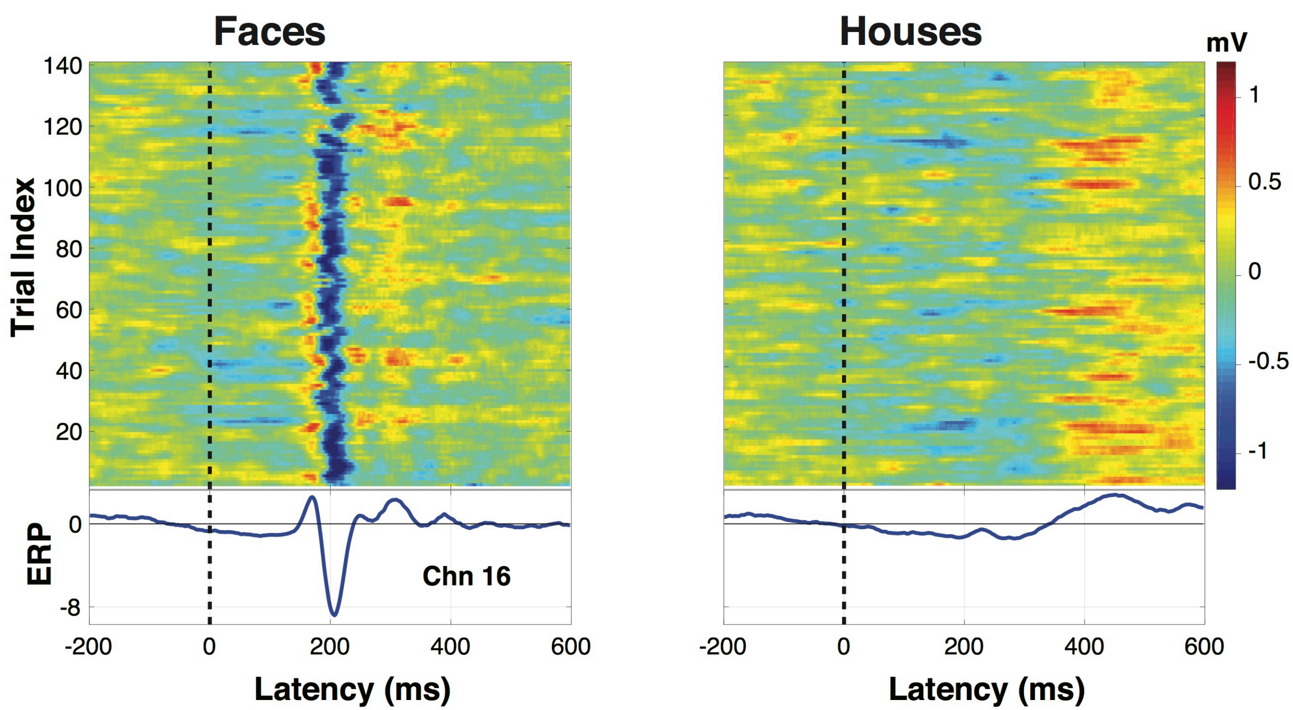
ECoG Data: MImi in action



Martinez-Cancino et al 2018 (under review in Neuroimage)

ECoG Data: Event Related Potential Image

Channel 16



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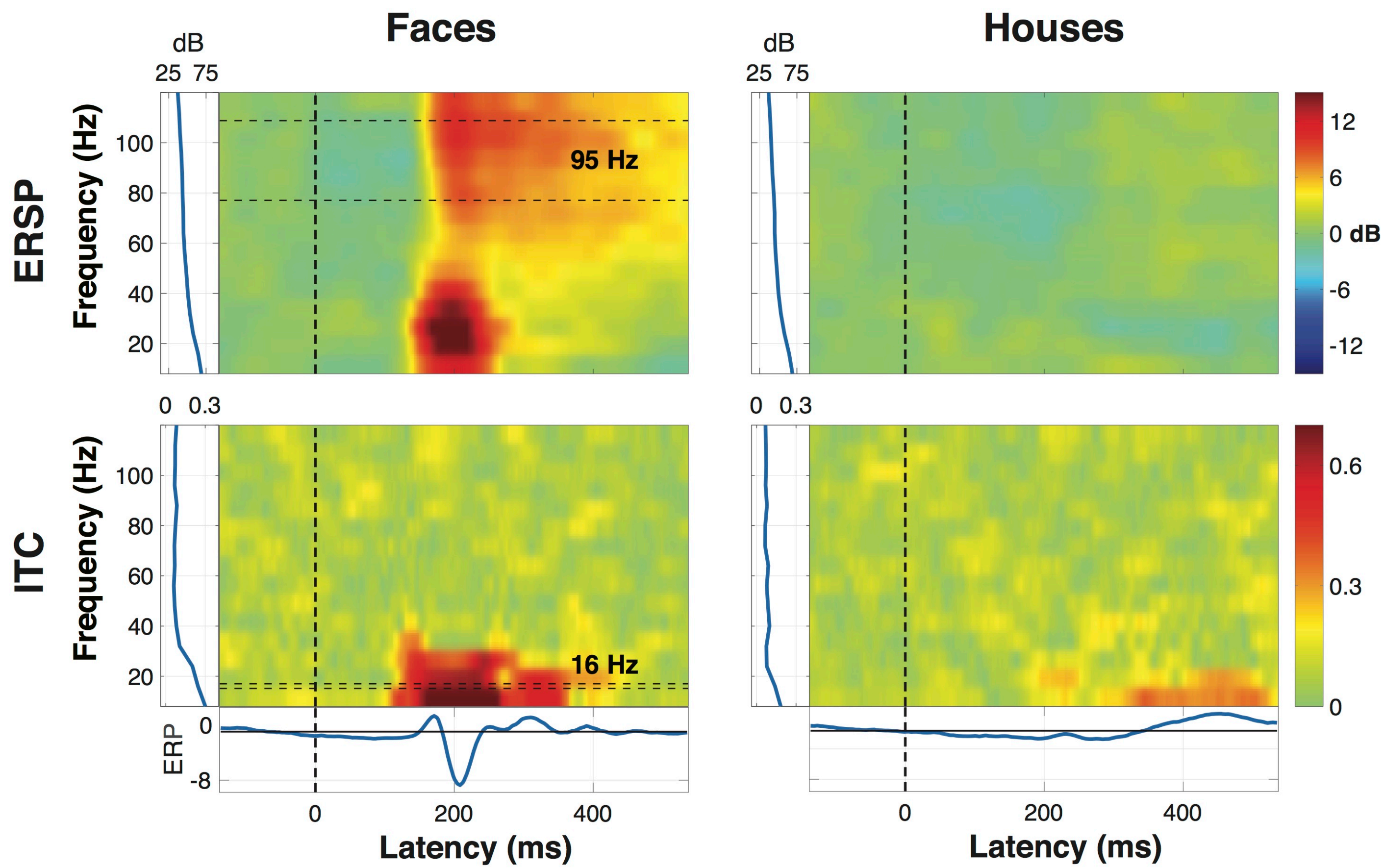
ECoG Data: Time-Frequency Decomposition



[2, 120]Hz FFTs and Hanning window tapering
Generated using EEGLAB function *newtimef.m*

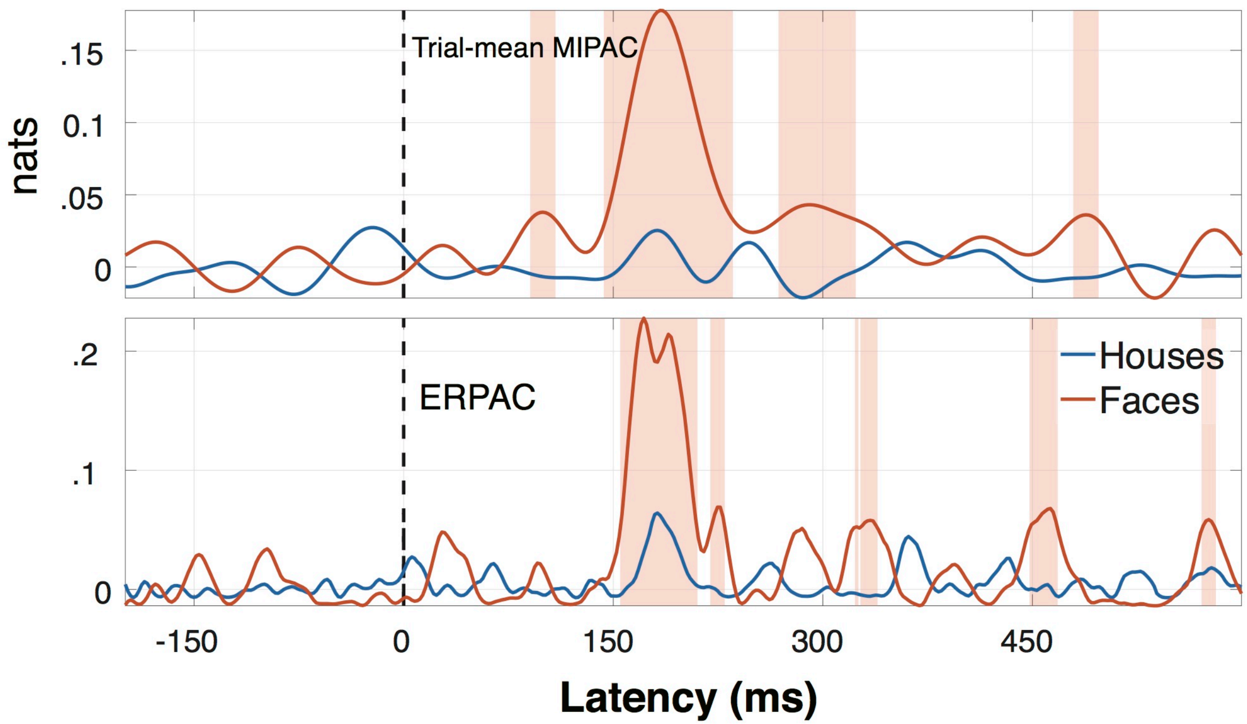
Martinez-Cancino et al 2018 (under review in Neuroimage)

ECoG Data: MIPAC vs ERPAC

Event-related MIPAC and ERPAC (***Voytek et al. 2014***) were computed

$$f_{phase} = 16\ Hz$$

$$f_{amp} = 95Hz$$



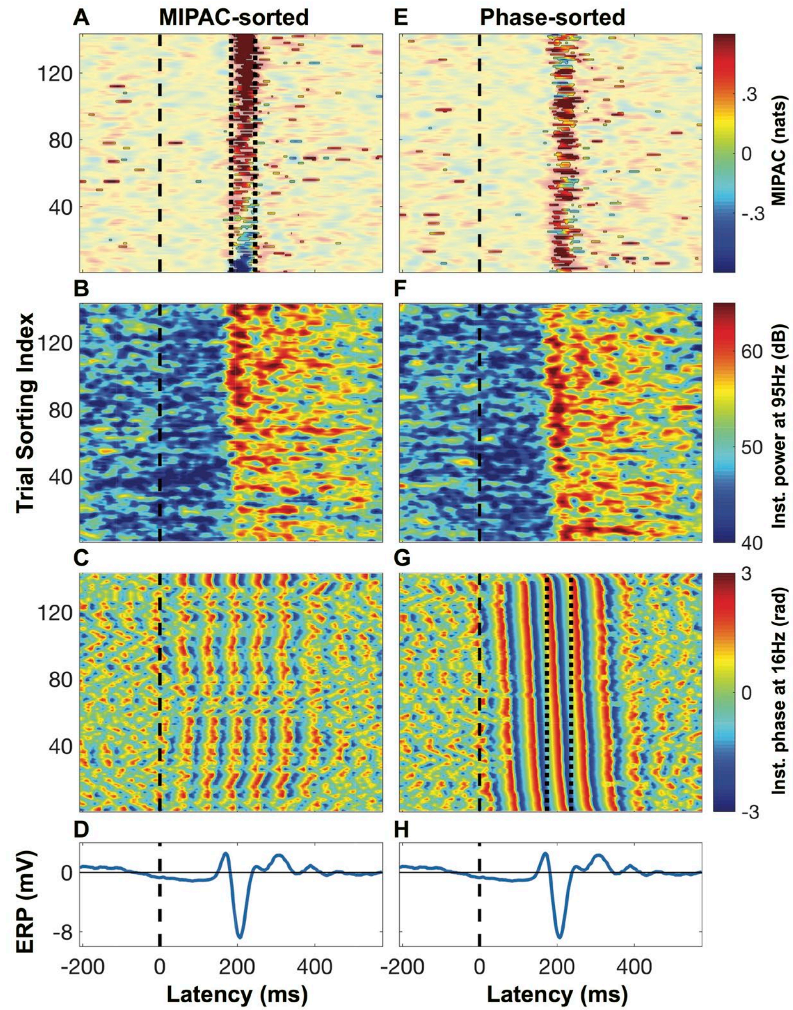
Martinez-Cancino et al 2018 (under review in Neuroimage)

ECoG Data: MIPAC Image

ER-MIPAC computed for ***Faces*** presentation

$$f_{phase} = 16\ Hz$$

$$f_{amp} = 95Hz$$



Martinez-Cancino et al 2018 (under review in Neuroimage)

Conclusions

- An approach to estimating dynamical PAC in electrophysiological signals was proposed
- The method was validated on simulated PAC signals
- Application to human ECoG data showed positive results

DEMO

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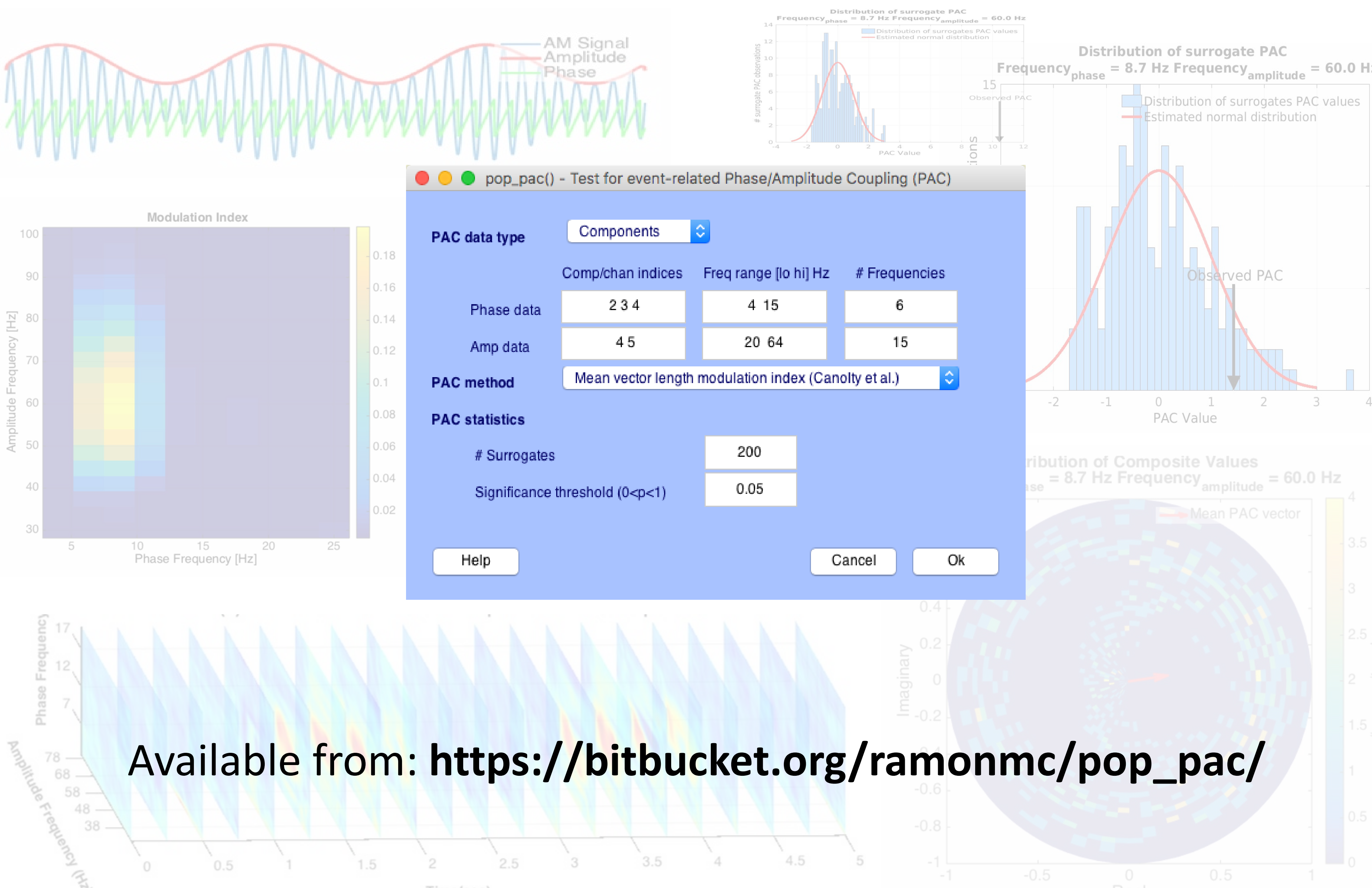

Available from: **https://bitbucket.org/ramonmc/pop_pac/**

Acknowledgments

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Joseph Heng

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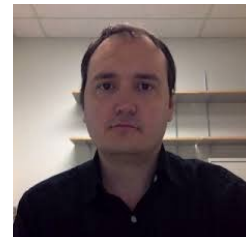

Roberto Sotero

Scott Makeig

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