Signal & Data Analysis in Neuroscience 2020

Spectral Analysis

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1

Outline – Frequency domain

- ☑ Introduction
- ☑ Fourier Transform
- ☑ Sampling Theory
- ☑ Systems
- ☑ Filters
- ☑ Windows
- ■ Spectral Analysis

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2

Parseval's theorem

The Fourier transform is unitary → the sum (or integral) of the square of a function is equal to the sum (or integral) of the square of its transform.

Continuous Fourier transform

$$\int_{-\infty}^{\infty} |x(t)|^2 \, dt = \int_{-\infty}^{\infty} |X(f)|^2 \, df$$

Discrete Fourier transform

$$\sum_{n=0}^{N-1} |x[n]|^2 = \sum_{k=0}^{N-1} |X[k]|^2$$

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Signal energy

- The energy spectral density describes how the energy (or variance) of a signal or a time series is distributed with frequency.

$$\Phi(\omega) = \left| \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-i\omega t}\, dt \right|^2 = \frac{F(\omega)F^*(\omega)}{2\pi}$$

$$\Phi(\omega) = \left| \frac{1}{\sqrt{2\pi}} \sum_{n=-\infty}^{\infty} f_n e^{-i\omega n} \right|^2 = \frac{F(\omega)F^*(\omega)}{2\pi}$$

(only for finite energy signals)

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4

Signal Power

$$Power = \frac{Energy}{Time}$$

$$S = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} |x(t)|^2 dt$$

$$S = \lim_{T\to\infty} \frac{1}{2T} \int_{-\infty}^{\infty} |X_T(f)|^2 df$$

Equal By Parseval's Theorem

$$\hat{S}[f] = |DFT\{x[n]\}|^2 = \left| \frac{1}{N} \sum_{n=0}^{N-1} x[n] e^{\left(\frac{-j2\pi nf}{N}\right)} \right|^2$$

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5

Correlation & Convolution

- Correlation

$$R_{g,h}(t) = Corr(g,h)_t = \sum_{i=-\infty}^{\infty} g_i h_{t+i}$$

$$R_{g,h}(t) = Corr(g,h)_t = Corr(h,g)_{-t} = R_{h,g}(-t)$$

- Convolution

$$(g*h)_t = \sum_{i=-\infty}^{\infty} g_{t-i} h_i$$

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6

Wiener-Khinchin theorem

- The power spectrum is the Fourier transform of the auto-correlation function
- Power spectrum $S(f) = \int_{-\infty}^{\infty} R(\tau) e^{-j2\pi f\tau}\, d\tau$
- Autocorrelation $R(\tau) = \int_{-\infty}^{\infty} S(f) e^{j2\pi f\tau}\, df$

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7

Power spectral density

- Amount of power per unit (density) of frequency (spectral) as a function of the frequency

Power Spectrum	Spectral Density
$S_{x,x}(\omega) = \sum_{m=-\infty}^{\infty} R_{x,x}(m) \cdot e^{-j\omega m}$	$P_{x,x}(\omega) = \frac{S_{x,x}(\omega)}{2\pi}$
$S_{x,x}(f) = \sum_{m=-\infty}^{\infty} R_{x,x}(m) \cdot e^{\frac{-2\pi fm}{f_s}}$	$P_{x,x}(f) = \frac{S_{x,x}(f)}{f_s}$

Average power

$$\overline{P}(\omega_1, \omega_2) = \int_{\omega_1}^{\omega_2} P_{x,x}(\omega) d\omega - \int_{-\omega_2}^{-\omega_1} P_{x,x}(\omega) d\omega = 2 \cdot \int_{\omega_1}^{\omega_2} P_{x,x}(\omega) d\omega$$

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8

Spectrum Estimation - Problems

- Leakage problems and side lobes.
- Increased length of signal leads to increase in number of discrete frequency but not to increased accuracy at each frequency.

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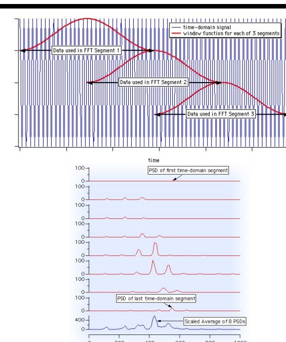
9

Spectrum Estimation Methods

- Non parametric estimators
- Correlogram estimators
- Parametric estimators
- Subspace estimators

10

Example – Welch estimator



11

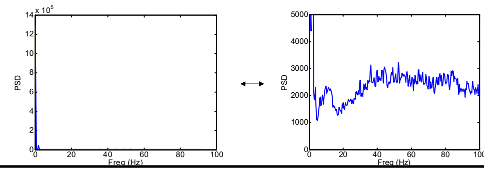
Things we find in the spectrum:

- DC
- White noise
- Harmonics

12

Direct Current (DC)

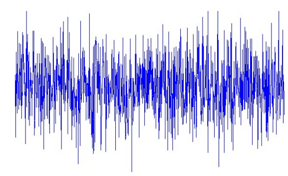
- DC is transformed into energy at frequency 0.
- Unless DC is removed the power it adds is typically huge compared to all other frequencies.



13

White noise

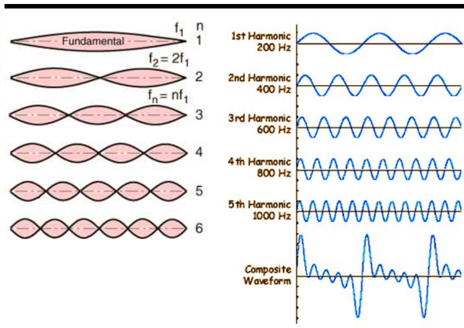
- White noise is a random signal (or process) with a flat power spectral density.



- Zero correlation at t≠0.
- There are also pink & red/brown noises.

14

Harmonics



15

Do we have harmonies?

- Many biological processes lead to the formation of harmonies.
- Any square wave (for example a sudden change in a parameter) is transformed to multiple harmonies.
- The multiple frequencies may describe the same underlying process.

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16

Temporal & spectral resolution

- Using **windowed estimation** (Welch/Bartlett) leads to a temporal / spectral resolution tradeoff.
- For a recording of ***T*** seconds sampled at ***s*** samples/sec and assessed using a ***w*** sample window:

Number of windows: $\frac{T \cdot s}{w}$

Spectral resolution (Δf): $\frac{s}{w}$

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17

Relative & absolute power

- The absolute power depends heavily on the normalization of the signal.
- The relative power enables detecting the statistics of the signal at unfiltered frequencies.

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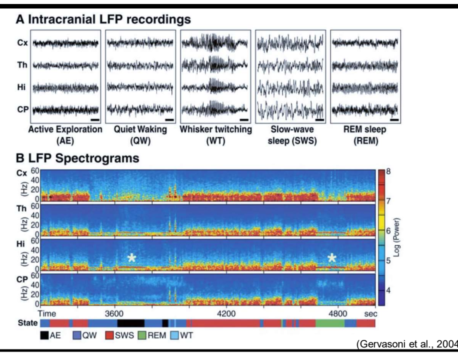
18

Spectogram

- In many cases the signal is not stationary.
- However, assuming stationarity over short intervals leads to usage of the spectrogram.
- Power spectral density over short periods of time using a sliding window over the signal
- Temporal resolution vs. spectral resolution…

19

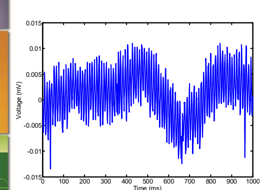
Spectrogram
Identification of behavioral states

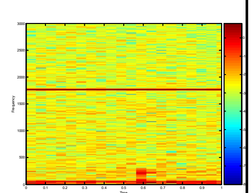


(Gervasoni et al., 2004)

20

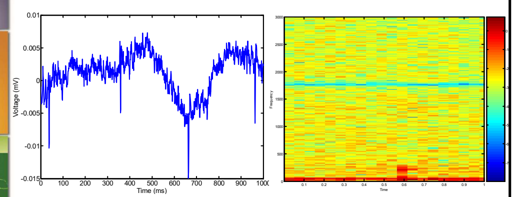
Original signal





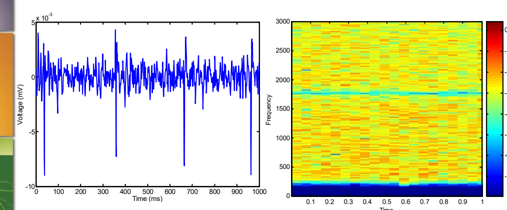
21

Following notch filter (~1800Hz)

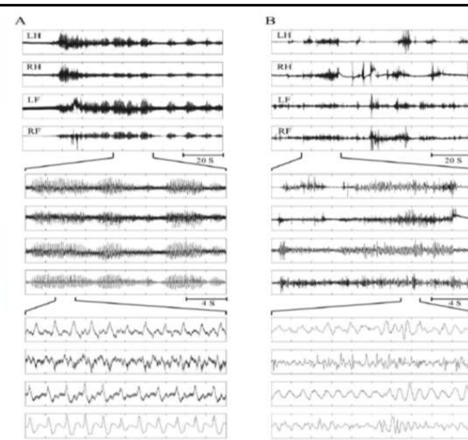


22

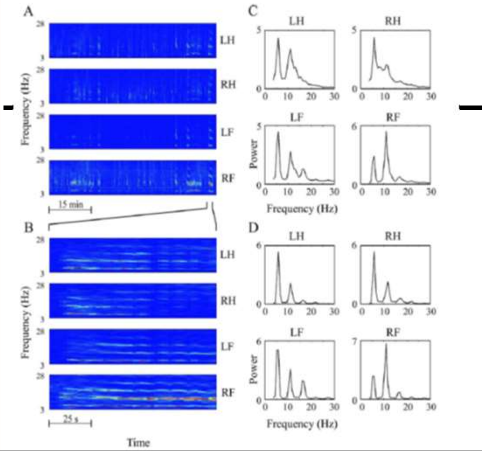
Following high pass (~300Hz)



23

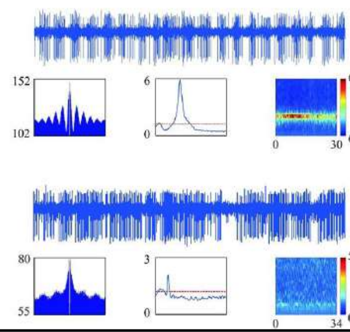


24



25

GP activity - Parkinsonian primate



26

Cross spectrum I

- Multiplication of the Fourier transforms of the signals.

$$\hat{S}_{y,x}(\omega) = \frac{1}{N} Y(\omega) X^*(\omega)$$

27

Cross spectrum II

- Cross Spectral Density – defined as the transform of the cross correlation

$$S_{x,y}(\omega) = \sum_{m=-\infty}^{\infty} R_{x,y}(m) \cdot e^{-j\omega m}$$

- Two unrelated signals sharing common frequencies will have significant cross spectral density over finite length of time.

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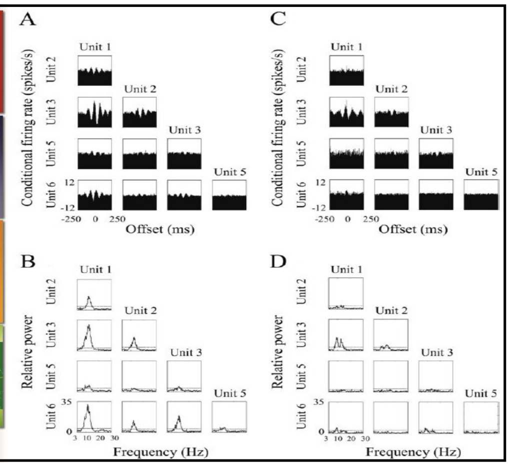
28



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29

Coherence

- Coherence - ratio of the cross spectral density to the power spectral density of the two signals

$$C_{x,y}(f) = \frac{\left|S_{x,y}(f)\right|^2}{S_{x,x}(f) \cdot S_{y,y}(f)}$$

- Normalizes to the spectrum of the two signals and thus relates only to the relation between the signals and not to their structure.

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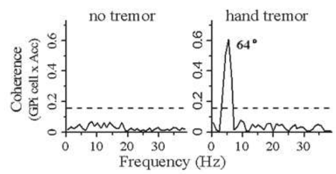
30

Coherence example



(Dostrovsky et al)

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31

Coherence
Significance

- Coherence range is 0→1.
- Confidence limit:

$$1-(1-\alpha)^{\frac{1}{(N-1)}}$$

α is the probability (e.g. 0.99) and N is the number of windows (Rosenberg et al., 1989)

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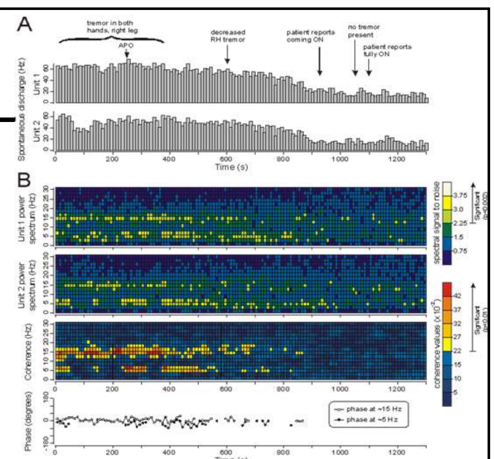
32



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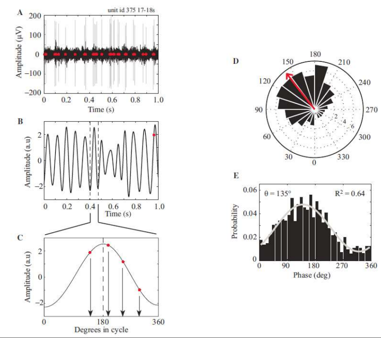
33

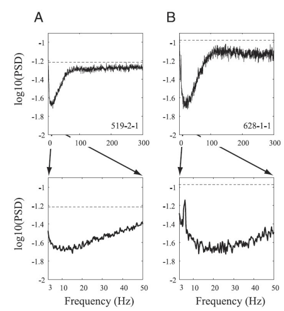
Phase relation



34

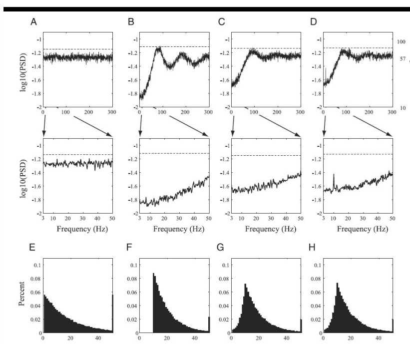
Spectrum of a spike train

Normal and Parkinsonian primates



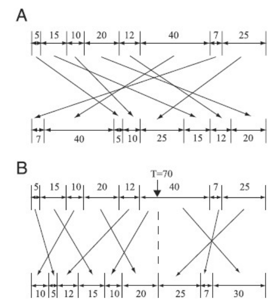
35

Refractory period spectral effect



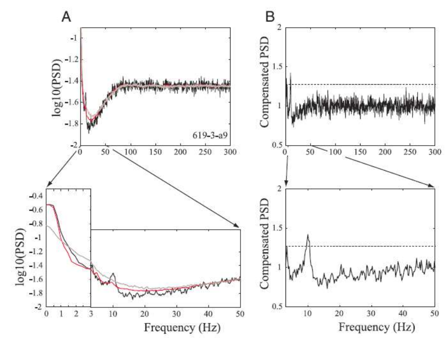
36

Shuffling
Global and Local



37

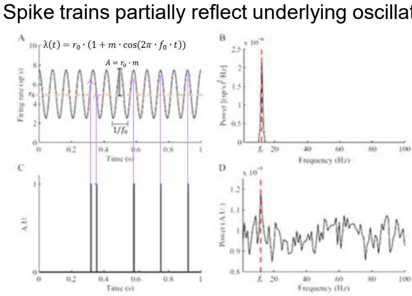
Spectral compenstation



38

Rate dependent oscillations

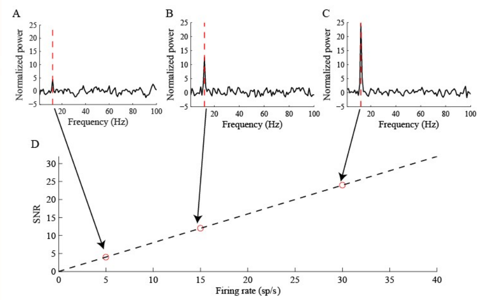
- Spike trains partially reflect underlying oscillations.



(Matzner & Bar-Gad, PLoS Comp. Bio.2015)

39

Rate dependent oscillations



40

Power spectrum

- An inhomogeneous spike train over a period (T):

$$S_{\rho_T}(f) = \frac{1}{T}\left[\int_0^T \lambda(t)\, dt + \left|\int_0^T \lambda(t) e^{-i2\pi f t} dt\right|^2\right]$$

- Using the simple case of cosine rate modulation over a base frequency (f_0):

$$\begin{aligned} S_{\rho_T}(f) = {} & r_0 + r_0 m \,\mathrm{sinc}(2 f_0 T) \\ & + r_0{}^2 T \mathrm{sinc}^2(fT) \\ & + r_0{}^2 T m \,\mathrm{sinc}(fT)\,\mathrm{sinc}[(f - f_0)T] + r_0{}^2 T m \,\mathrm{sinc}(fT)\,\mathrm{sinc}[(f + f_0)T] \\ & + \frac{r_0{}^2 T m^2}{4} \mathrm{sinc}^2[(f - f_0)T] + \frac{r_0{}^2 T m^2}{4} \mathrm{sinc}^2[(f + f_0)T] \\ & + \frac{r_0{}^2 T m^2}{2} \mathrm{sinc}[(f - f_0)T]\,\mathrm{sinc}[(f + f_0)T] \end{aligned}$$

41

Spectral peak - function of the rate

The peak power ($f = f_0$) is

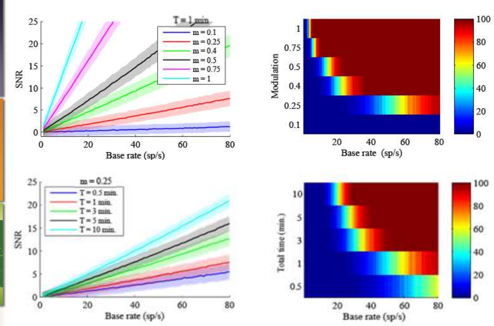
$$S_{\rho T}(f = f_0) = r_0 \cdot (1 + \frac{r_0 T m^2}{4})$$

The baseline power ($f \neq f_0$) is

$$S_{\rho_T}(f \neq f_0) = r_0$$

42

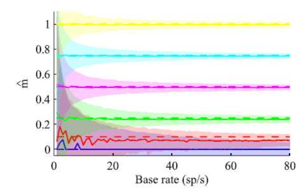
Spectral peak magnitude
Modulating factors



43

The modulation index estimator

$$\hat{m} = \left| \frac{2 \cdot \sqrt{\hat{S}_{\rho_T}(f = f_0) - \hat{r}_0}}{\hat{r}_0 \sqrt{T}} \right|$$



An objective measure of the oscillation magnitude.

44