MSc in Artificial Intelligence and Robotics MSc in Control Engineering A.Y. 2019/20

Neuroengineering

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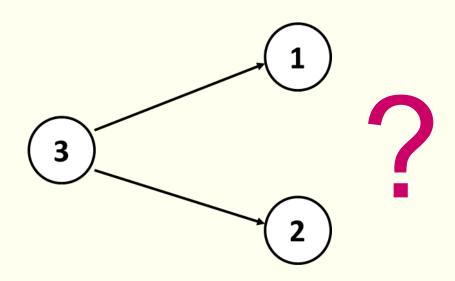
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9- BRAIN NETWORKS III

Learning objectives

- 1. Understand the two main approaches to a multivariate dataset
- 2. Describe the pairwise and the multivariate approaches
- 3. Define a method based on a multivariate, spectral AR model
- 4. Illustrate how it can be used to build brain networks at different frequency ranges
- 5. Compare the advantages and limitations of pairwise vs multivariate approaches

4 Pairwise and multivariate approaches

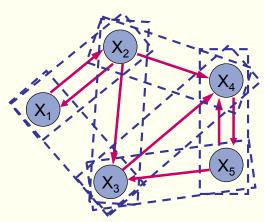


1 - Pairwise approach

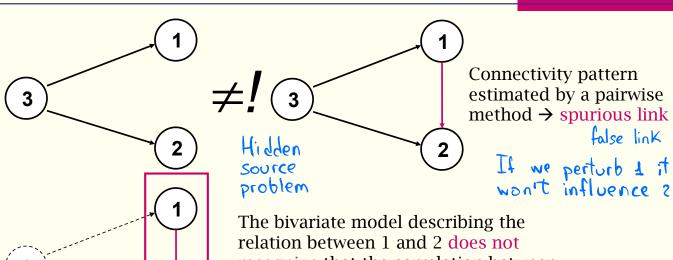
All signals in the dataset are taken pairwise and causality is assessed:



But the set of two time series does not contain all possible relevant information → limitation of the Granger definition (Granger, 1980)



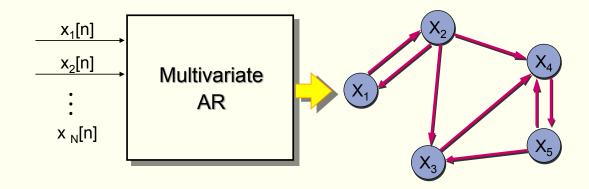
Limitations of the pairwise approach



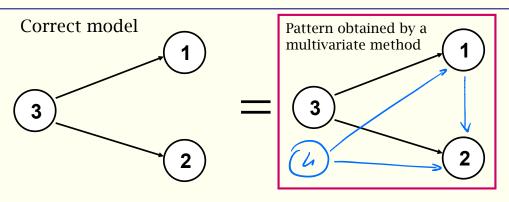
The bivariate model describing the relation between 1 and 2 does not recognize that the correlation between the two signals is due to a common effect of 3 (which is not included in the model)

2 - Multivariate approach

The connectivity pattern is obtained by a unique generation model estimated on the entire set of data and takes into account all their interactions:



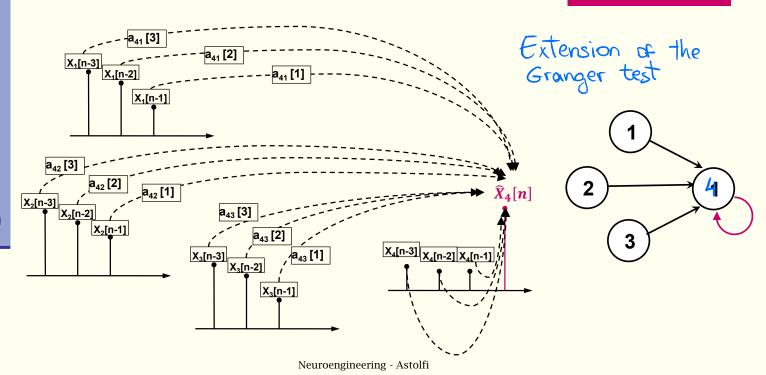
2 - Multivariate approach



If we have another signal not in our model we could again have spurious links

Multivariate methods, by building a unique model based on all the signals, use all the information at disposal and thus allow a better comprehension of the relationship between the signals

Multivariate Autoregressive Models (MVAR)



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Multivariate Autoregressive Models (MVAR)

- Given a set of N signals: $\overline{X} = [x_1[1] \ x_2[1] \ \cdots \ x_N[1]]^T$
- A Multivariate Autoregressive Model of dimension N is:

$$x_{1}[n] = -\sum_{k=1}^{p} a_{11}[k]x_{1}[n-k] - \sum_{k=1}^{p} a_{12}[k]x_{2}[n-k] - \cdots - \sum_{k=1}^{p} a_{1N}[k]x_{N}[n-k] + e_{1}[n]$$

$$x_{2}[n] = -\sum_{k=1}^{p} a_{21}[k]x_{1}[n-k] - \sum_{k=1}^{p} a_{22}[k]x_{2}[n-k] - \cdots - \sum_{k=1}^{p} a_{2N}[k]x_{N}[n-k] + e_{2}[n]$$

$$\vdots$$

$$x_{N}[n] = -\sum_{k=1}^{p} a_{N1}[k]x_{1}[n-k] - \sum_{k=1}^{p} a_{N2}[k]x_{2}[n-k] - \cdots - \sum_{k=1}^{p} a_{NN}[k]x_{N}[n-k] + e_{N}[n]$$

Multivariate Autoregressive Models (MVAR)

• The model parameters are N · N · p:

$$\overline{a}[1] = \begin{bmatrix} a_{11}[1] & \cdots & a_{1N}[1] \\ \vdots & \ddots & \vdots \\ a_{N1}[1] & \cdots & a_{NN}[1] \end{bmatrix} \quad \overline{a}[2] = \begin{bmatrix} a_{11}[2] & \cdots & a_{1N}[2] \\ \vdots & \ddots & \vdots \\ a_{N1}[2] & \cdots & a_{NN}[2] \end{bmatrix} \quad \cdots \quad \overline{a}[p] = \begin{bmatrix} a_{11}[p] & \cdots & a_{1N}[p] \\ \vdots & \ddots & \vdots \\ a_{N1}[p] & \cdots & a_{NN}[p] \end{bmatrix}$$

And the N variances of the residuals:

$$S_E = \begin{vmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_N \end{vmatrix}$$

 $S_{E} = \begin{bmatrix} \sigma_{1} \\ \sigma_{2} \\ \vdots \end{bmatrix}$ Total number of parameters to be estimated: $N \cdot N \cdot p + N = N(N \cdot p + 1)$

$$\sum_{k=0}^{p} A[k]X[n-k] = E[n]$$

$$\overline{A}(f)\overline{X}(f)=\overline{E}(f)$$

$$\overline{A}(f)\overline{X}(f) = \overline{E}(f)$$
 Where: $A_{ij}(f) = \sum_{k=0}^{p} a_{ij}[k]e^{-j2\pi fTk}$

$$\overline{A}(f) = \begin{bmatrix} A_{11}(f) & \cdots & A_{1N}(f) \\ \vdots & \ddots & \vdots \\ A_{N1}(f) & \cdots & A_{NN}(f) \end{bmatrix} \qquad \overline{X}(f) = \begin{bmatrix} X_1(f) \\ \vdots \\ X_N(f) \end{bmatrix} \qquad \overline{E}(f) = \begin{bmatrix} E_1(f) \\ \vdots \\ E_N(f) \end{bmatrix}$$

$$\overline{X}(f) = \begin{bmatrix} X_1(f) \\ \vdots \\ X_N(f) \end{bmatrix}$$

$$\overline{E}(f) = \begin{bmatrix} E_1(f) \\ \vdots \\ E_N(f) \end{bmatrix}$$

Partial Directed Coherence (PDC)

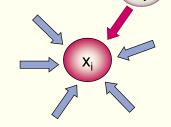
• PARTIAL DIRECTED COHERENCE (PDC) from j to i is defined on the basis of matrix A (Baccalà and Sameshima, 2001):

$$\pi_{ij}(f) = |A_{ij}(f)|^2$$

• Different normalization of PDC are provided, for instance (Astolfi et al, 2007):

$$\pi_{ij}(f) = \frac{\left|A_{ij}(f)\right|^2}{\sum_{m=1}^{N} \left|A_{im}(f)\right|^2}$$

Where:
$$\sum_{n=1}^{N} \boldsymbol{\pi}_{in}(f) = 1$$



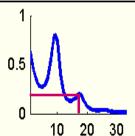
$$\sum = 7$$

Partial Directed Coherence (PDC)

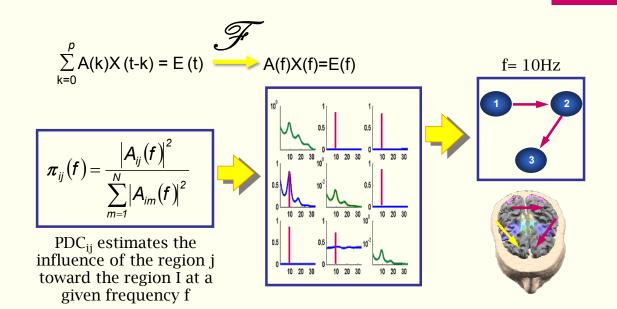
• Since $A_{ij}(f) \neq A_{ji}(f)$

$$\pi_{ij}(f) \neq \pi_{ji}(f)$$

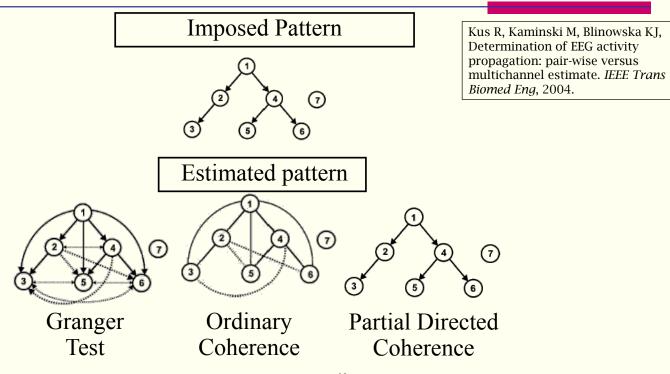
The value of PDC_{ij} at a certain frequency f_0 represents the existence of a causality link directed from j to i



From Spectral Indices to Brain Networks



Comparison between different estimators



Neuroengineering - Astolfi

Pairwise Vs multivariate estimators

- Bivariate approach:
 - Advantages:
 - No limit to the number of signals
 - To be used when short data segments are available
 - Limitations:
 - Reduced accuracy

Pairwise Vs multivariate estimators

- Multivariate approach:
 - Advantages:
 - Better estimation performances
 - Allows for inserting all data sources in the model
 - Limitations:
 - Limitation in the number of channels/signal that can be modeled → more data required

Self-evaluation

- 1. Show an example of network for which a pairwise approach is less accurate than a multivariate one
- 2. Given the PDC estimator, indicate, for each of the following sentences, if they are true or false:
 - a) $PDC_{i \rightarrow j}$ is always equal to $PDC_{j \rightarrow i}$
 - b) The normalized PDC $\in [-\infty, \infty]$
 - c) PDC can always avoid the problem of the "hidden source"
- 3. List two advantages and a limitation of the pairwise and of the multivariate approach