

---

---

---

---

---

---

---

---



---

---

---

---

---

---

---

---



---

---

---

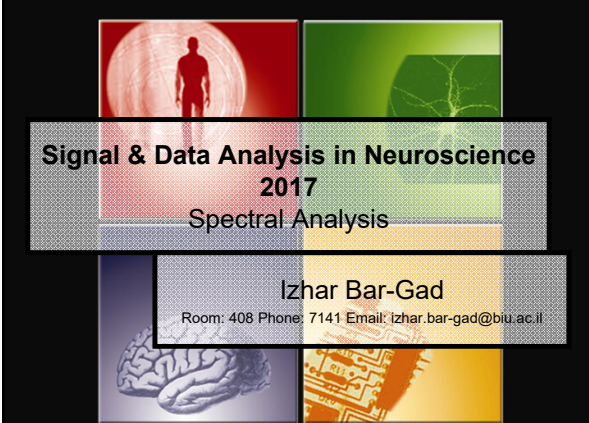
---

---

---


---

---




**Signal & Data Analysis in Neuroscience**  
2017  
Spectral Analysis

**Izhar Bar-Gad**  
Room: 408 Phone: 7141 Email: izhar.bar-gad@biu.ac.il



**Outline – Frequency domain**

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



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

---

---

---

---

---

---

---

---



---

---

---

---

---

---

---

---



---

---

---


---

---

---

---

---




### 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)





### Signal Power


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


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

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

Equal By Parseval's Theorem

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






### Correlation & Convolution

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

$$R_{g,h}(t) = Corr(g, h)_t = Corr(h, g)_{-t} = R_{h,g}(-t)$$
- Convolution
$$(g * h)_t = \sum_{l=-\infty}^{\infty} g_{t-l} h_l$$



---

---

---

---

---

---

---

---



---

---

---

---

---

---

---

---



---

---

---





---

---

---

---




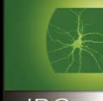
---

### 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  $R(\tau) = \int_{-\infty}^{\infty} S(f) e^{j2\pi f\tau} df$

IBG

### Power spectral density





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

Power Spectrum	Spectral Density
$S_{x,x}(\omega) = \sum_{m=-\infty}^{\infty} R_{x,x}(m) \cdot e^{-j\omega m}$	$P_{x,x}(\omega) = \frac{S_{x,x}(\omega)}{2\pi}$
$S_{x,x}(f) = \sum_{m=-\infty}^{\infty} R_{x,x}(m) \cdot e^{-\frac{j2\pi fm}{f_s}}$	$P_{x,x}(f) = \frac{S_{x,x}(f)}{f_s}$

Average power

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

IBG

### 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.

IBG

---

---

---

---

---

---

---



---

---

---

---

---

---

---



---

---


---

---

---


---

---

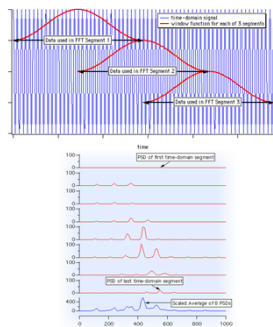



### Spectrum Estimation Methods

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



### Example – Welch estimator





### Things we find in the spectrum:

- DC
- White noise
- Harmonics

---

---

---

---

---

---

---

---



---

---

---

---

---

---

---

---



---

---

---





---

---

---

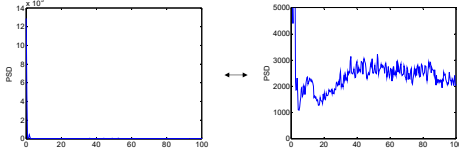
---

---










## 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.

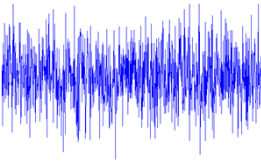


IBG





## White noise

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

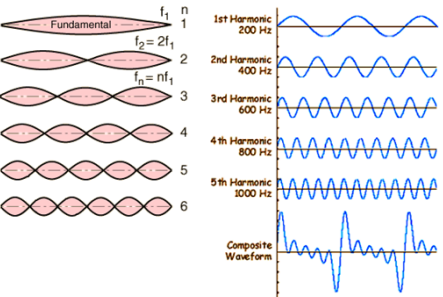


- Zero correlation at  $t \neq 0$ .
- There are also pink & red/brown noises.

IBG

## Harmonics



IBG

---

---

---

---

---

---

---

---



---

---

---

---

---

---

---

---



---

---

---





---

---

---

---




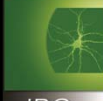
---

### 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.

IBG





### 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 ( $\Delta f$ ):  $\frac{s}{w}$

IBG

### 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.

IBG

---

---

---

---

---

---

---

---



---

---

---

---

---

---

---

---



---

---

---


---

---

---

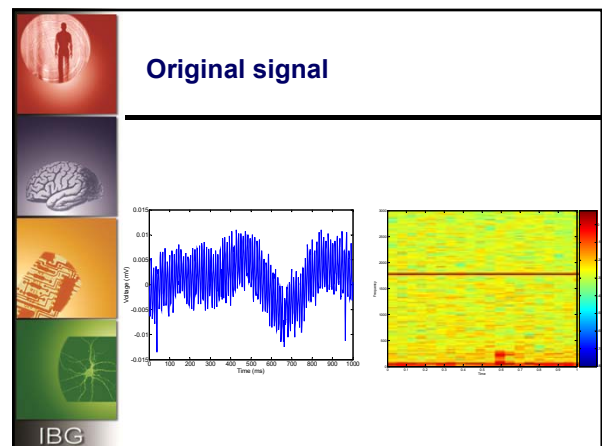
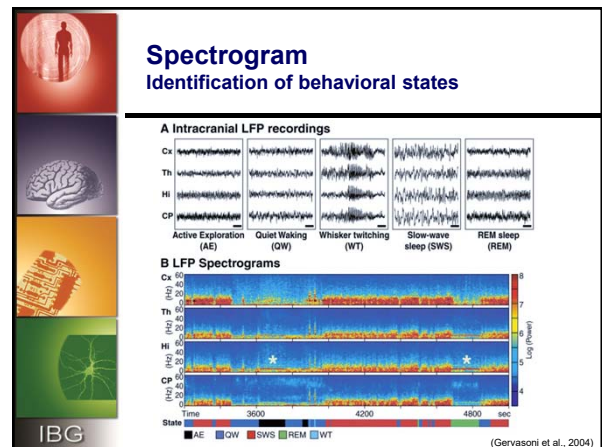
---

---



## Spectrogram

- 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...



---

---

---

---

---

---

---

---



---

---

---

---

---

---

---

---



---

---

---

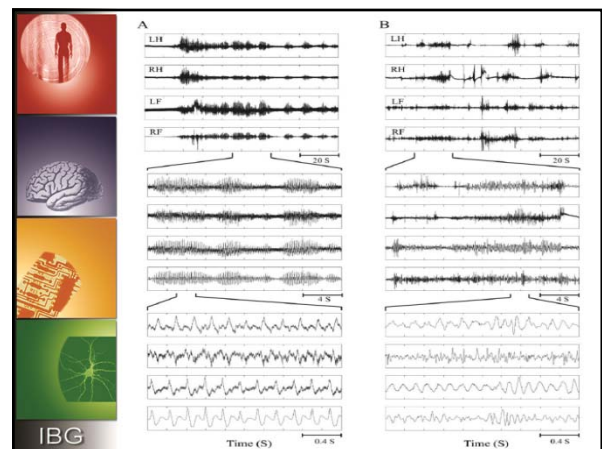
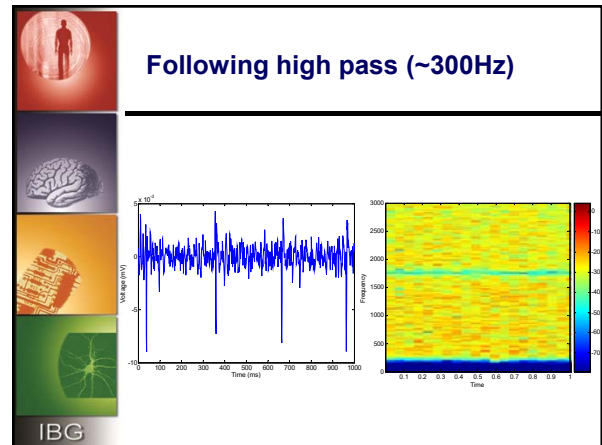
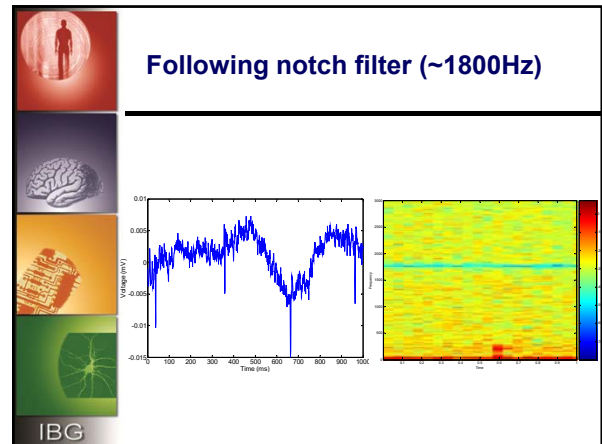
---

---

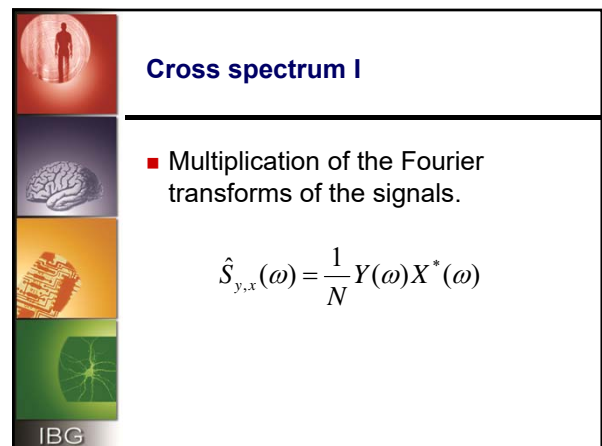
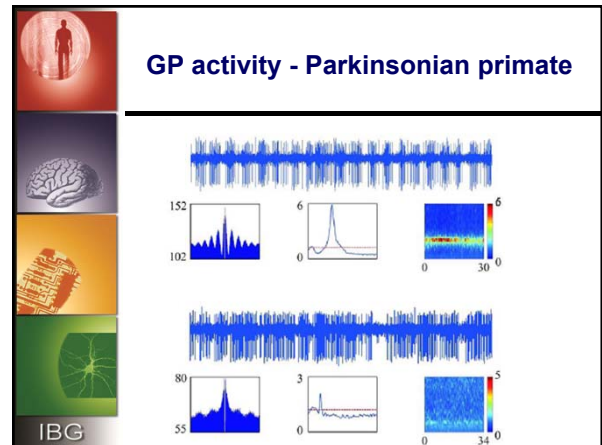
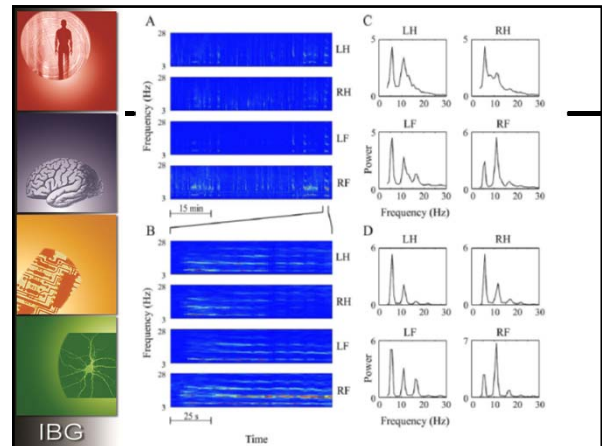
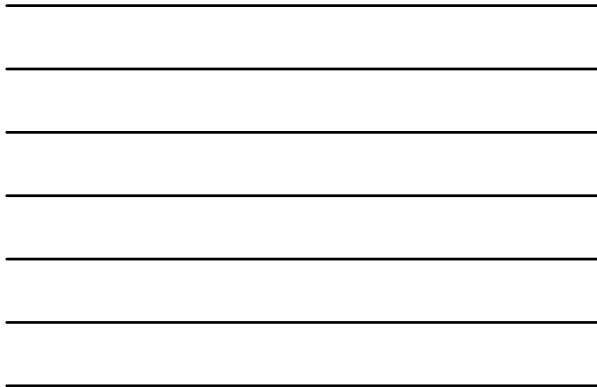
---

---

---







---

---

---

---

---

---

---

---



---

---

---

---

---

---

---

---



---

---

---


---

---

---

---

---

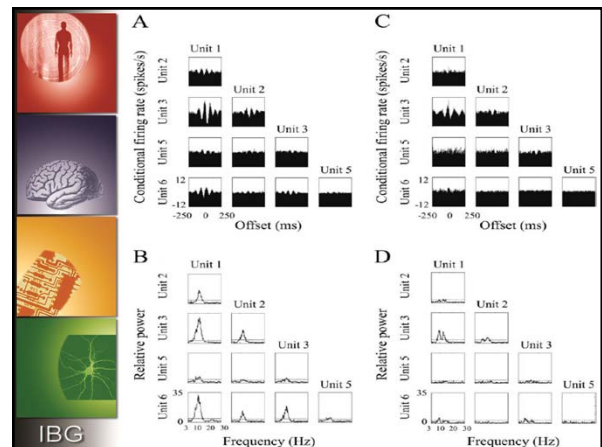



## Cross spectrum II

- 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.





## Coherence

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

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

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

---

---

---

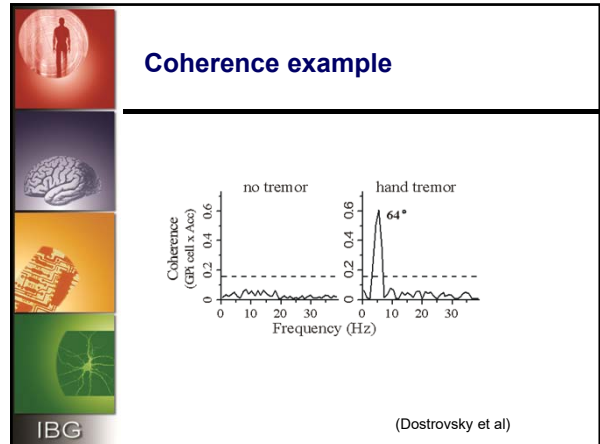
---

---

---

---

---




---

---

---

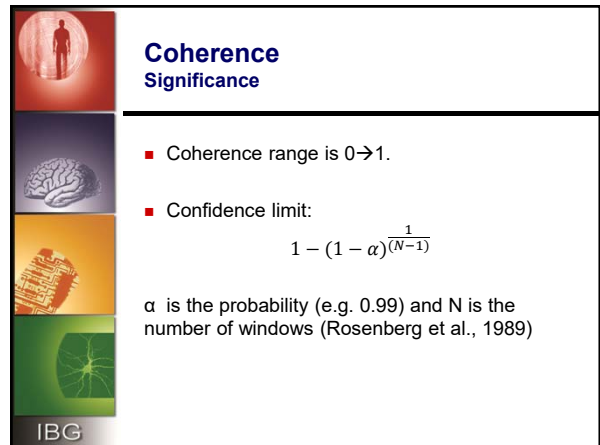
---

---

---

---

---




---

---

---

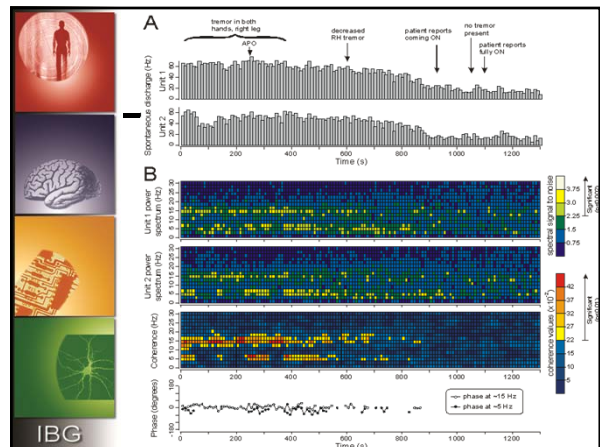
---

---

---

---

---



---

---

---

---

---

---

---

---

