

Non-oscillatory time-frequency signatures

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Overview

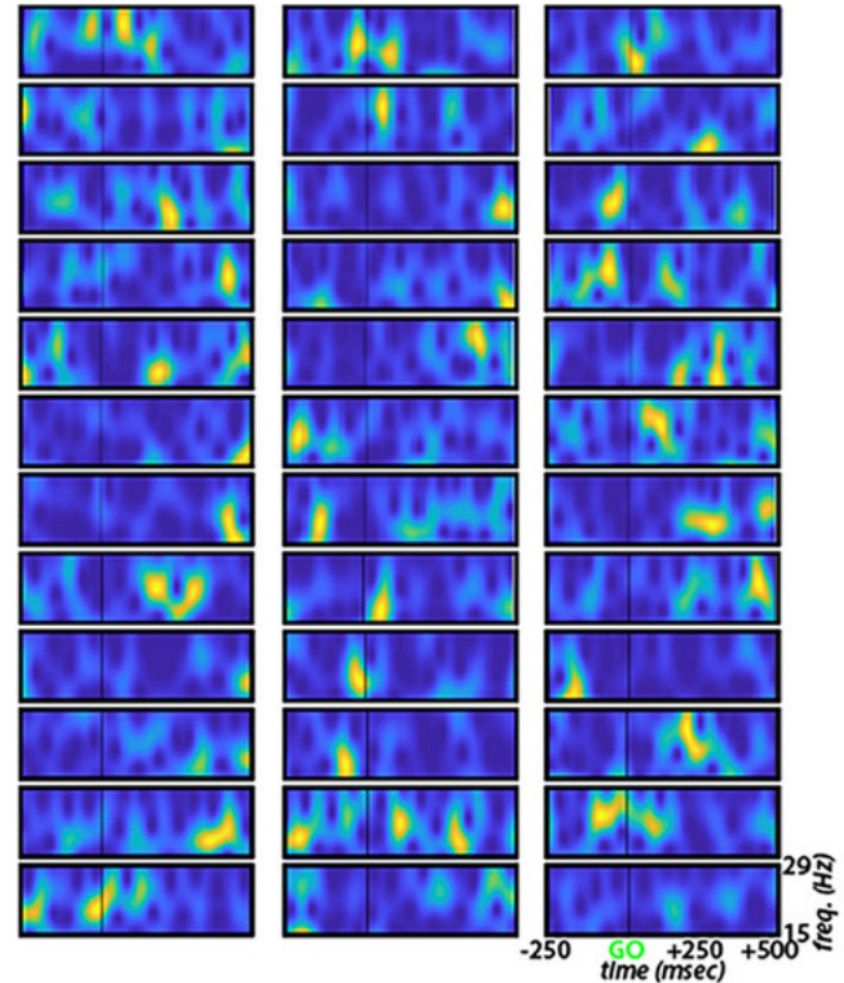
The sinusoid wave in field potential analysis
and the assumptions of “oscillations”

What happens when the assumptions break
down

Interpreting signatures that are not oscillatory

Practical demonstration

Tools for you moving forward

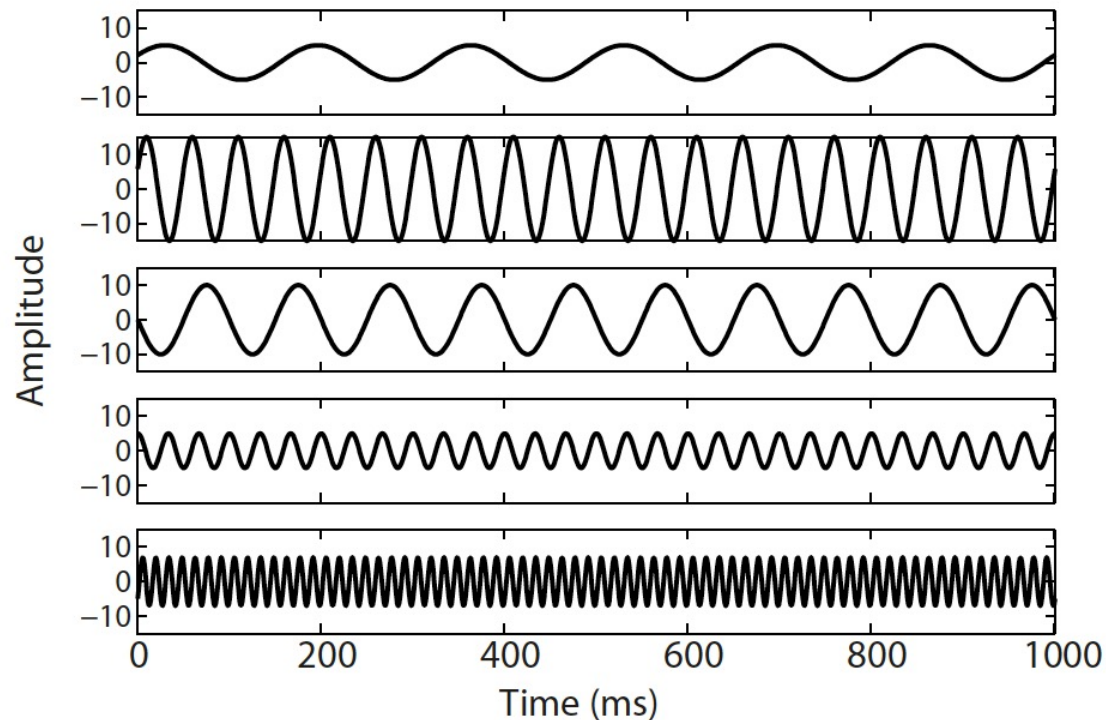


A pit stop on the way from amplitude to phase



The sine wave in time-frequency analysis

A) Individual sine waves



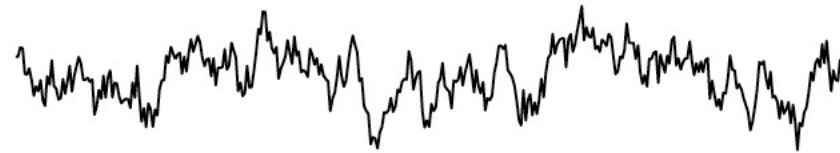
In what ways have we utilized sine waves so far?

- As bandpass filters
- At different frequencies for broadband TF analysis (i.e., to make ERSPs)
- Complex – to extract amplitude and phase
- Windowed using Gaussian distributions - wavelets

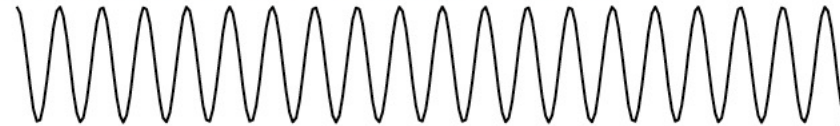
The sine wave in time-frequency analysis



A) EEG data



B) No temporal weighting (Fourier transform)

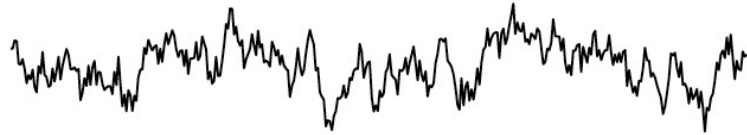


What assumptions might a kernel like this introduce into our results, interpretation?

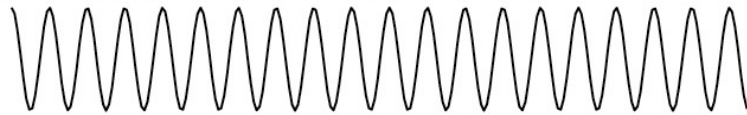
- Presence of that specific frequency
- Length of the signal (number of cycles we include)
- Regularity (the underlying signal is a sine wave)

The sine wave in time-frequency analysis

A) EEG data



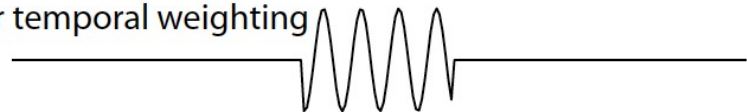
B) No temporal weighting (Fourier transform)



C) Strong temporal weighting



D) Boxcar temporal weighting



E) Gaussian temporal weighting

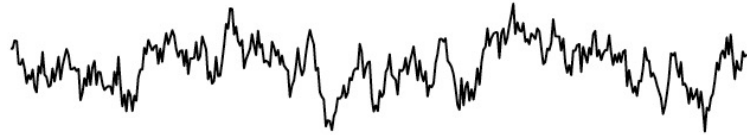


What assumptions might a kernel like B introduce into our results, interpretation?

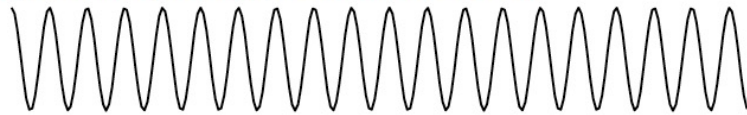
- Presence of that specific frequency
 - *Use kernels at multiple frequencies*
- Length of the signal (number of cycles we include)
 - *Use a windowed kernel, like E*
- Regularity (the underlying signal is a sine wave)

The sine wave in time-frequency analysis

A) EEG data



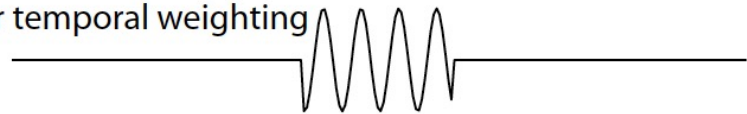
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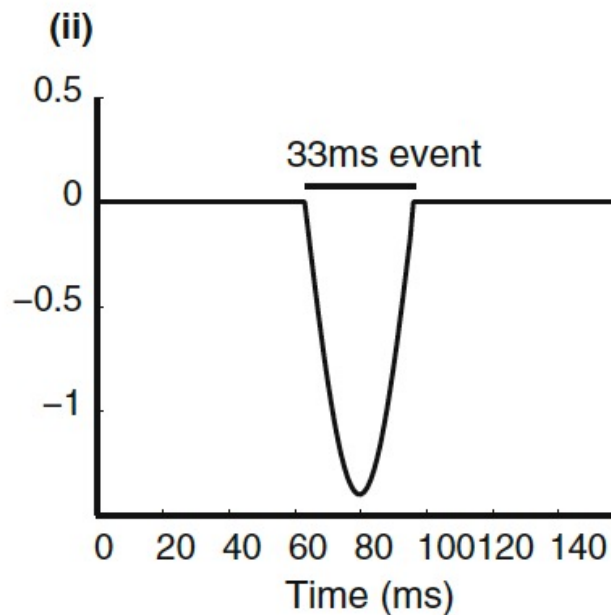
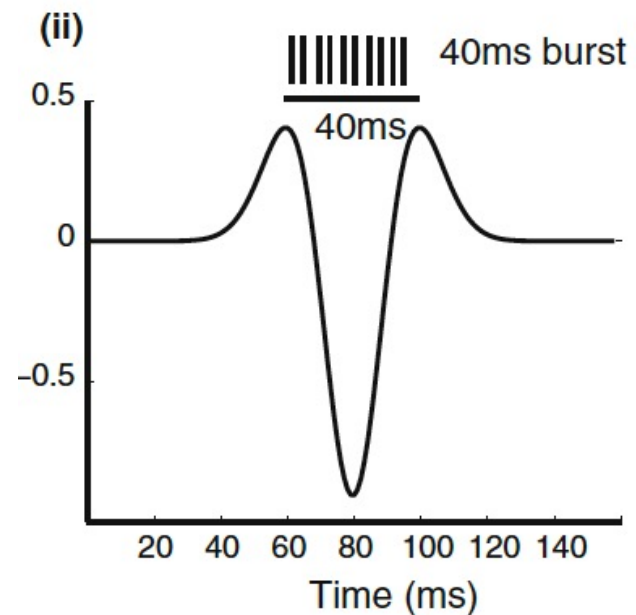


What assumptions might a kernel like B introduce into our results, interpretation?

- Presence of that specific frequency
 - *Use kernels at multiple frequencies*
- **Length of the signal (number of cycles we include) *****
 - *Use a windowed kernel, like E*
- Regularity (the underlying signal is a sine wave)

What happens if a signal is not oscillatory?

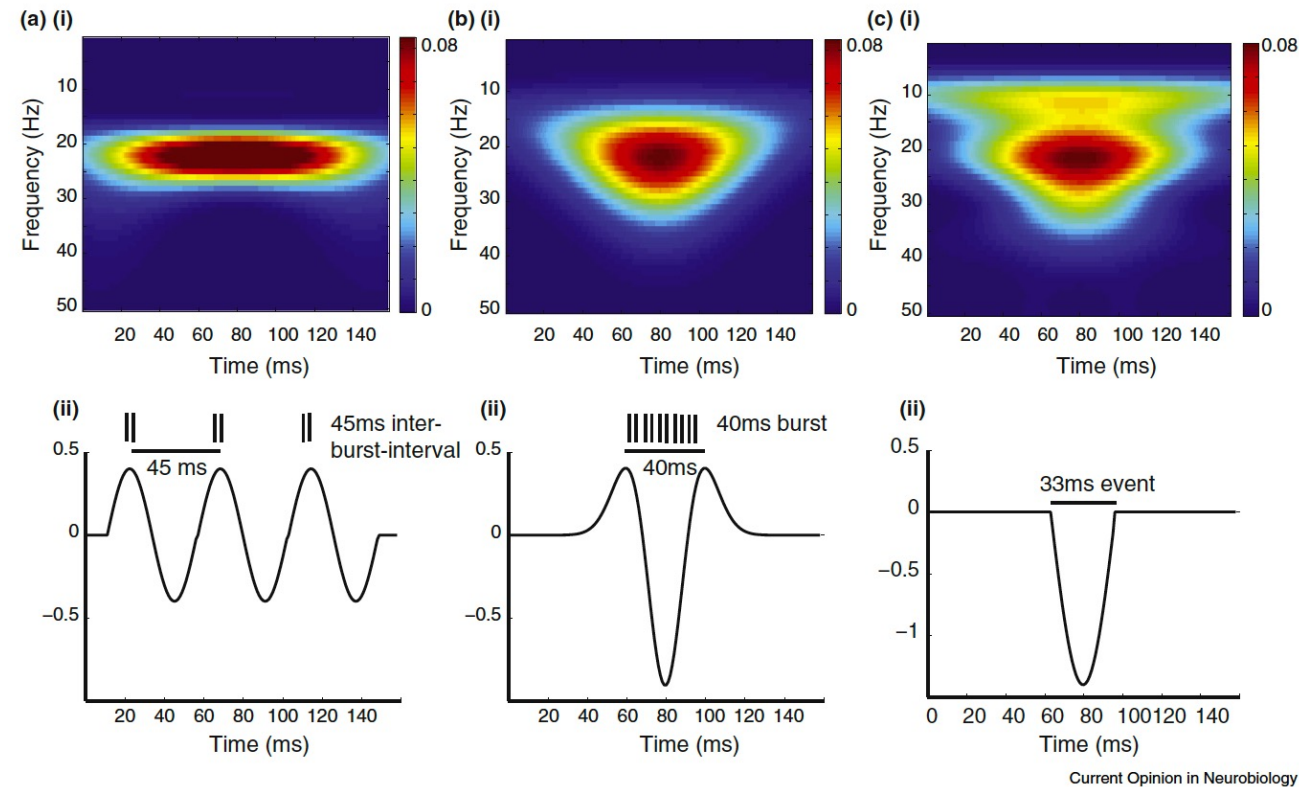
Non-oscillatory: the underlying signal in the data is not *ongoing*, or does not exhibit sinusoidal properties (i.e., incomplete cycles)



Jones (2016) – “When brain rhythms aren’t rhythmic”

What happens if a signal is not oscillatory?

Some modeled waves that all produce beta-range amplitude when analyzed using complex Morlet wavelets:



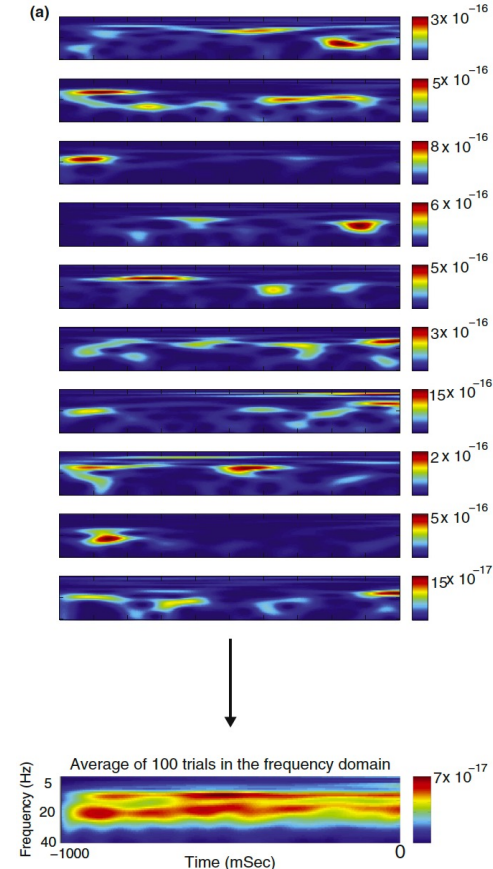
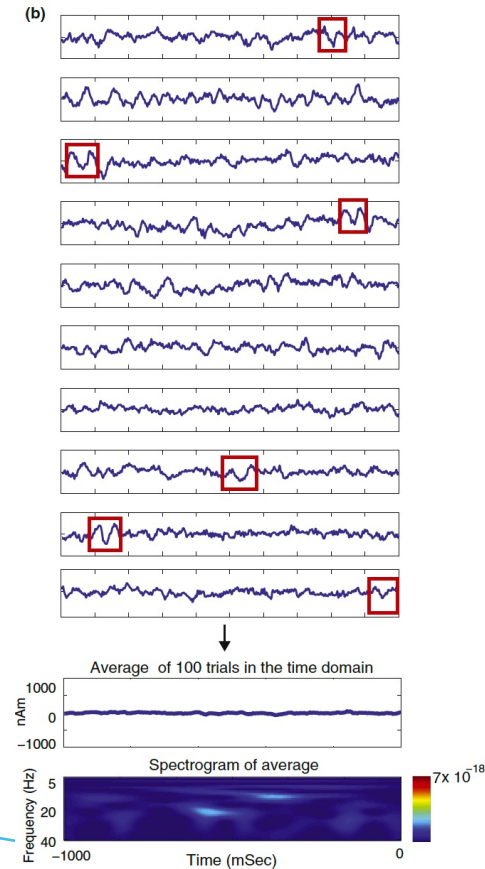
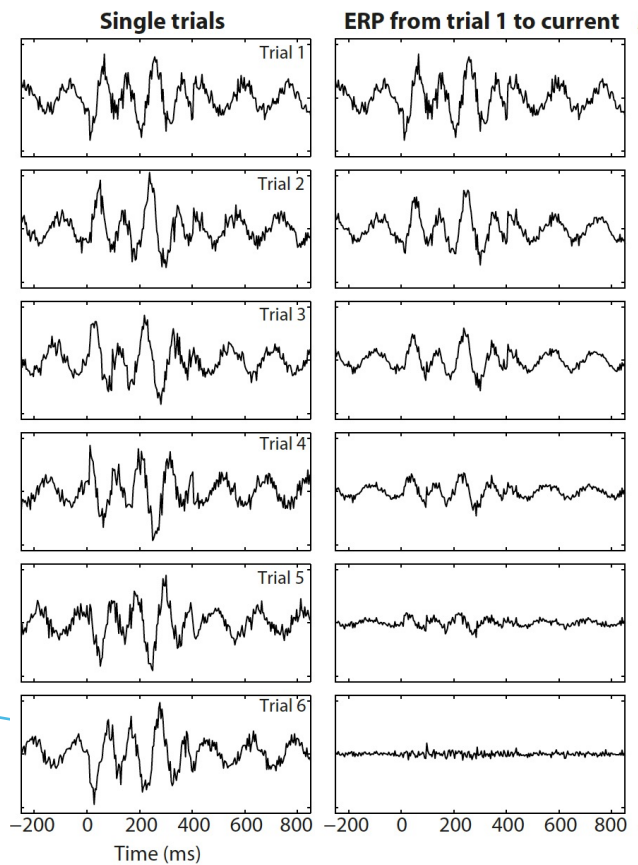
Current Opinion in Neurobiology

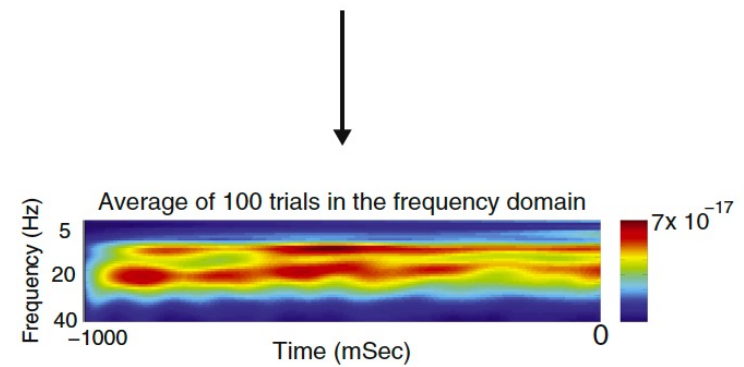
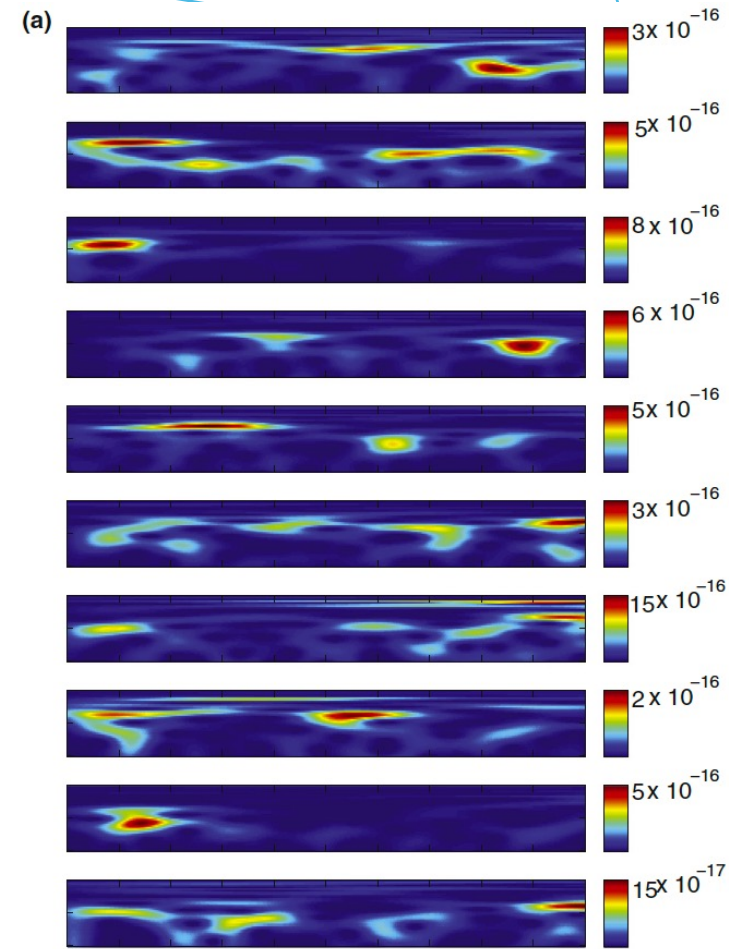
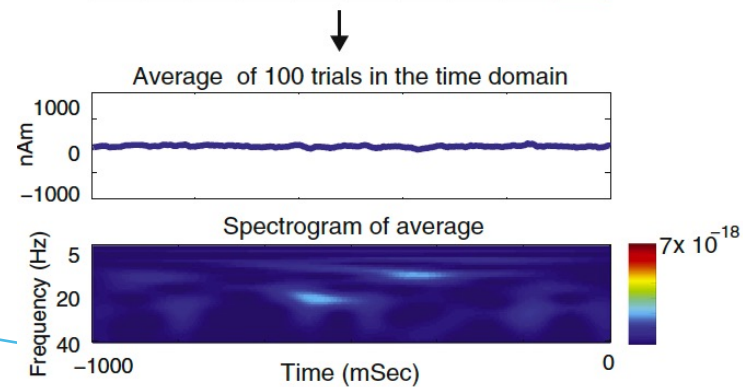
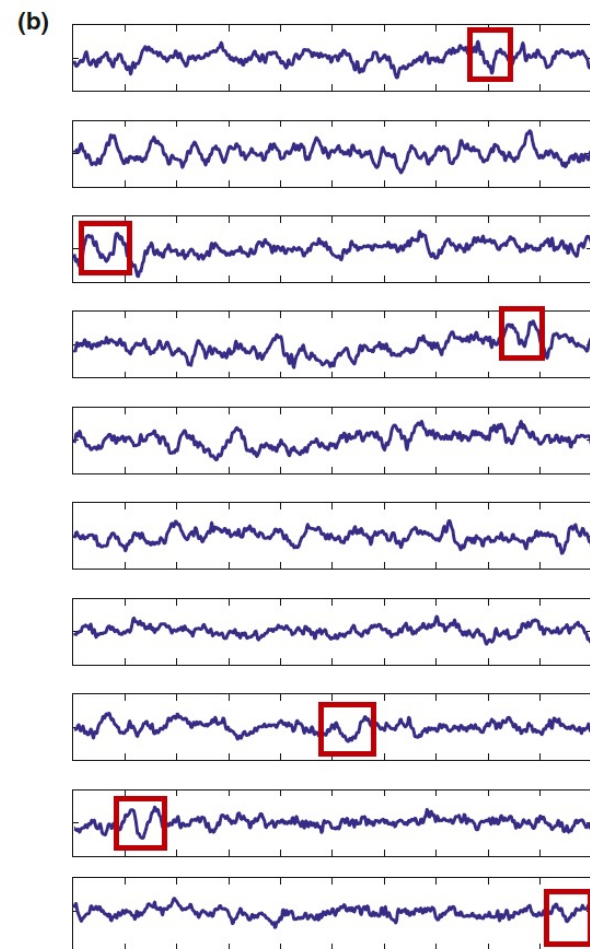
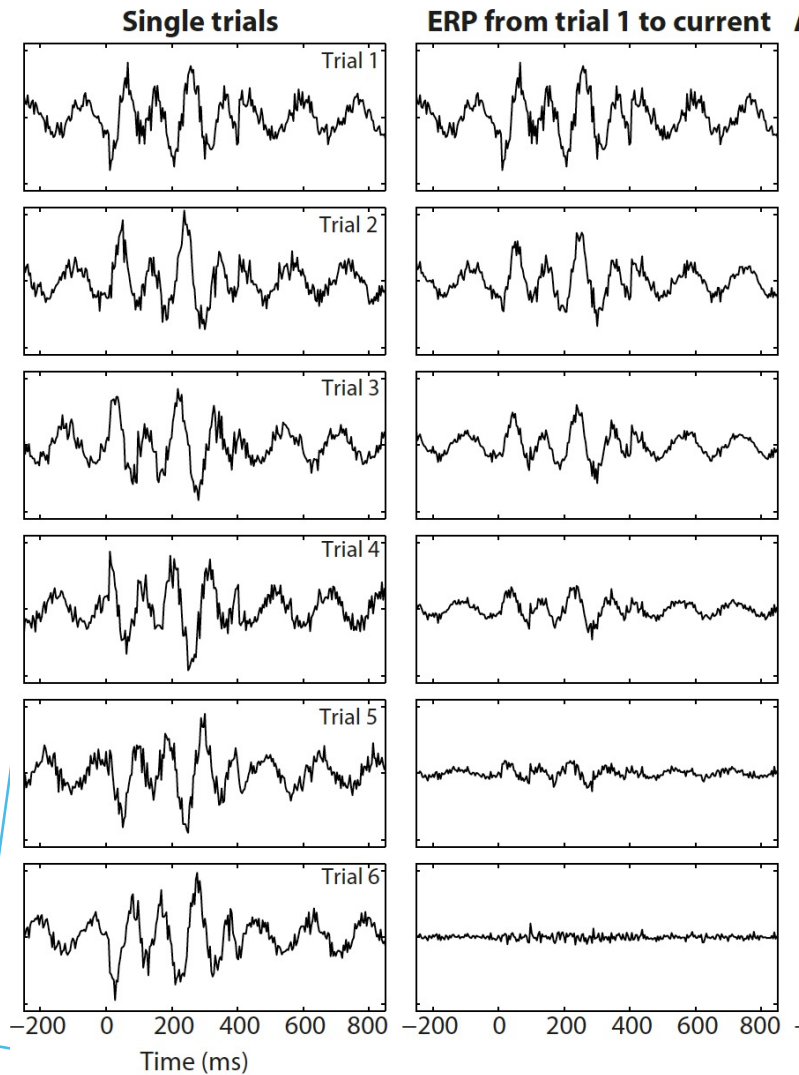
If we're using wavelets, we can tell how long the beta event lasts. So why is this a problem?

What happens if a signal is not oscillatory?

Recall ERP logic...

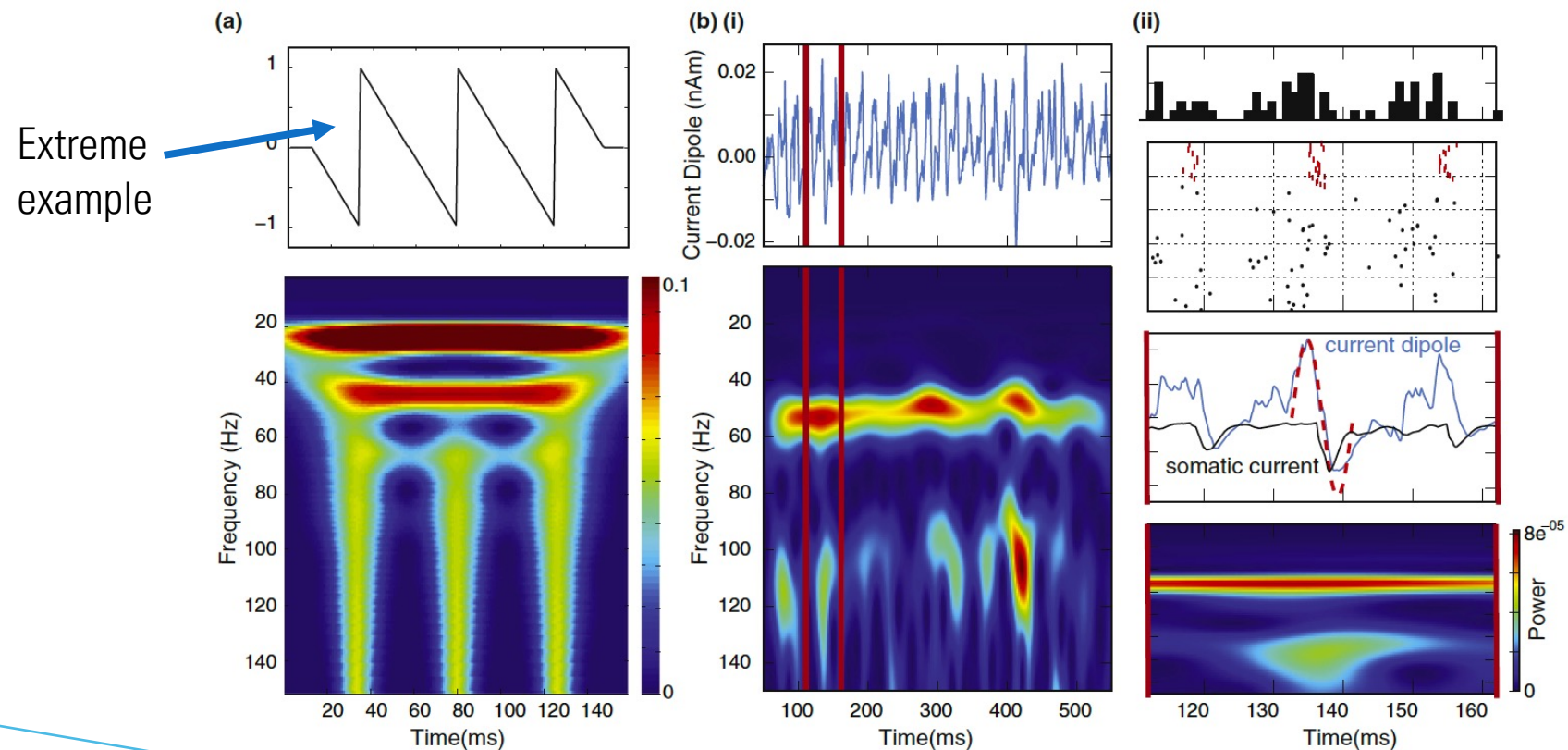
ERP logic does not apply to measures of amplitude because a signal cannot have negative amplitude.

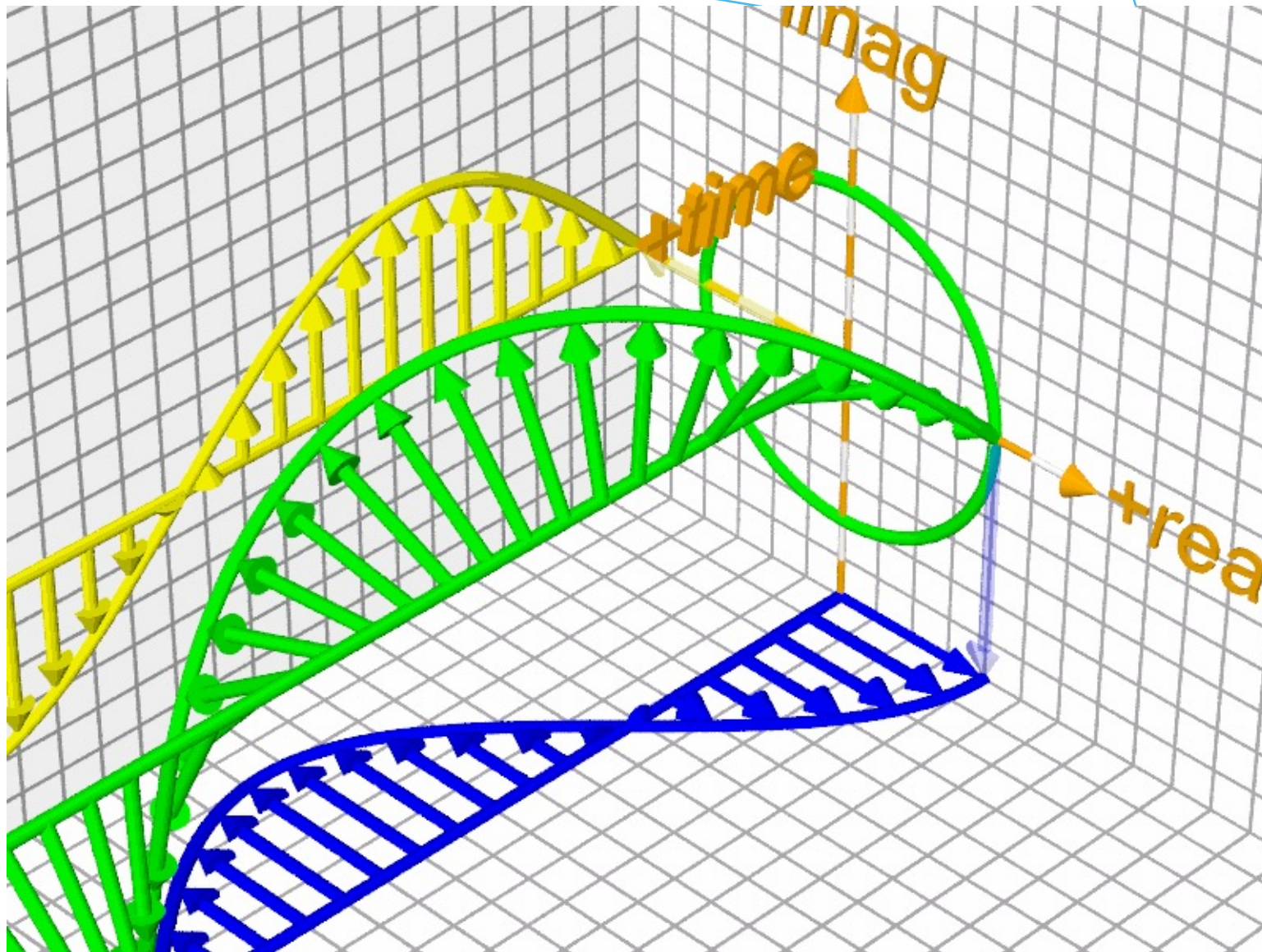
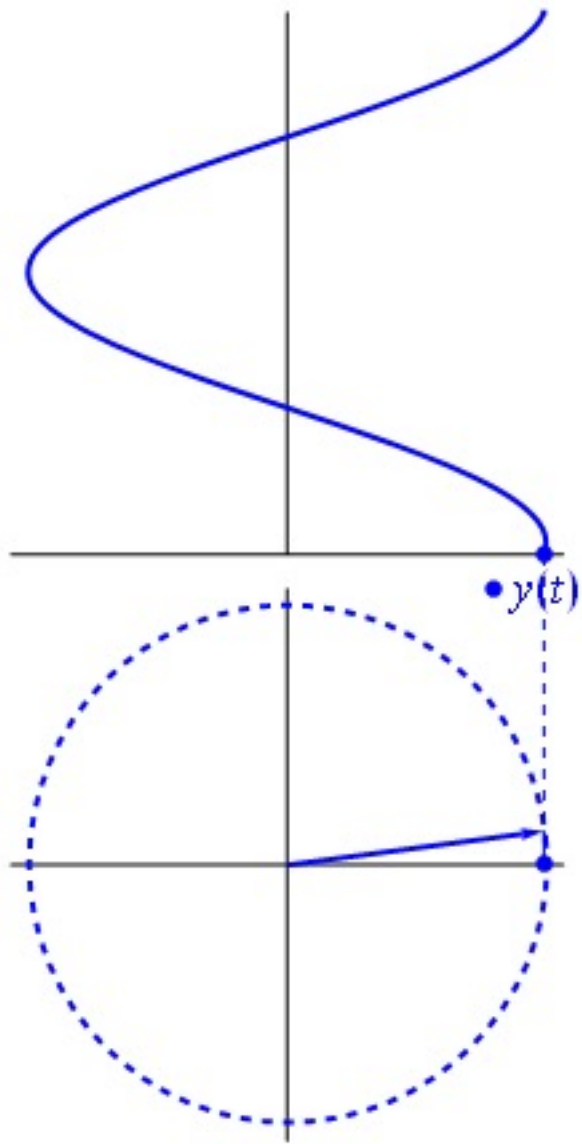




What happens if a signal is not oscillatory?

Irregular signals with sharp phase shifts can lead to spurious amplitude measurements.





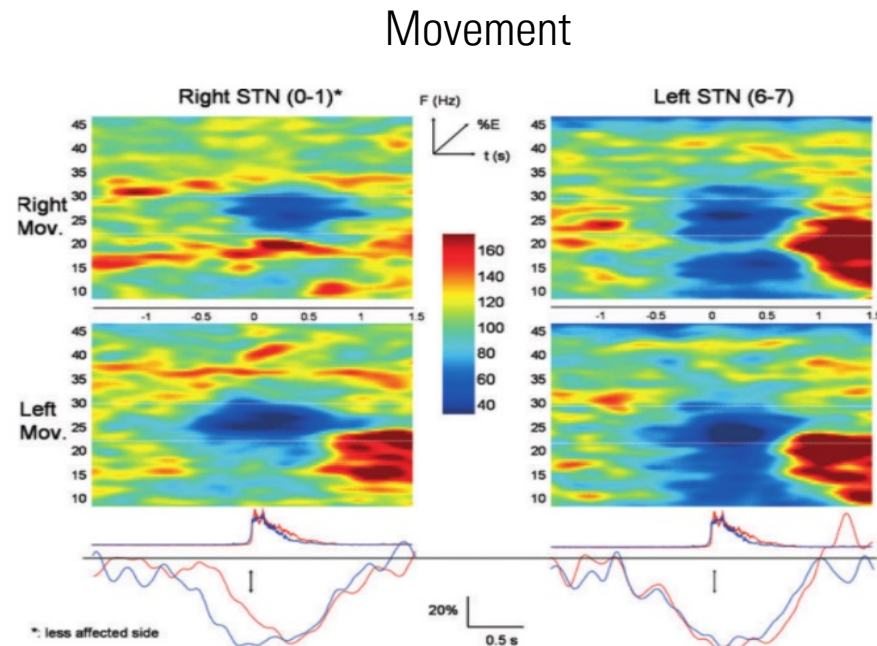
Regular, sinusoid-based phasors are not intended to handle this problem – they are intended to extract instantaneous phase and power.
Also – how meaningful is phase outside the context of a sinusoid wave?

Why does it matter?

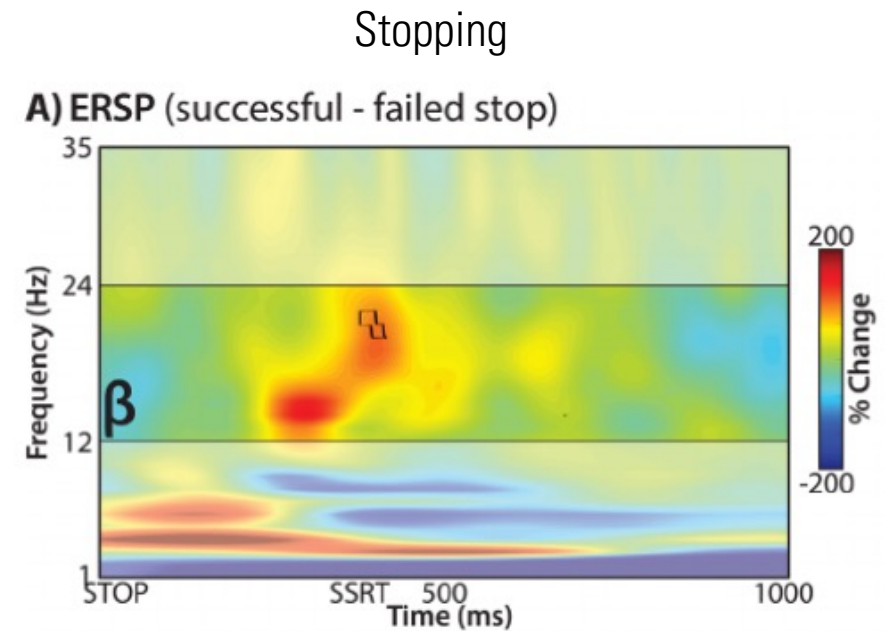
For a quick, epoch-wide FFT (i.e., to get a spectrogram), it might not matter.

It does matter when interpreting the length of effects, linking signals to behavior, and considering mechanisms!

Using beta as an example:



[Figure from Alegre et al., 2005]

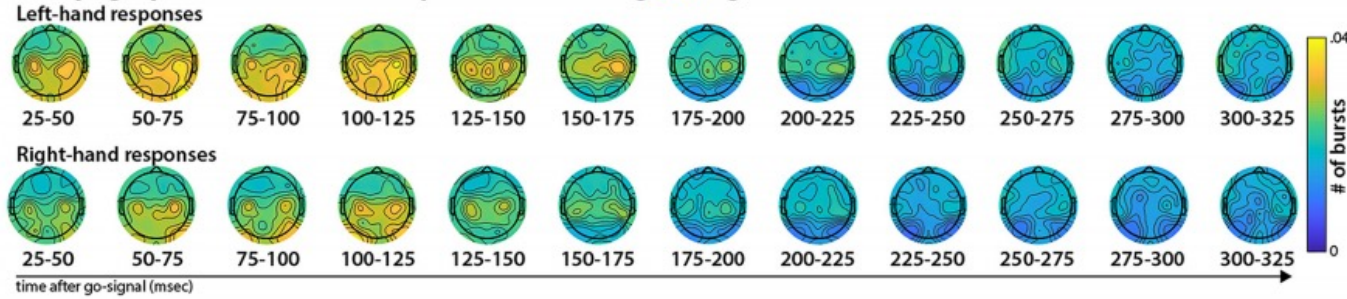


[Figure from Wessel et al., 2016]

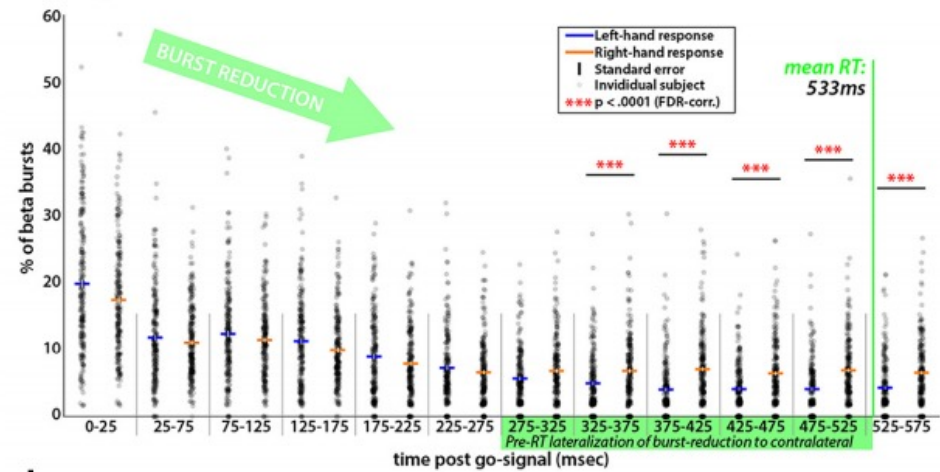
Movement

Stopping

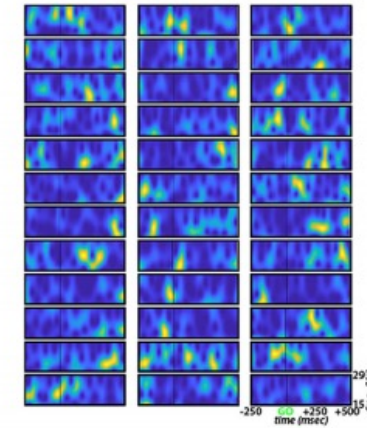
a Topographical distribution of β -bursts following GO-signals



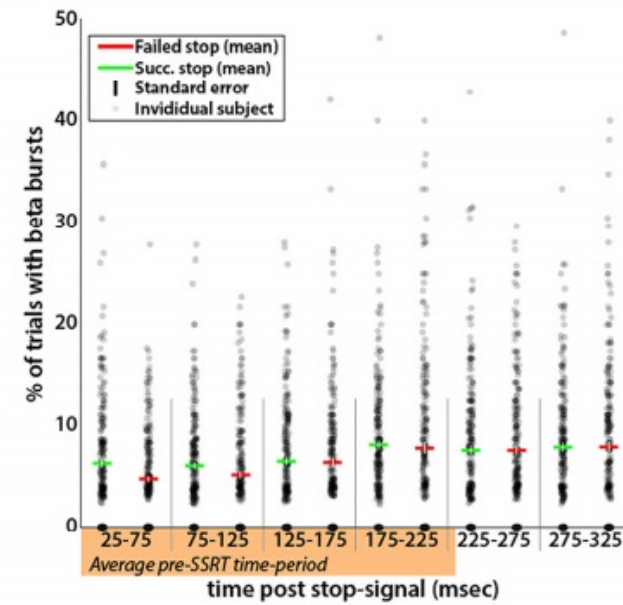
b Temporal distribution at RIGHT motor electrode C4



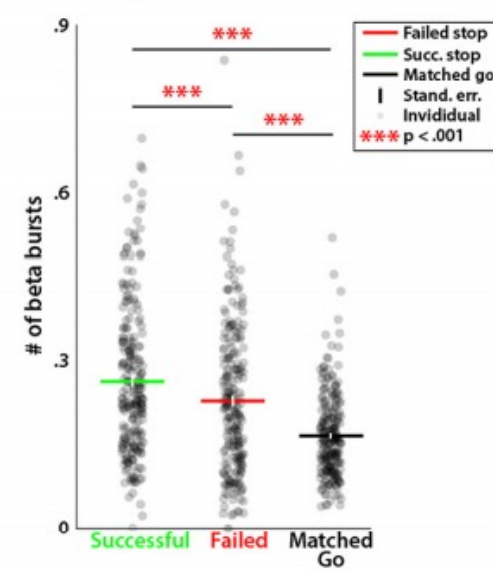
c C4: Individual trial data



b Temporal distribution at electrode FCz



c FCz β -bursts before SSRT

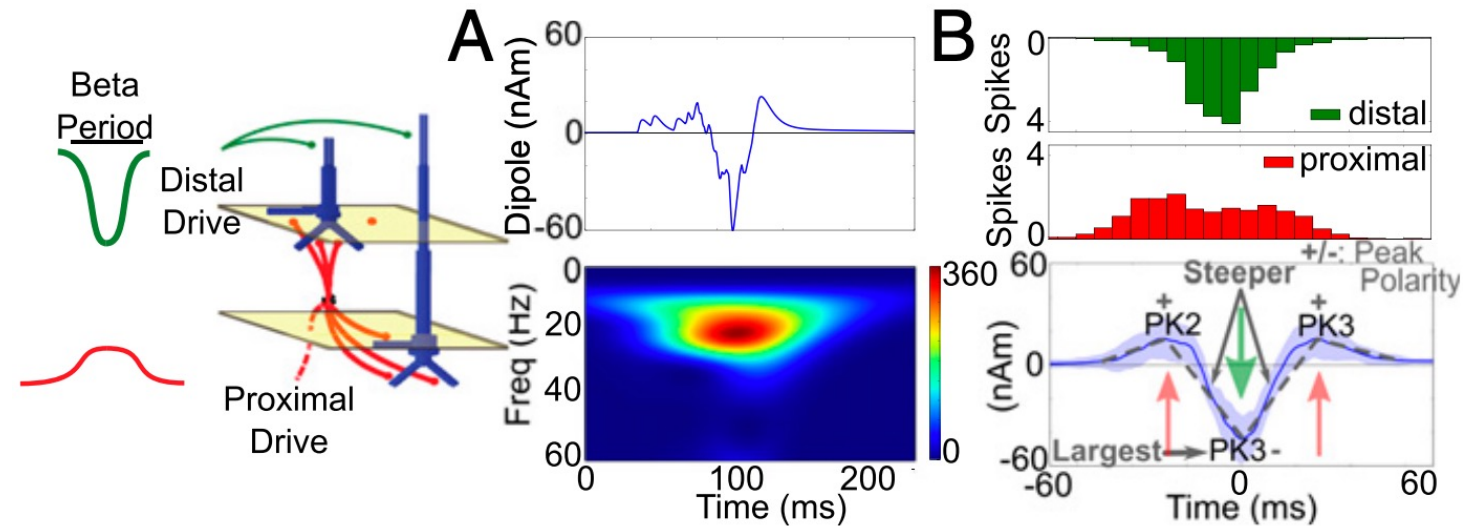


[Figures from Wessel 2020, J Neuro]

Why does it matter?

In addition, understanding characteristics of neural signals at the single trial level allows us to do some interesting things...

Including linking field potentials to mechanisms.

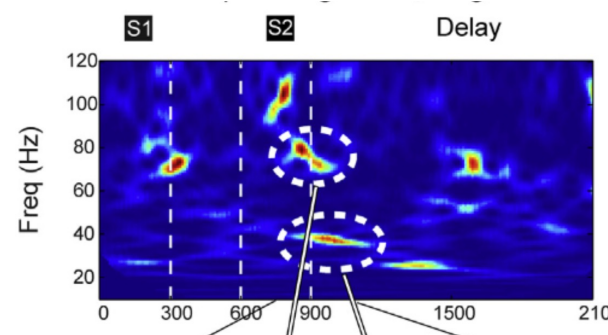
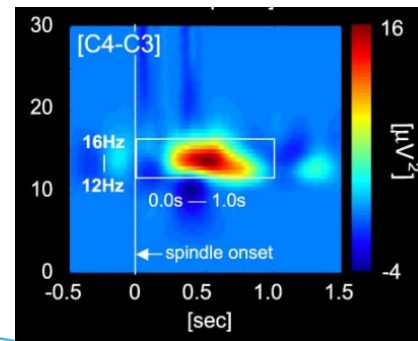
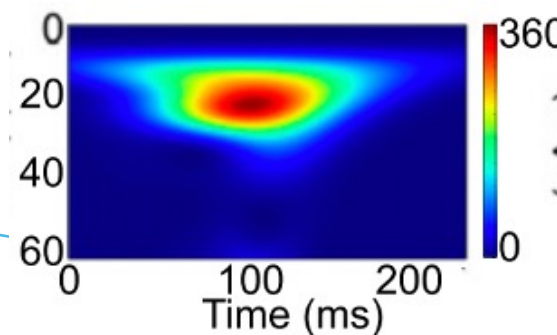


[Figure from Sherman et al., 2016]

Some non-oscillatory signals to be aware of

- Beta bursts – Shin et al., 2017 (ELife).
 - Appear to reflect inhibited information-processing in neocortex during movement, perception.
- Alpha bursts – Sherman et al., 2016 (PNAS).
 - Currently unclear how alpha bursts can be functionally differentiated from beta.
- Sleep spindles – Schabus et al., 2004 (Sleep)
 - Appear to have an important role in memory consolidation
- Gamma bursts – Lundqvist et al., 2016 (Neuron).
 - Prefrontal gamma bursts increase with working memory load.

...and clinical indicators!



An interim summary

Not all brain signals are **oscillatory**. Sine-wave based analysis methods don't account for this, and it becomes a problem especially when

- Averaging jittered, transient amplitude measurements.
- Dealing with signals that have sharp phase transitions.

Understanding non-oscillatory signals is important because

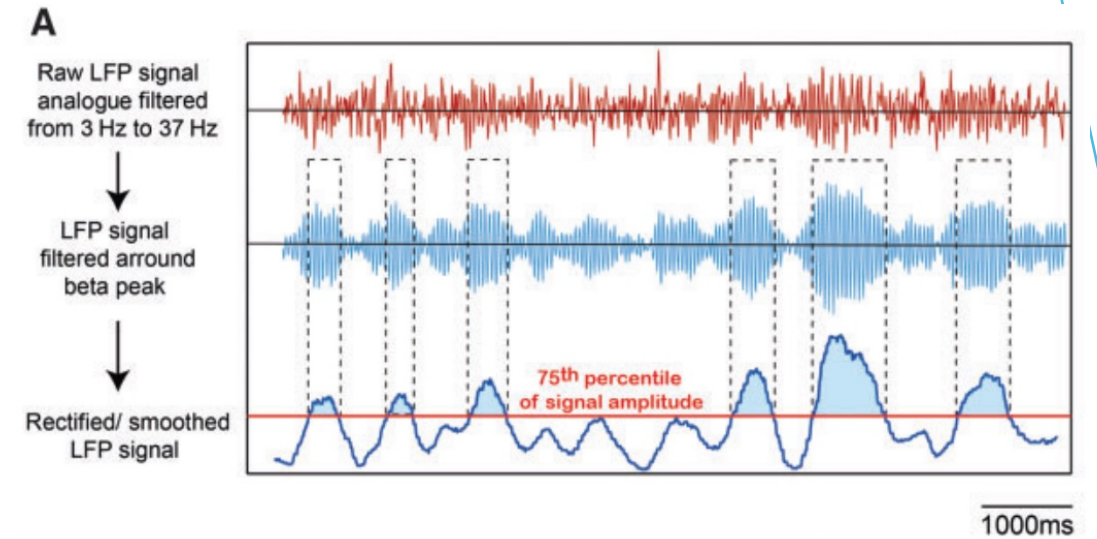
- They may better represent the nature of the cognitive process.
- They are likely more predictive of behavior.
- They allow you to make closer predictions about mechanisms.

Now, let's get into the practical details of extracting these signals...

How do we analyze non-oscillatory signals?

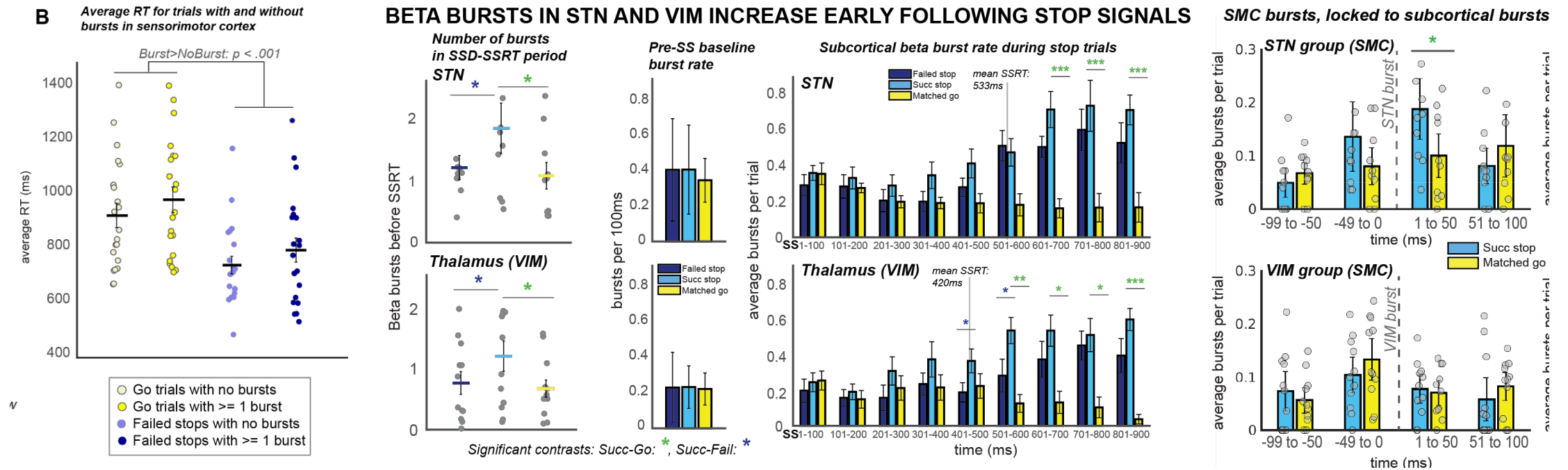
Today, I'll show you an example of how to use sinusoid-based methods that you already know to extract transient, burst-like signals.

1. Convert time-domain data to TF data (weighting time resolution)
2. Extract the power at frequencies of interest
3. Apply an amplitude cutoff
4. Statistically analyze your bursts



[Tinkhauser et al., 2017, Brain]

How do we analyze non-oscillatory signals?



The background features several thin, light blue lines that intersect to form various geometric shapes, including triangles and quadrilaterals, creating a modern, abstract design.

Practical demonstration in MATLAB

Additional tools for analyzing and understanding non-oscillatory signatures

This view of neural signatures represents a departure from canonical approaches of studying neural signals, especially EEG. As such, best approaches and tools are still being developed.

Here are some examples of such tools to get you started. 😊



Modelling non-oscillatory signatures

Fieldtrip's ft_dipolesimulation: “simulates channel-level time-series data that consists of the the spatial distribution of the the field or potential of one or multiple dipoles.”

- Specify levels of background white noise.
- Set specs of meaningful neural signal to include.

Cons:

- No GUI
- Requires you to know what you're doing

https://www.fieldtriptoolbox.org/reference/ft_dipolesimulation/

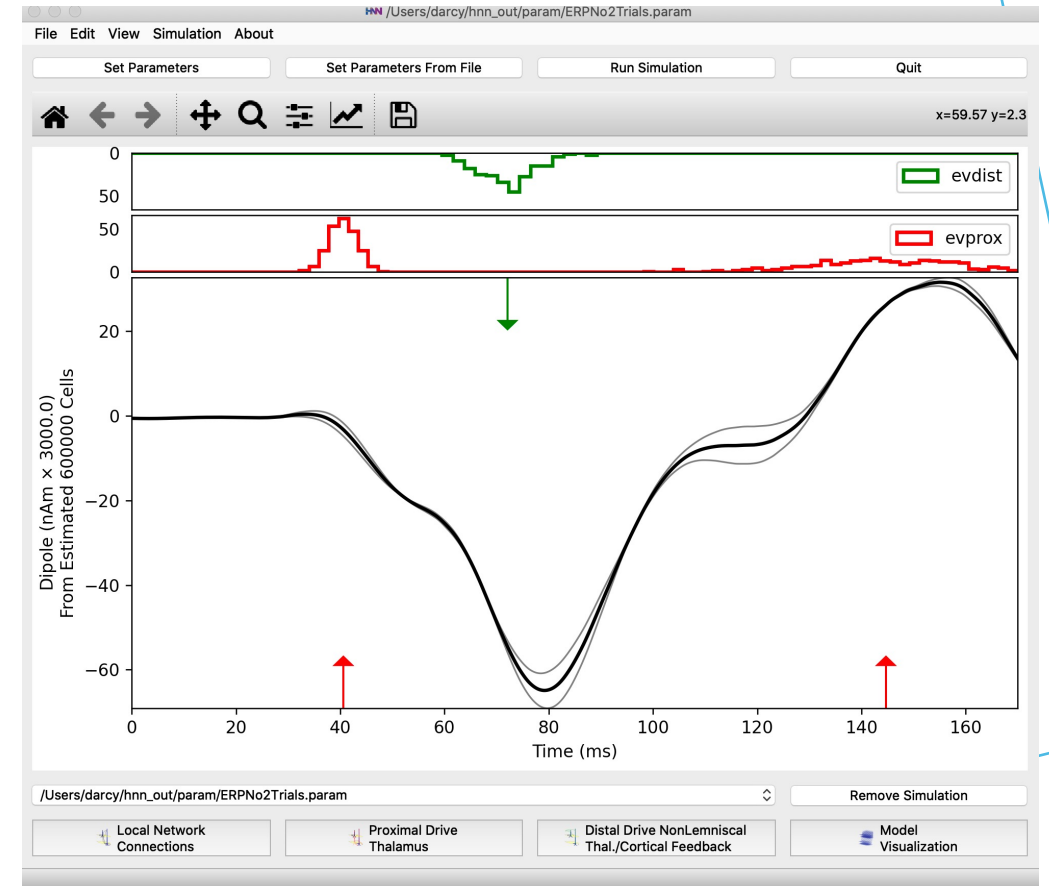


Modelling non-oscillatory signatures

Human Neocortical Neurosolver: model source-level, biophysically-realistic EEG/MEG data (ERPs and TF) using a simulated cortical circuit model.

Pros: simple GUI, Cons: not a MATLAB package, source-level simulations

<https://hnn.brown.edu/>



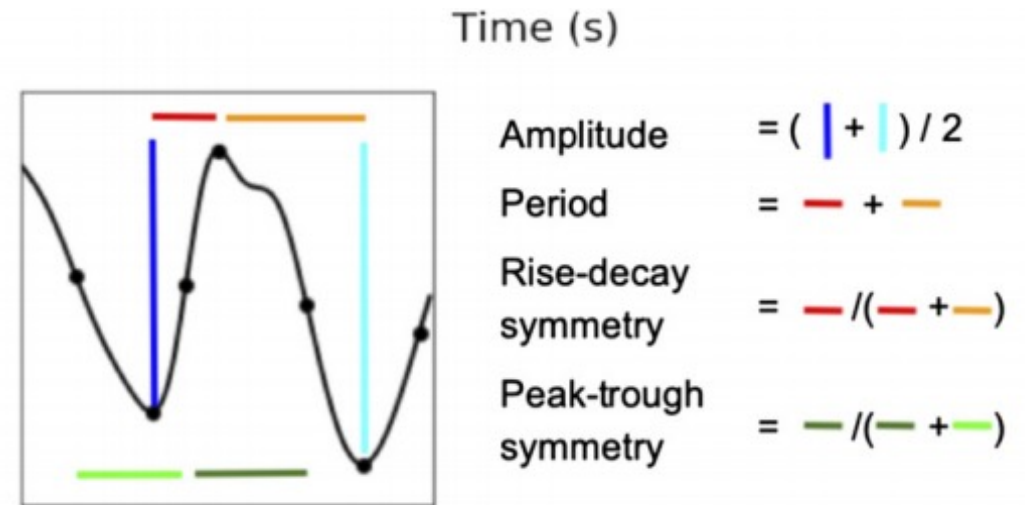
Getting granular data from non-osc. signatures

Bycycle Python package: quantify neural features in the time-domain, cycle-by-cycle.

- Doesn't use narrow-band filters or methods with sinusoidal basis.
- Cole and Voytek, 2019 (J Neurophys)

<https://github.com/bycycle-tools/bycycle>

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Questions?