MSc in Artificial Intelligence and Robotics
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Neuroengineering

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7- BRAIN NETWORKS I

we have seen the brain organization in layers and how neurons communicate and work for the same purpose.

Learning objectives

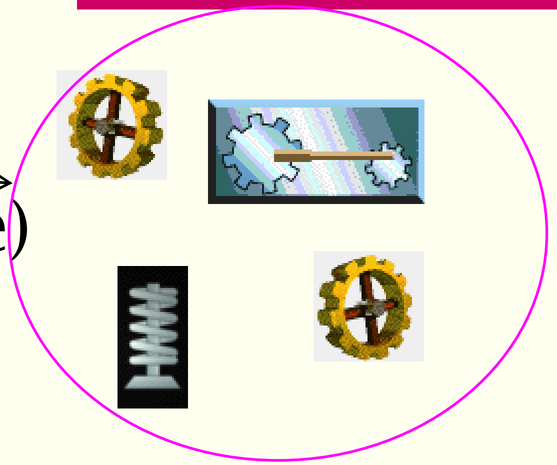
it means that we will be using networks of units, and these units can be single neuron, columns, region or brain.

1. Understand the need for the multivariate analysis of the brain activity
2. List the different definition of brain connectivity and their main properties
3. Remember the definition of ordinary coherence and the spectral matrix
4. Illustrate (at least) two possible ways to compute it
5. Describe its properties and limitations

Multivariate analysis of biological signals

Univariate Analysis:

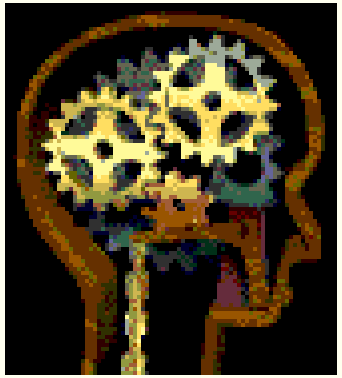
- We analyse each signal (physiological correlate) independently from the others



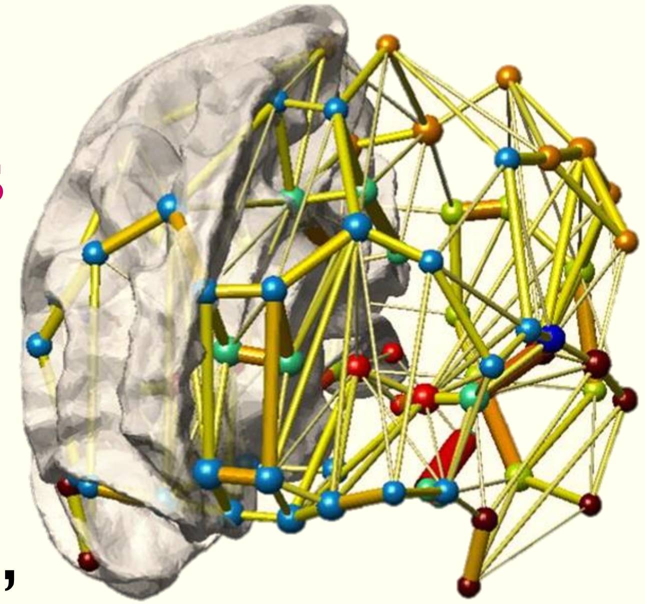
Multivariate Analysis:

- When multiple biological signals are available, and they are related to different parts of the same system (or to different systems, interconnected) we need to analyse the signals AND their interdependency

interaction between sigle parts



Network Neuroscience



Through an integrative perspective, network neuroscience aims to map, record, analyze and model the elements and interactions of neurobiological systems

Objective: to estimate dynamic brain networks at all levels (among molecules, neurons, brain areas and social systems)

Convergence of empirical and computational advancements, to study network dynamics and integrate network processes across spatiotemporal domains.

once we merge info that can be derived from a single region analisys with info that can be provided by the networks, we can reach the goal of modelling the brain circuits (our brain work)

Understanding the brain functions

Modeling of the brain circuits

- Brain motor & cognitive functions
- Brain plasticity
- Clinical applications

to understand what happens in the brain as a consequence of a patology

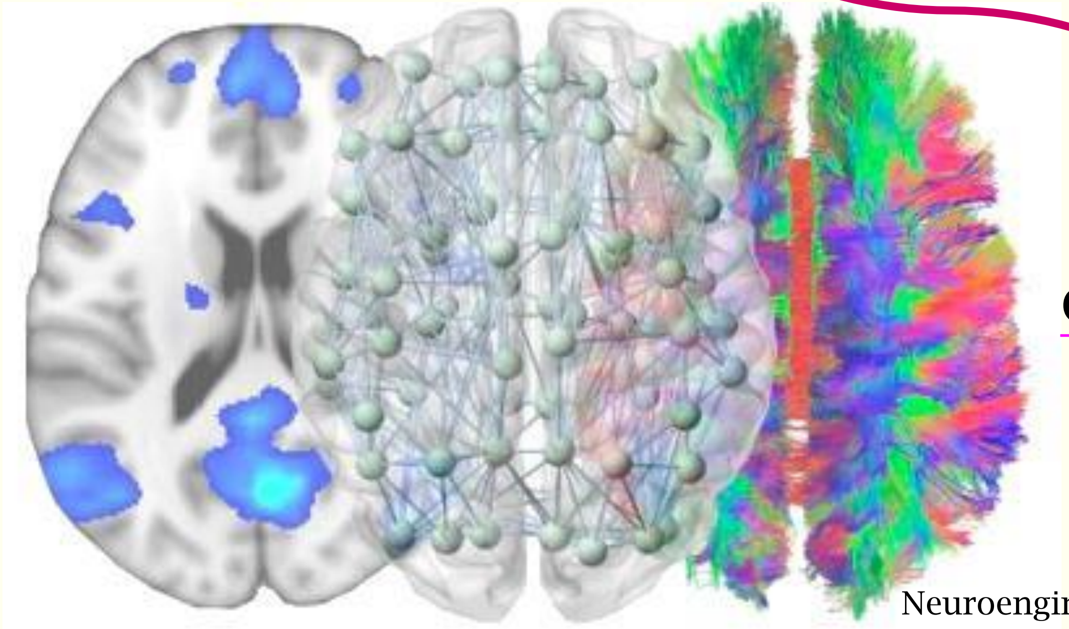
- Industrial applications

Brain activity

Brain connectivity

ANATOMICAL and FUNCTIONAL CONNECTIVITY

any analysis for which more than one signal is considered at a time

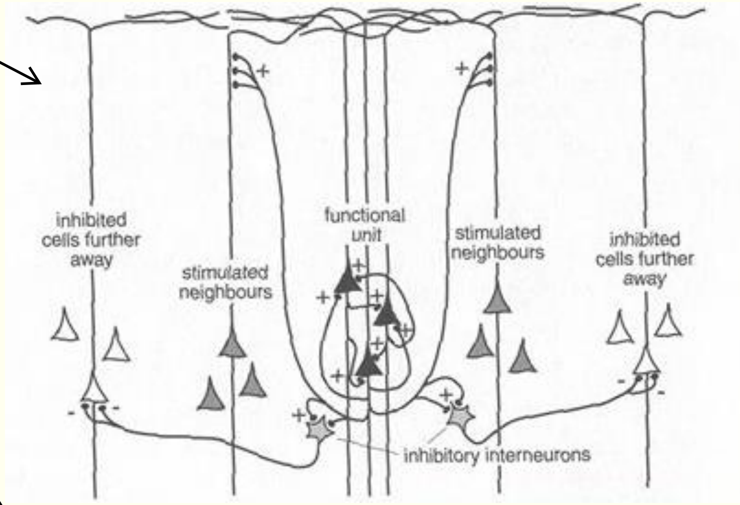


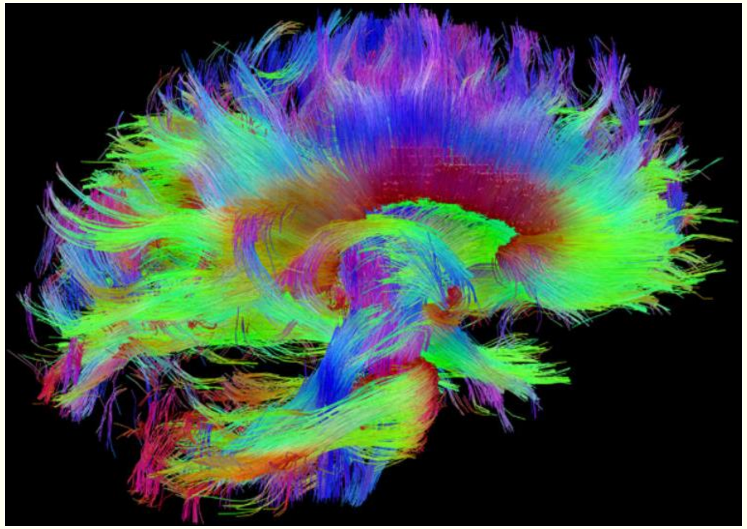
It describes the existence of phisical links between different units. This link can be axon or fibers

It can be measured in vivo or/and non invasively with high accuracy. We can buid maps and networks of physical connection between the regions of the brain at many levels

Anatomical connectivity

- Physical or structural connections linking sets of neurons or neuronal elements
- Relatively stable at shorter time scales (seconds to minutes) the network doesn't change
- At longer time scales (hours to days), structural connectivity patterns are likely to be subject to significant morphological change and plasticity
- Invasive tracing studies
- Noninvasive diffusion weighted imaging techniques





Contrary to the anatomycal connectivity, this is not due to the existence of a phisical link between 2 nodes, so we have region 1 and region 2, to connect them there is always a phisical link but it is not always used and not in the same way (like a street but the cars don't cross or cross in a different amount)

Functional connectivity

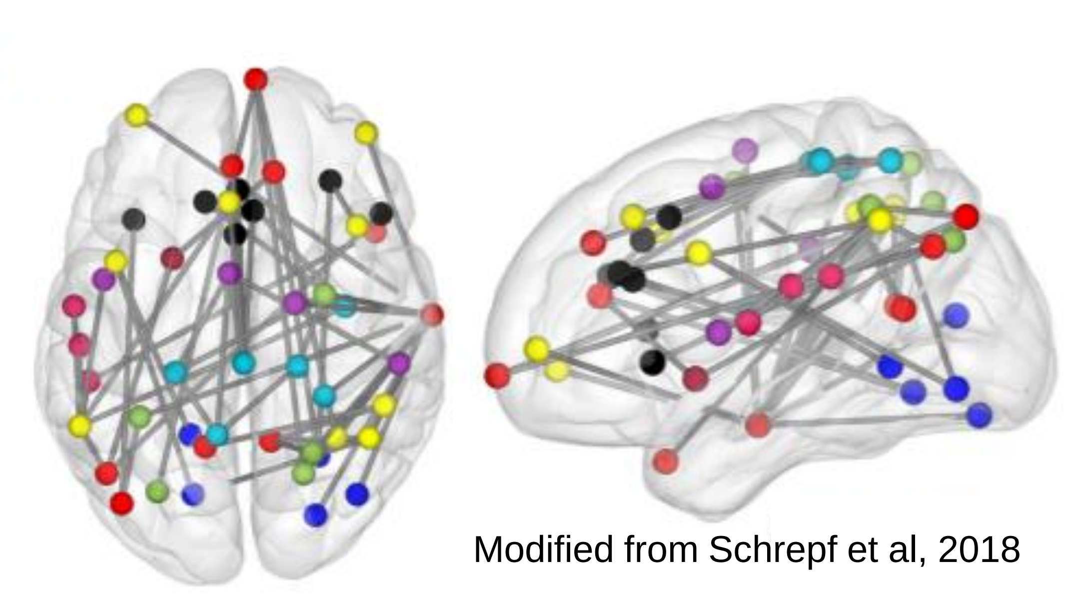
2 cells or two regions of the cells have to be syncronized

- Statistical dependence between distributed and often spatially remote neuronal units
- Highly time-dependent (milliseconds)

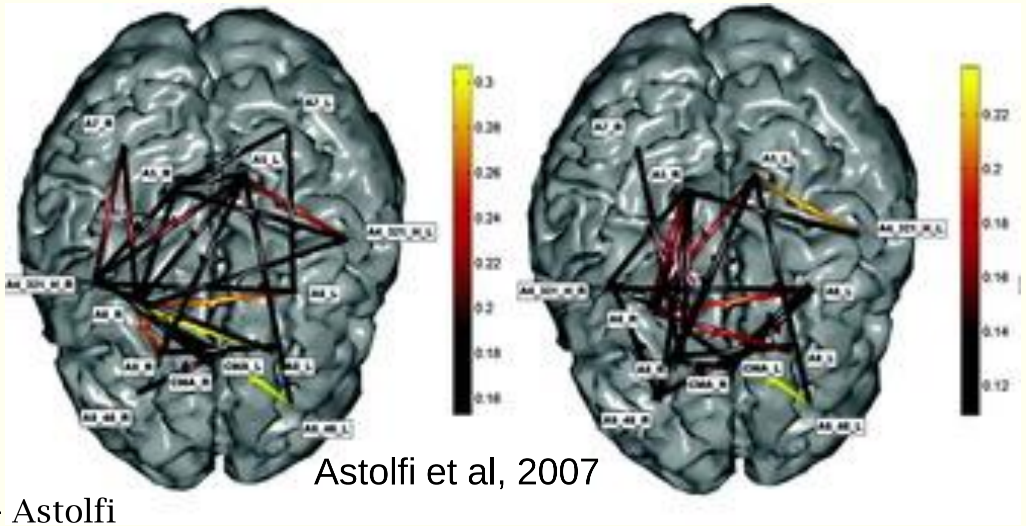
2 things happen at the same time

what happens here is correlate to what happens there

- Correlation or causation
- Different approaches:
  - model-based
  - model-free
  - data-driven



Modified from Schrepf et al, 2018



Astolfi et al, 2007

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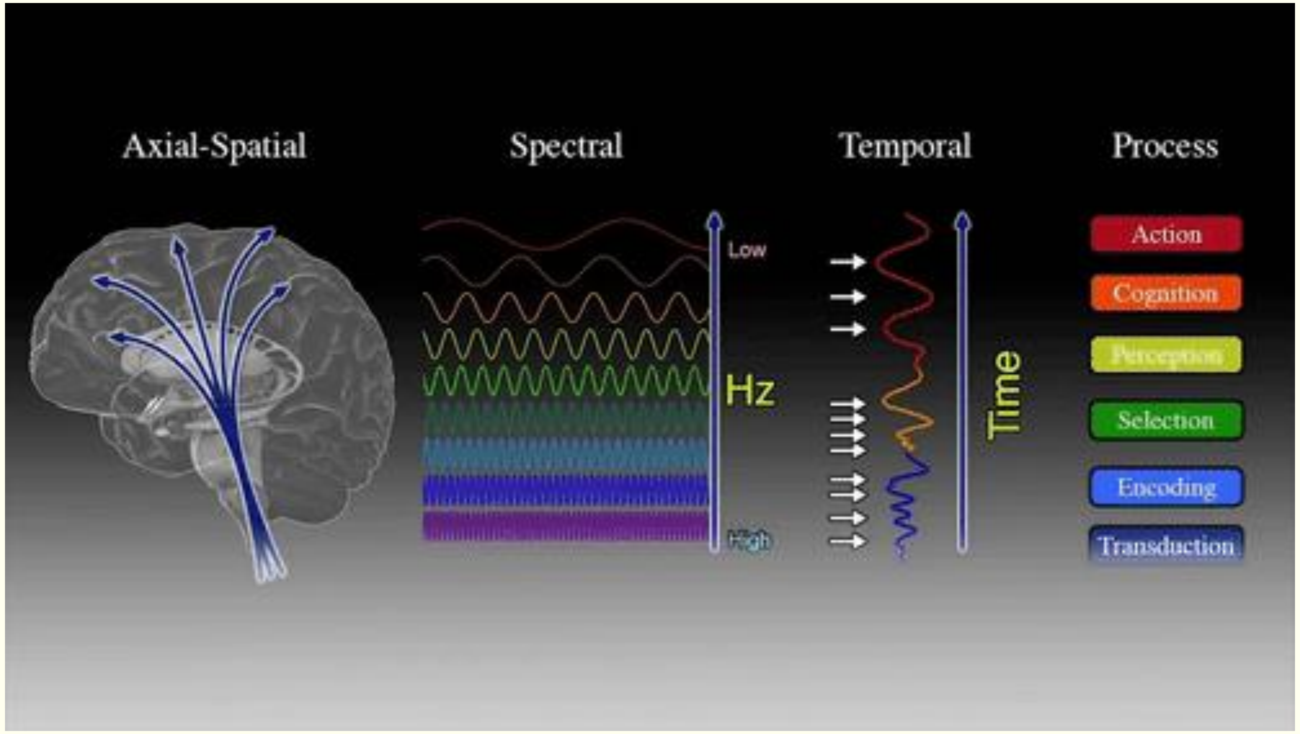
correlation in the frequency domain

Synchronicity in the brain

we are able to measure activity distant from the sources thanks to this synchronization. And this synchronization can be achieved at different frequencies

- “Cells that fire together wire together” (Hebbian Theory)
- Brain rhythms:



https://www.youtube.com/watch?v=OCpYdSN_kts&feature=youtu.be

to measure the synchronous activity of two regions of the brain, we can quantify if the cativity of one or more regions of the brain is occurring at the same time or not. so we start from correlation between signals and to look at a temporal correlation between signals. It's interesting to move from the temporal domain to the frequency domain

Fourier transform

SPECTRAL MATRIX: function for multivariate analisys. It contains info about the power spectral density of signals

Auto- and cross-correlation

Given a time series $x[n]$ with sampling interval T:

- Autocorrelation function:

it can be defined for continuous signals and time series

time series itself

time shift time series

$$r_{xx}[k] = \sum_{n=-\infty}^{\infty} x^*[n] x[n+k]$$

$\tau =$

UNIVARIATE ANALISYS

Given two time series x[n] and y[n]:

- Cross-correlation function:

when 2 reagions are syncronous there can be a delay but this delay must constant in time

$$r_{xy}[k] = \sum_{n=-\infty}^{\infty} x^*[n] y[n+k]$$

BIVARIATE ANALISYS:
we have 2 signals

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Autocorrelation and spectral analysis

not all time series can't be transformed with Fourier, only that that are some specific properties (for ex. periodical or limited in time signals)

- Fourier Transform of a time series:

in napoleon troup

$$X(f) = \sum_{n=-\infty}^{\infty} x[n] \exp(-j2\pi f n T)$$

- Power Spectral Density (PSD): obtained from Fourier

$$S_{xx}(f) = |X(f)|^2$$

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PSD can also be computed with this method

- Wiener- Khinchin Theorem: PSD can be computed by Fourier-transforming the autocorrelation function:

middle of 20th century

$$S_{xx}(f) = \sum_{n=-\infty}^{\infty} r_{xx}[k] \exp(-j2\pi f k T)$$

Cross-correlation and bivariate spectral analysis

Given two time series x[n] and y[n]:

- Mutual Power Spectral Density:

Fourier transform of the 2 time series

$$S_{xy}(f) = X(f)Y^{*}(f)$$ complex coniugate of them

$$S_{yx}(f) = Y(f)X^{*}(f)$$

- It's symmetrical : $\boxed{S_{xy} = S_{yx}}$ the formula is different but the result is the same
- Wiener- Khinchin Theorem: $S_{xy}=S_{yx}$ can be computed as the Fourier-transform of the cross-correlation function:

$$\boxed{S_{xy}(f) = \sum_{n=-\infty}^{\infty} r_{xy}[k] \exp(-j2\pi f kT)}$$

Meaning of the theorem

in the case in which we have 2 time series we consider also the y signal

Time domain

Frequency domain

If the Fourier transformation doesn't exist we use the Wiener-Khinchin Theorem

$x[n], y[n]$ $\xrightarrow{\mathcal{F}}$ $\cancel{X}(f), Y(f)$

in this case we can reach the PSD by moving to the autocorrelation function that always exists, and then the autocorrelation function can always be transformed with Fourier transform

$R_{xx}[k], R_{yy}[k], R_{xy}[k], R_{yx}[k]$ $\xrightarrow{\mathcal{F}}$ $S_{xx}(f), S_{yy}(f), S_{xy}(f), S_{yx}(f)$

Spectral Matrix *S(f)*

it's at the bases of all measures of connectivity based on sinchronicity of the data.

- Spectral matrix of the signals:

the elements of the matrix are functions not number

$$S(f) = \begin{bmatrix} S_{xx}(f) & S_{xy}(f) \\ S_{yx}(f) & S_{yy}(f) \end{bmatrix}$$

$\boxed{\text{SYMMETRICAL}}$

S_{xx}, S_{yy} = Power Spectral Density of x and y, respectively → how the power of the signal is distributed at different frequencies

S_{xy}, S_{xy} = Mutual Power Spectral Density of x and y → how the two signals share power at different frequencies

they are the same

it's the basic block of the family of coherence

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Ordinary Coherence

- Ordinary Coherence is the linear correlation between two signals at a given frequency:

it's a function of frequency not a number

bivariate method with 2 timeseries

$$C_{xy}(f) = \frac{\left|S_{xy}(f)\right|^2}{\left|S_{xx}(f)\right|\left|S_{yy}(f)\right|}$$

comprised between 0 and 1

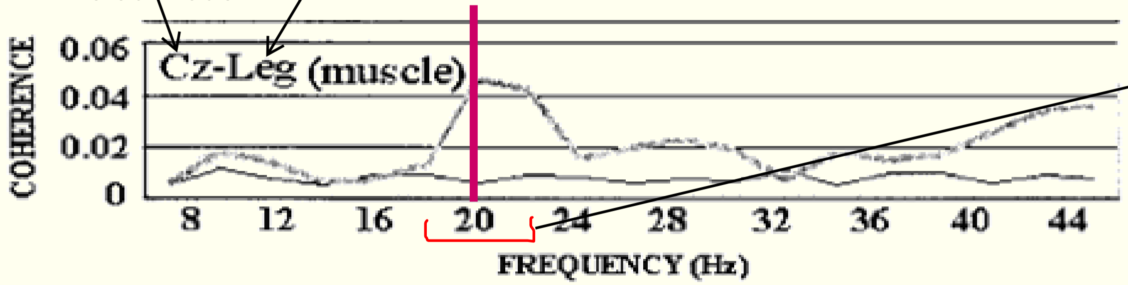
- It's the Mutual Power Spectral Density divided by the product of their individual Power Spectral Densities.

normalization of the numerator

- Normalized to take into account the ratio of exchanged power on the total power of the signals in this case we have the coherence computed between 2 time series which are measured from the biological activity of the brain and muscles.

Properties of the Ordinary Coherence

- It's spectral
- It's normalized between 0 and 1



our interest is in this range because in this range there is the range controlling the muscle contraction

- For a given frequency f_0:
  - $C_{xy}(f_0)=0$ => the two signals are independent at that frequency because there isn't a relation between x and y signals
  - $C_{xy}(f_0)=1$ => the two signals are maximally correlated at that frequency the PSD = MPSD, so the whole power is shared between x and y signal

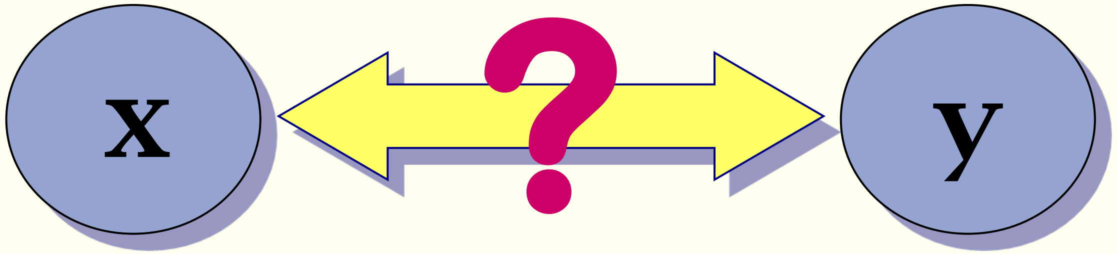
Limitations

we don't know if there is an effect from one region to the other or not

- No information about the direction of the interaction:

$$C_{xy}(f) = \frac{\left|S_{xy}(f)\right|^2}{\left|S_{xx}(f)\right|\left|S_{yy}(f)\right|} = C_{yx}(f)$$

- It measures synchronicity but not causality:



- It's bivariate (what if the time series are more than 2?)

References

- Hari & Puce, Chapter 9 (Coherence and other measures of association, Some issues with coherence calculations)
- Cohen, Chapter 25

Self-evaluation

1. Explain the difference between anatomical and functional/effective connectivity
2. Explain the difference between correlation and causation*
3. If C_{xy} is the ordinary coherence between x and y, indicate, for each of the following sentences, if they are true or false:
   a) C_{xy} is a function of frequency
   b) $C_{xy} \in [0, 1]$
   c) $C_{xy} = C_{yx}$
   d) C_{xy} can be computed also if the Fourier transform of x and y does not exist
4. Describe at least 2 advantages and 2 limitations of the ordinary coherence

*see also the next lecture