



Brain function and connectivity extracted from EEG recordings

Miquel Angel Mañanas

on behalf of BIOART GROUP at the UPC



CHALMERS
UNIVERSITY OF TECHNOLOGY

Imperial College
London



**Funded by
the European Union**

This project has received funding from the Horizon Europe Research and Innovation Programme under GA No. 101079392

Outline

- EEG recordings
- Event Related Potentials (ERPs)
- Brain Connectivity
 - ✓ What is brain connectivity?
 - ✓ EG connectivity
 - ✓ Case studies on EEG connectivity
 - ✓ Graph Theory
 - ✓ Examples



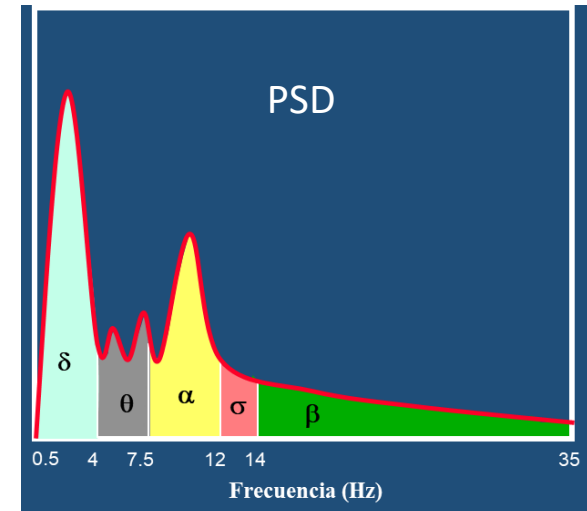
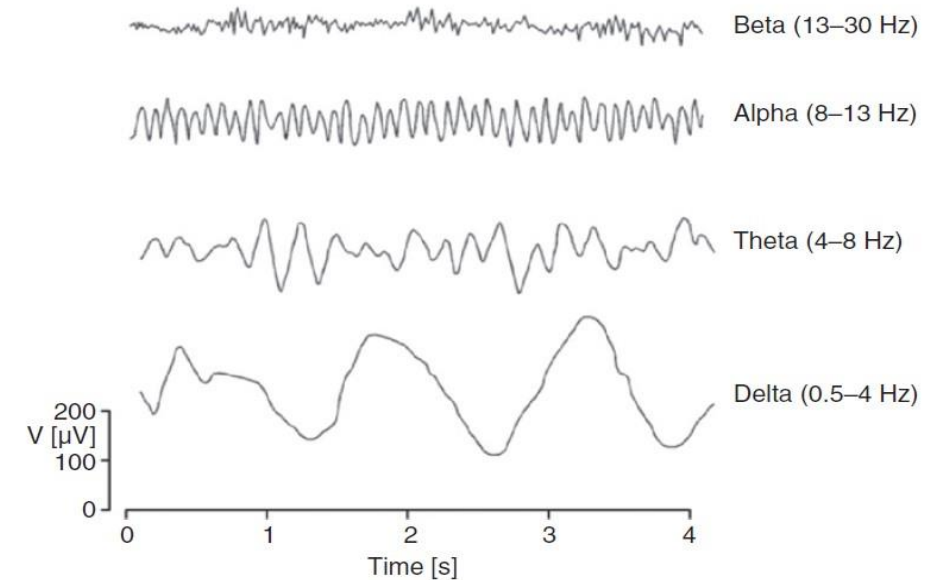
Outline

- **EEG recordings**
- Event Related Potentials (ERPs)
- Brain Connectivity
 - ✓ What is brain connectivity?
 - ✓ EG connectivity
 - ✓ Case studies on EEG connectivity
 - ✓ Graph Theory
 - ✓ Examples



EEG recordings

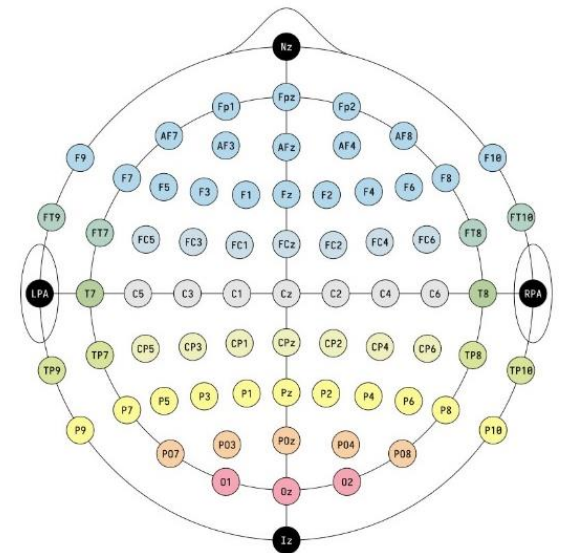
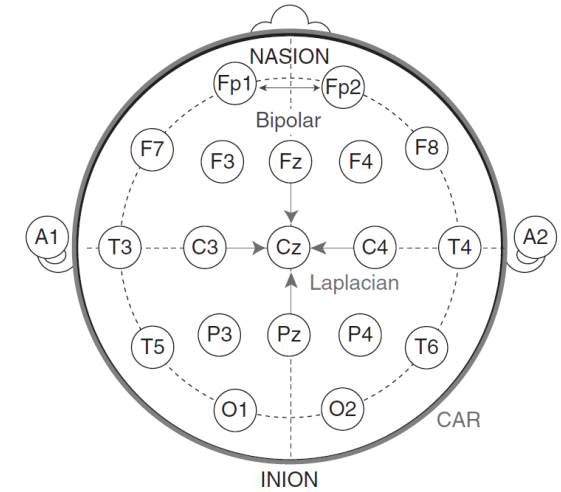
- Our brains are **continuously working**
- **Biochemistry exchanges** between cells **produce small electrical activity** when the neurons communicate among them.
- A single electric signal from neuron to neuron is not recordable but when **millions of neurons synchronize**, the electric field generated can be measured from the scalp
- These electroencephalographic (EEG) signals are **transmitted through tissue, bone, and hair** before they are recorded, and by then its **amplitude is very attenuated** (easily corrupted by artifacts)
- Characteristic frequency ranges and spatial distributions (correlated with functional states of the brain)
 - Delta, theta, alpha (mu), beta, gamma



EEG TECHNICAL FEATURES

✓ NUMBER OF ELECTRODES

- Will determine the amount of information that we can measure from the brain
- Commonly, the number of “recording” electrodes ranges between 8 and 128
- EEG systems used in research typically have 64 electrodes or more
- In addition to these electrodes, we usually need to add:
 - One reference: an electrode that is used to subtract the common mode noise from the recording electrodes
 - One ground electrode
- A higher number of electrodes will allow more detailed measurements from different brain areas
- High-density EEG are required for ICA or inverse modelling
- However, the increase in the number of electrodes comes with an increase in the cost and the complexity of both the experimental set-up and the data analysis



EEG TECHNICAL FEATURES

✓ EEG AMPLIFIER

- Responsible for accommodating, amplifying and converting the analog electrical signals captured by the scalp electrodes into digital signals that can be processed by a computer
- **EEG sampling rate** (a common sampling rate is 256Hz)
 - EEG bandwidth: 0.5 – 80 Hz
 - According to the Nyquist theorem, the minimum sampling rate to measure activity at 80Hz will be 160Hz
- **Resolution:** Number of bits used to encode the analog EEG signal voltage values into discrete numbers
- **Input range**
 - Maximum amplitude that can be recorded before saturation
 - The input-referred noise is the noise generated by the circuitry of the amplifier even in the absence of input signal and should be as low as possible to avoid contaminating the signal
- **Power supply:** cable-powered or battery-powered (duration and mobility)
- **Connectivity:** Wired or wireless-communication (mobility)



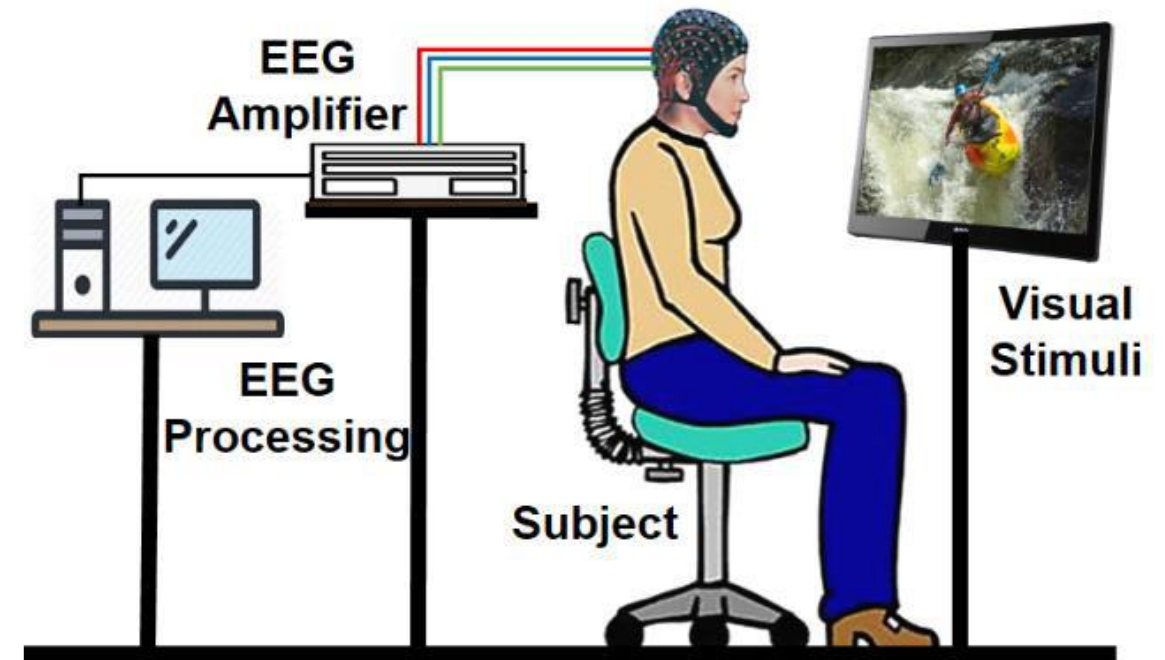
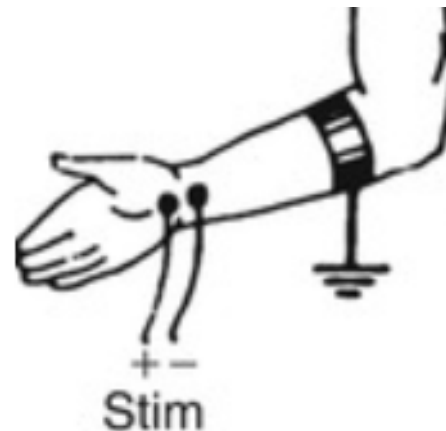
Outline

- EEG recordings
- **Event Related Potentials (ERPs)**
- Brain Connectivity
 - ✓ What is brain connectivity?
 - ✓ EG connectivity
 - ✓ Case studies on EEG connectivity
 - ✓ Graph Theory
 - ✓ Examples



ERP

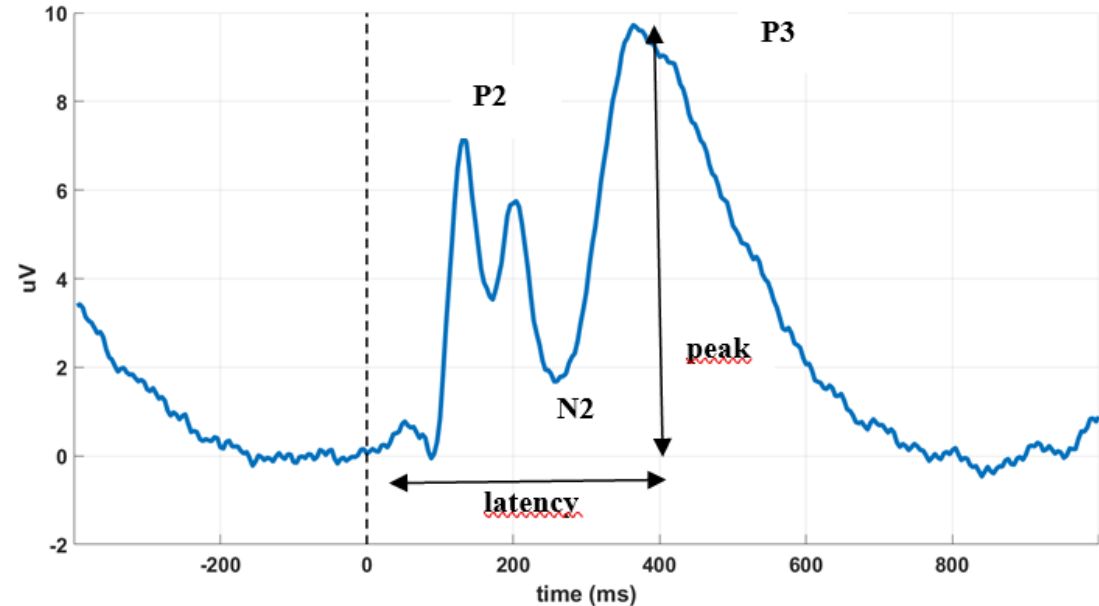
- EEG records the electrical activity of the cortex. Event-related potentials (ERP) are specific periods of the EEG that reflect the **cortex's response to different stimuli**:
 - **Cognitive events (visual, auditory ..)**
 - **Motor response/intention (MRCP)**
 - **Electrical or magnetic (somatosensory evoked potentials, SEP)**
- They can be described as scalp-recorded voltage fluctuations that are **time-locked to an event**
- Each stimulus produces an evoked potential embedded in the EEG



NOMENCLATURE

There are different ERPs associated with different local peaks, which are named using a **letter and a number**

- The **letter** indicates the **polarity** of the potential:
 - P**: positive peak
 - N**: negative peak
- The **number** represents the time (in ms) after the stimulus when the ERP appears (**latency**). For instance, the N100 is a negative potential that appears 100 ms after the event.
- In some cases, they can be named differently depending on their function, such as error-related negativity (ERN) (when the subject makes an error and she/he corrects) or the no-go N2 (in a go/no-go task)



TYPES OF ERPs

EXOGENOUS: early waves (<100 ms of the stimulus onset) that depend largely on the **physical properties** of the stimulus. Related to **sensory processing** and they are considered obligatory, thus they have clinical value as a **test of the integrity of the subcortical sensory pathways**

ex: N100 that appears when a stimulus is presented

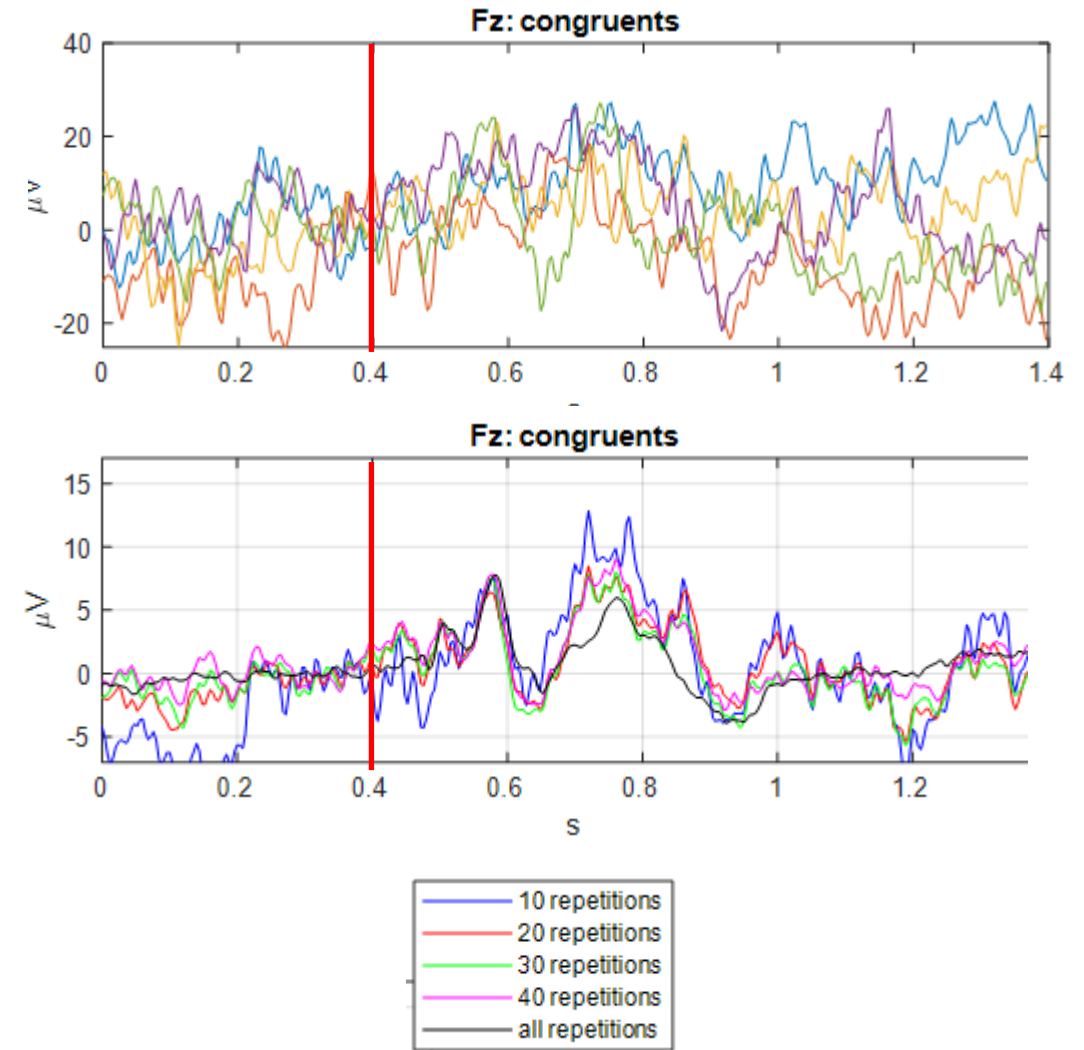
ENDOGENOUS: late waves (>100 ms of the stimulus onset) that reflect the **manner** in which the **subject evaluates the stimulus** (psychological effects of the stimulus). Therefore, it is considered a form of **controlled brain processing**

ex: P300 visual/auditory stimulus involved in processing information

IMPORTANT!! an ERP component does not exist independently of the specific experimental context in which it is measured!

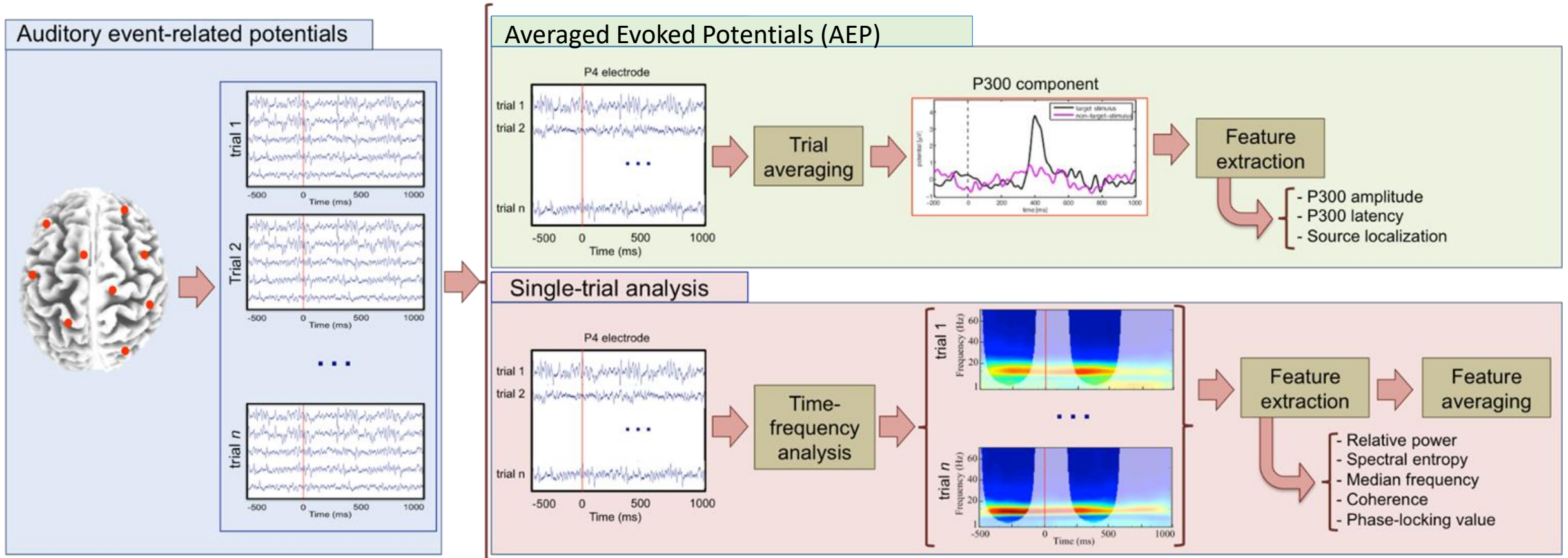
EEG Background is huge noise for ERP

- Each stimulus produces an evoked potential embedded in the EEG
- Since ERP are generally subtle in EEG, averaging of many epochs is needed to make them distinguishable
- Assumption: ERP amplitude adds constructively and EEG background noise diminishes destructively
- Each stimulus is followed by ERPs and every epoch is called **trial** or **repetition**
- SNR is increased \sqrt{N} times in amplitude (RMS) being N the number of trials



ERP ANALYSIS

There are two main strategies on ERP analysis:

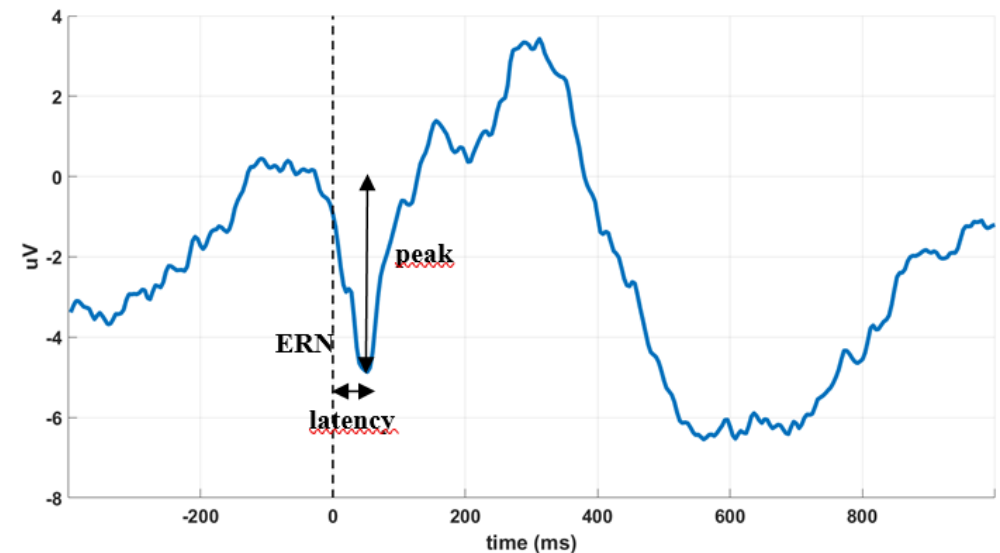


AEP Case study: Eriksen Flanker task stimuli

- Participants were required to respond to the center letter of a 5 letter array, designated as “target” with either a left-hand or right-hand response.
- Additional letters flanking the target letter either
 - favored the target response (compatible trials, HHHHH or SSSSS called congruent) or
 - primed the other response (incompatible trials, HSHHH or SSHSS called incongruent).
- Participant can realize to make an error and can correct it → ERN has been associated with the conscious detection of the commission of the error.

Stimulus	Type of Stimulus
HH H HH	Congruent
SSH S SS	Incongruent
SS S SS	Congruent
HHS H HH	Incongruent

Grand mean average of 9 subjects (response locked)

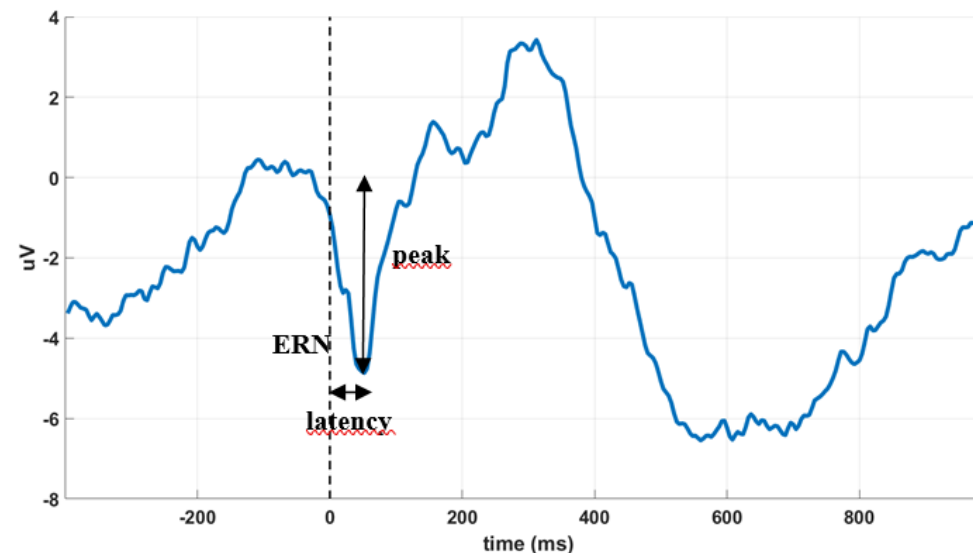


AEP Case study: Eriksen Flanker task stimuli

- Participants were required to respond to the center letter of a 5 letter array, designated as “target” with either a left-hand or right-hand response.
- Additional letters flanking the target letter either
 - favored the target response (compatible trials, HHHHH or SSSSS called congruent) or
 - primed the other response (incompatible trials, HSHHH or SSHSS called incongruent).
- Participant can realize to make an error and can correct it → ERN has been associated with the conscious detection of the commission of the error.

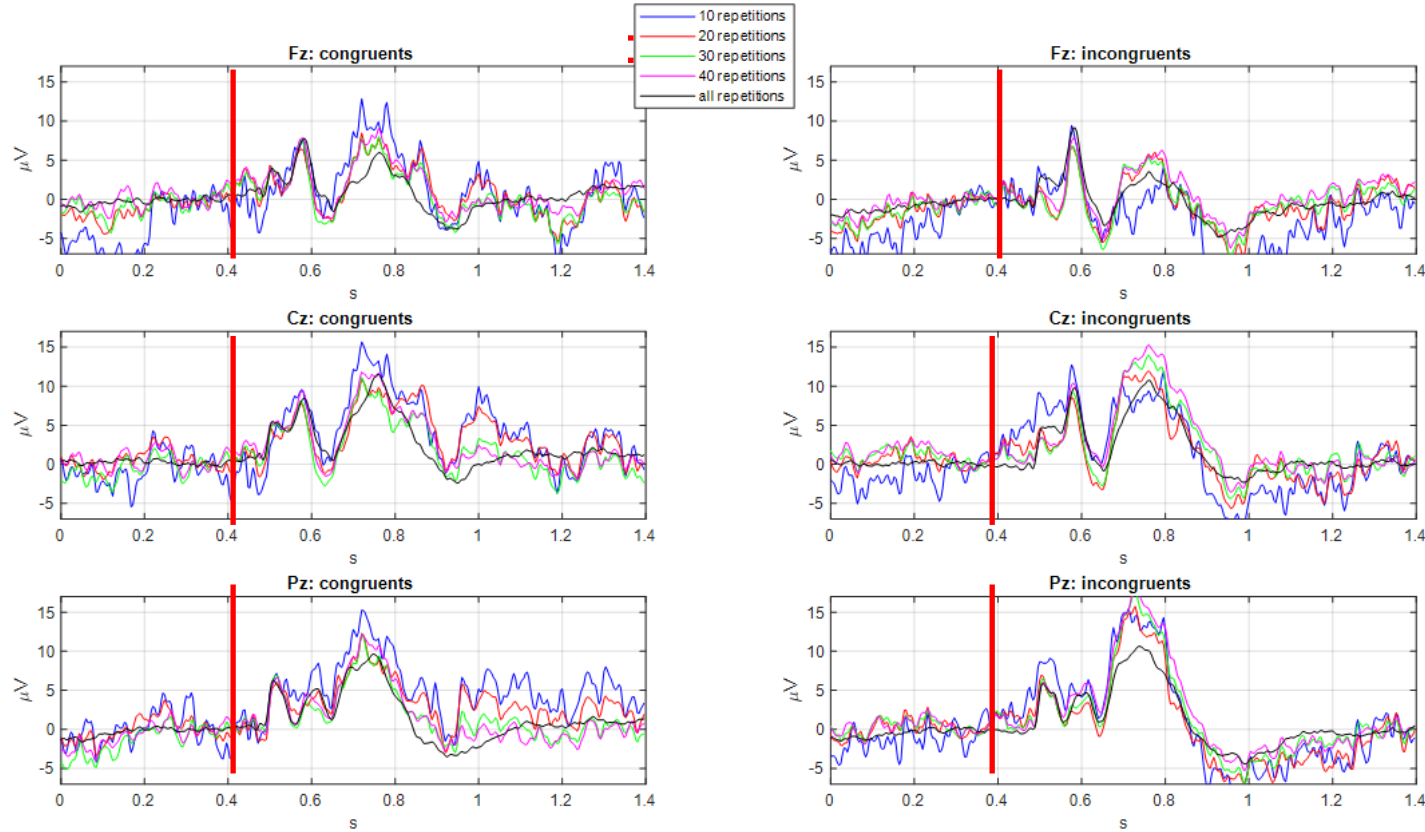
Stimulus	Type of Stimulus
HH H HH	Congruent
SSH S SS	Incongruent
SS S SS	Congruent
HHS H HH	Incongruent

Grand mean average of 9 subjects (response locked)

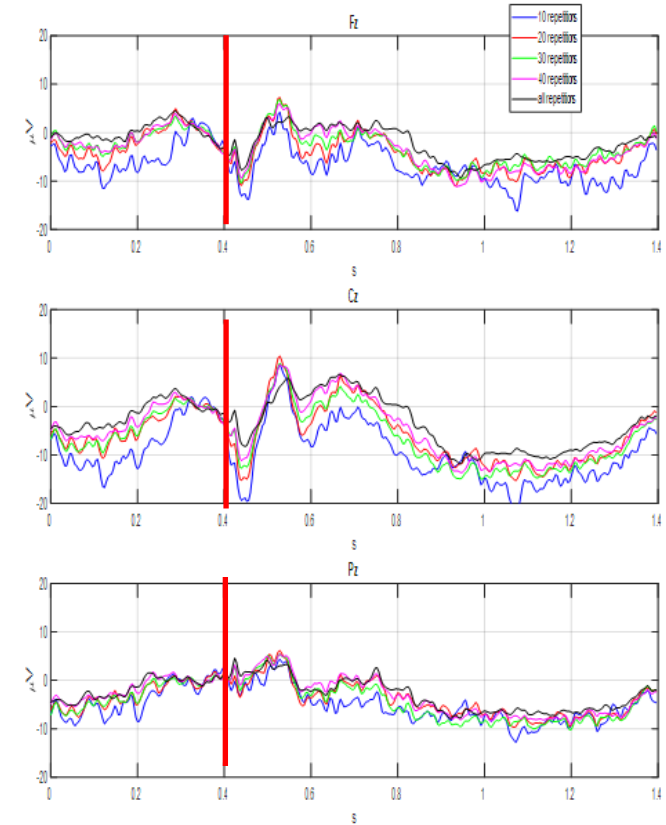


How many trials are necessary?

P300/P3

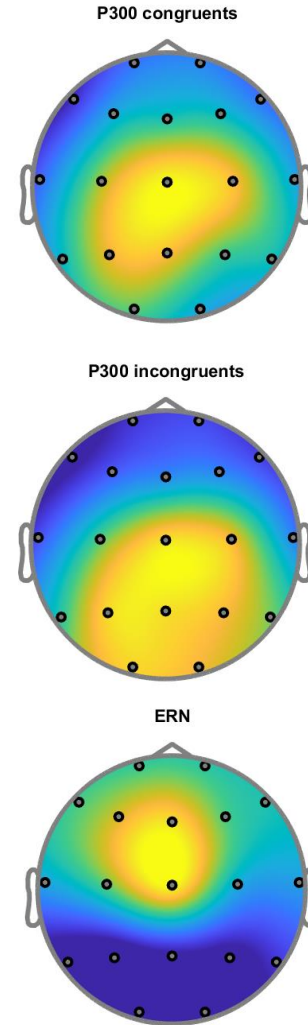
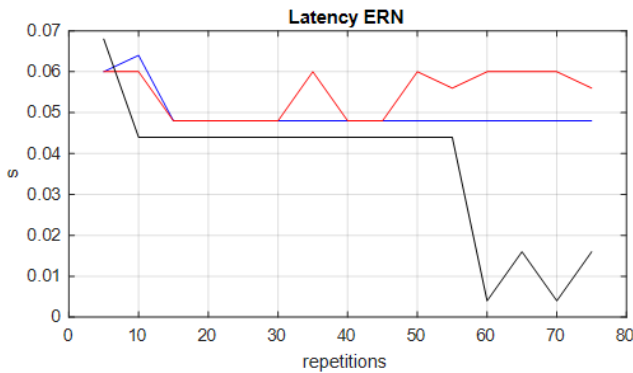
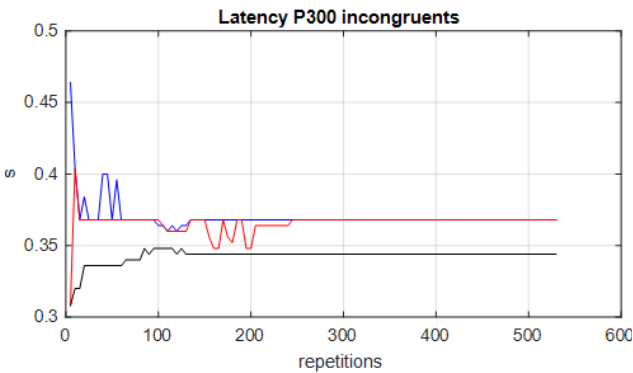
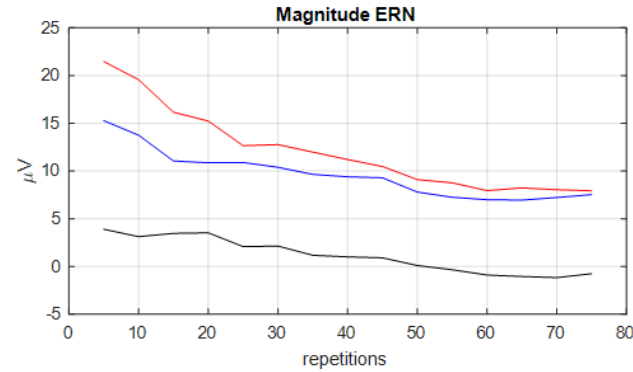
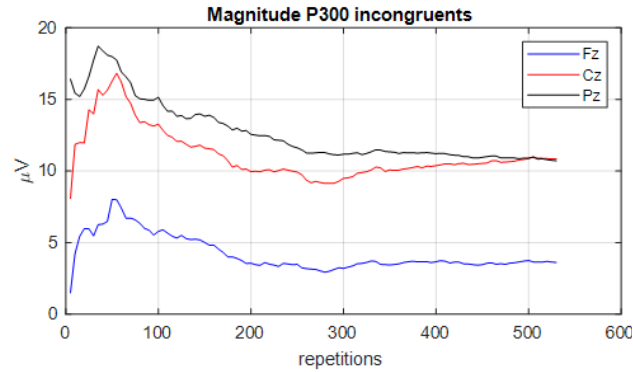


ERN



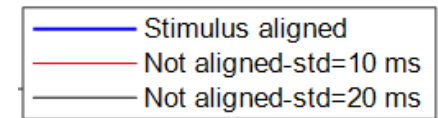
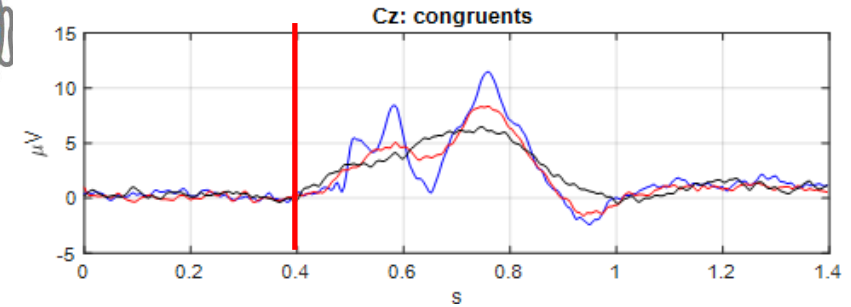
How many trials are necessary?

Influence of the number of repetitions/epochs on peak and latency calculated from the average epoch.

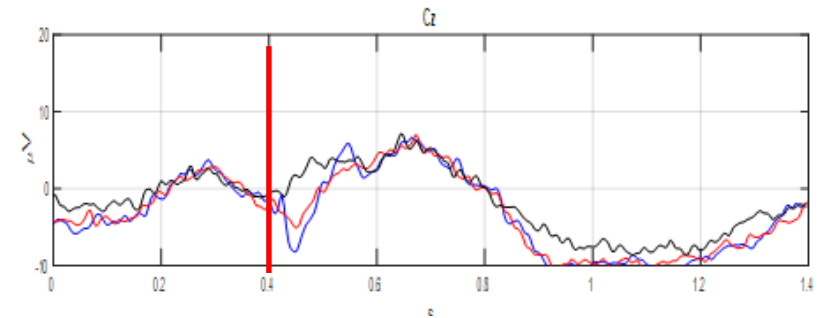


Time alignment is crucial!

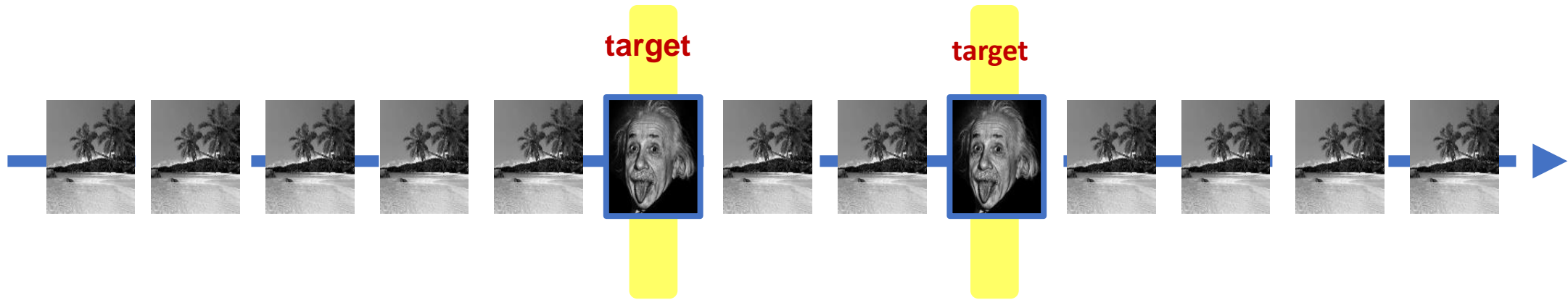
P300/P3:



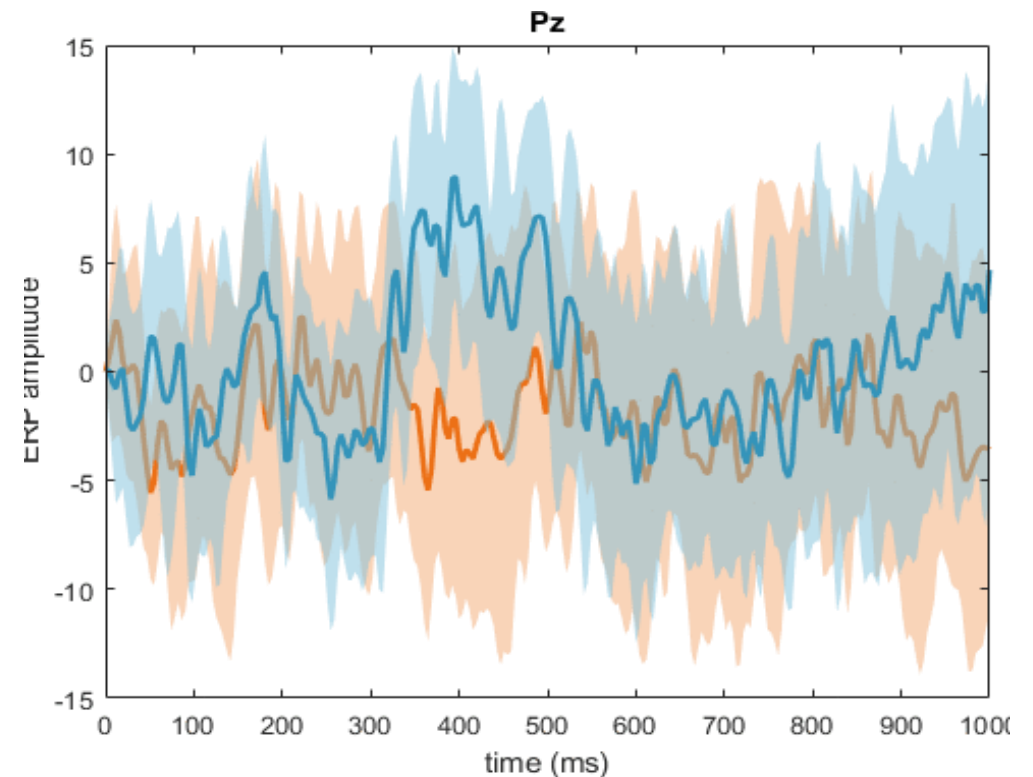
ERN:



AEP: Visual ood-ball task

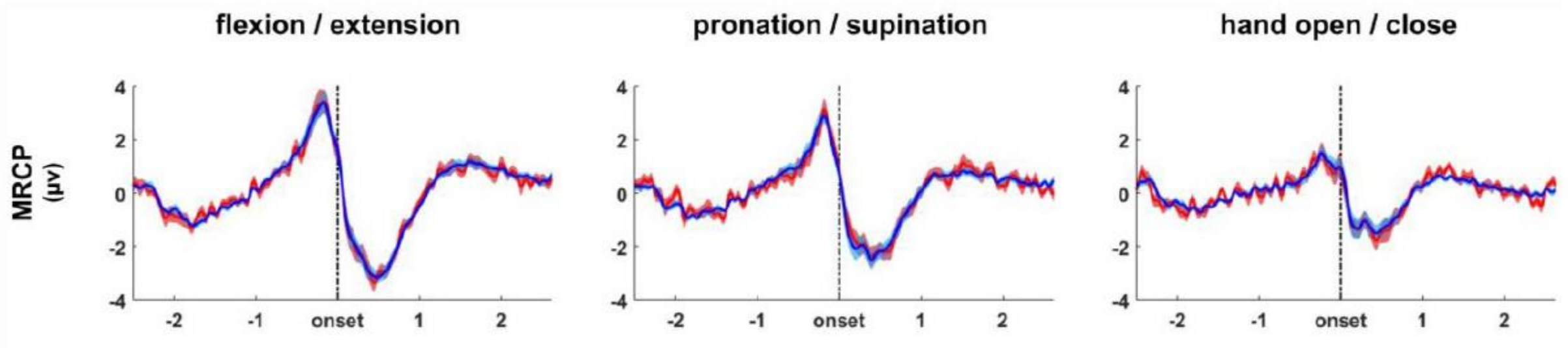


The ERP is clearly seen and the variance is reduced when the number of trials used in the averaging increases



MOVEMENT RELATED CORTICAL POTENTIAL

- They are a **type of ERP related to the movement**, independently if it is self-initiated or stimulus-related..
- They are **characterized by the maximum amplitude** and the **onset of the wave**. MRCPs appear for **1.5 or 2s before the trigger onset and 0.5 to 1s afterwards** and it is mainly located at channel **Cz**
- The **amplitude** ranges between **5 and 30 μV** and only occurs at frequencies around 0-5 Hz

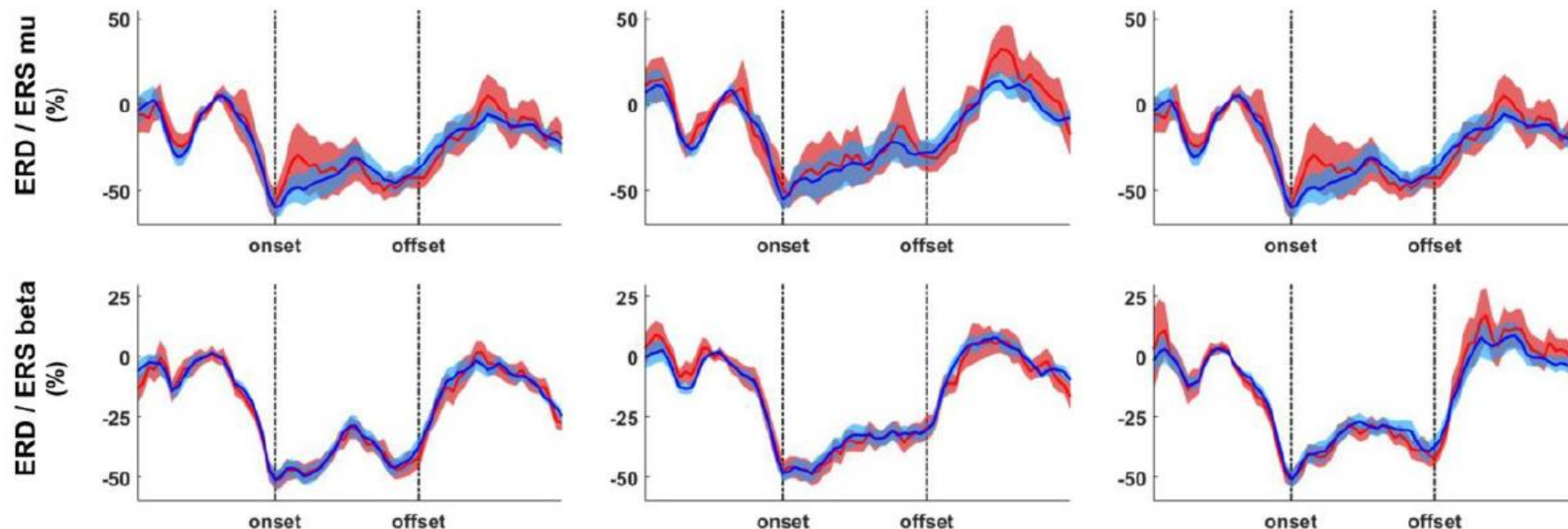


SENSORY MOTOR RHYTHMS (SMR)

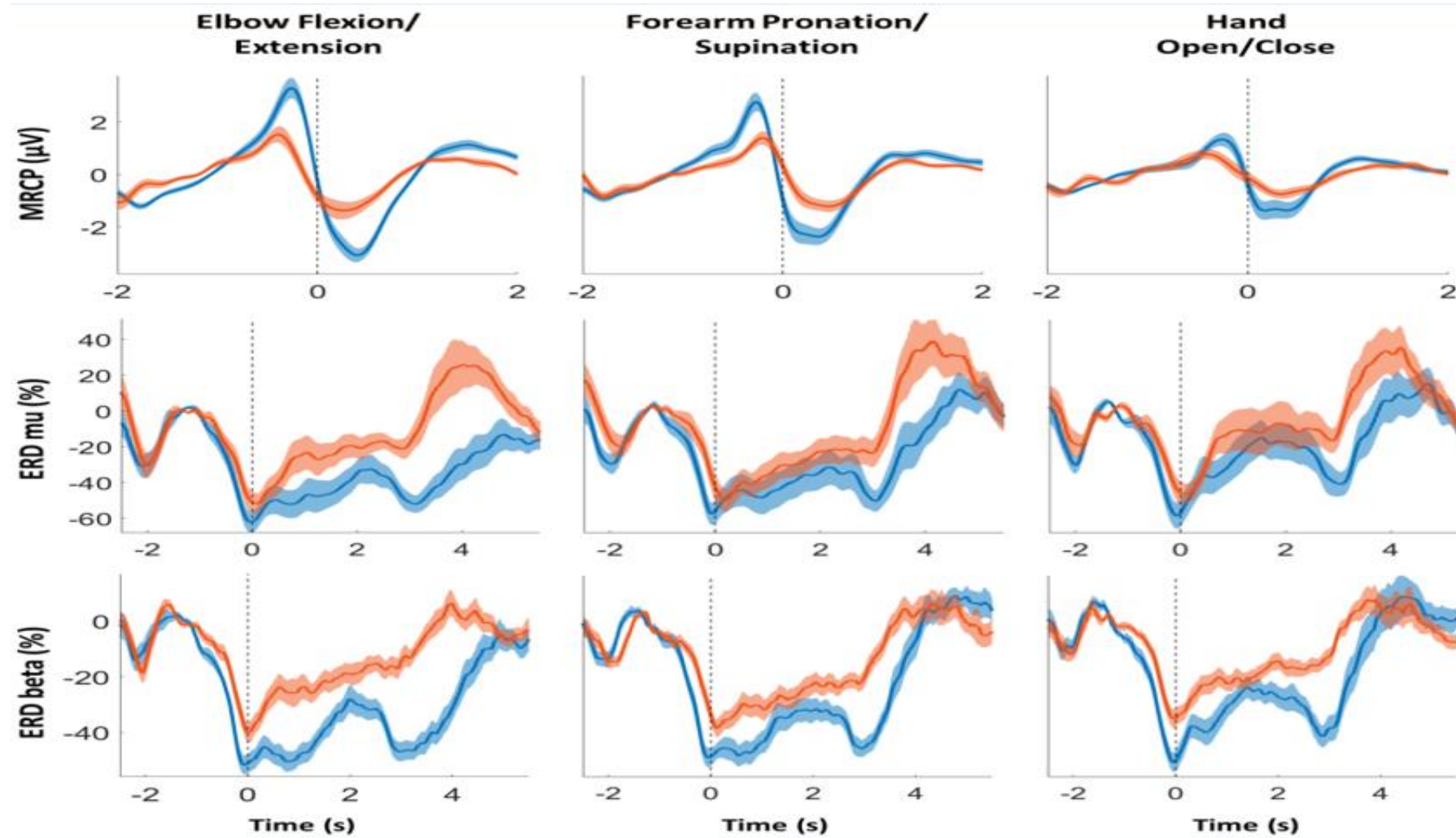
- They reflect **changes** in the **activity** of local interactions between main neurons and interneurons during motor intention and execution in the **frequency domain**
- They are considered to **indicate activation and subsequent recovery** of the motor cortex during the process of planning, execution and completion of the voluntary movement
- There exists 2 types:

ERD: ↓ of power frequency

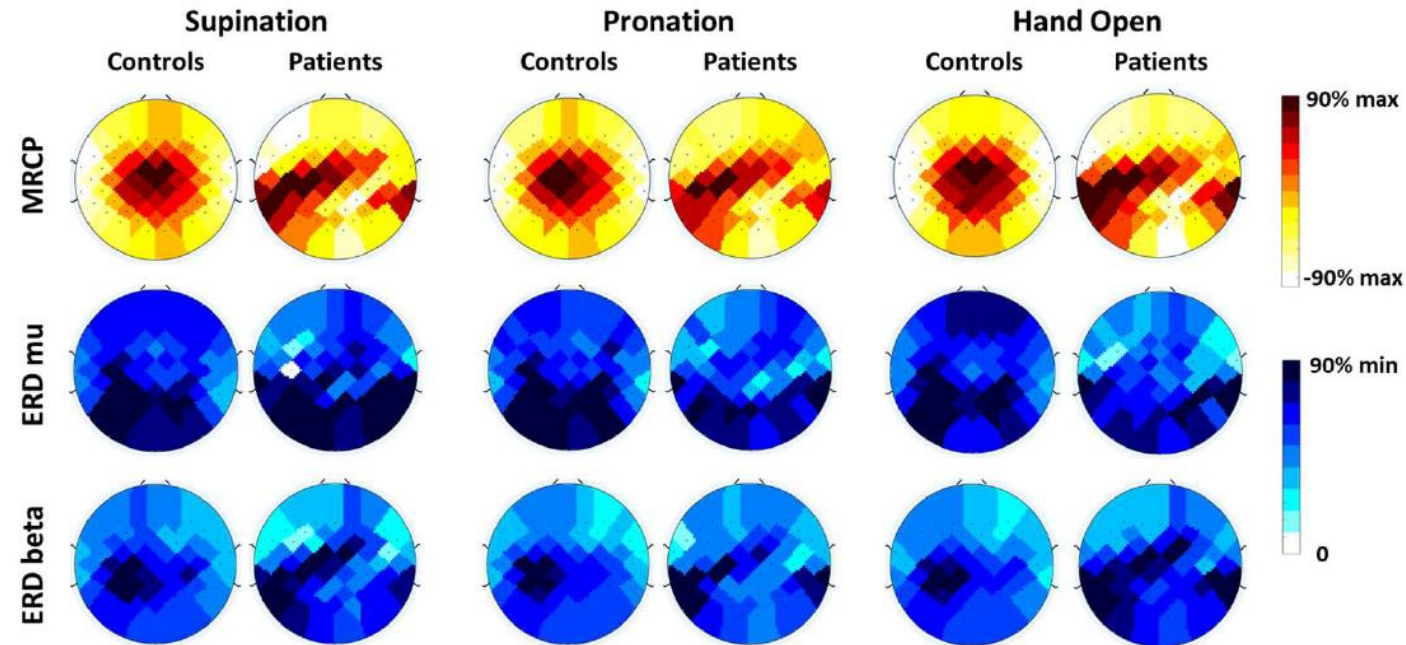
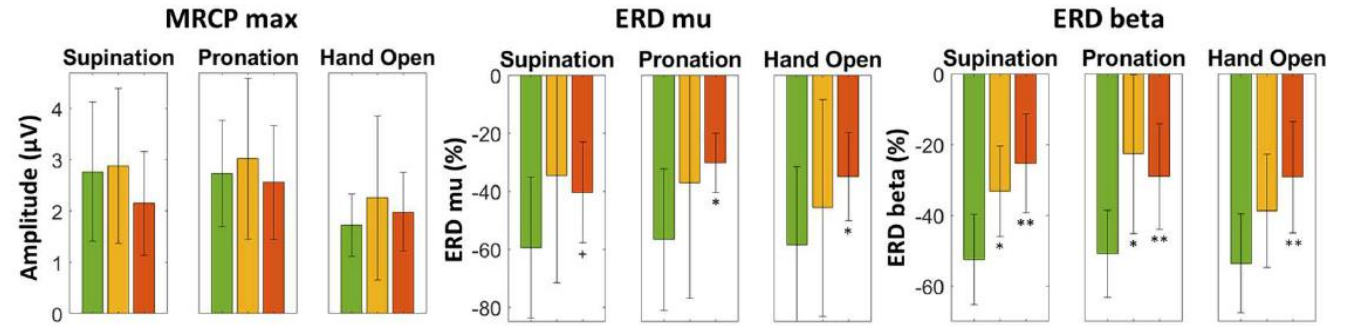
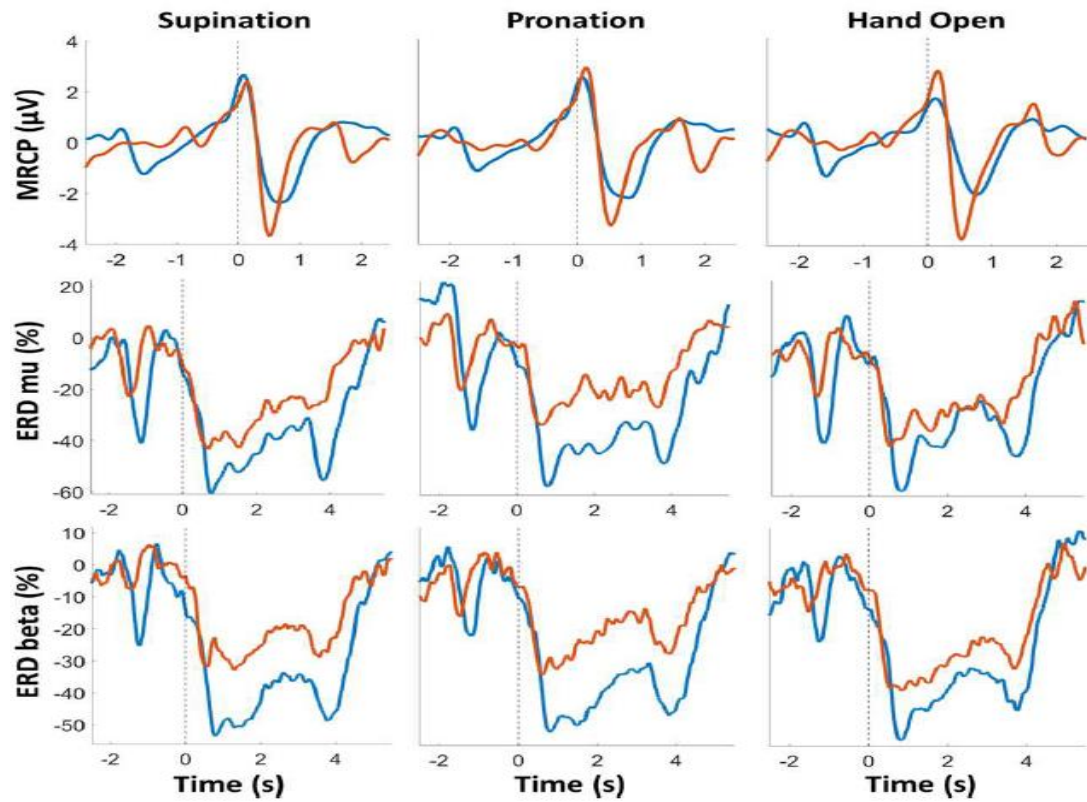
ERS: ↑ of power frequency



Even in MOTOR IMAGERY?



Is this affected by injury? (iSCI)



Borràs et al. 2023



Funded by
the European Union

Grant agreement
no. 101079392

SINGLE-TRIAL ANALYSIS

Single-trial analysis allows to

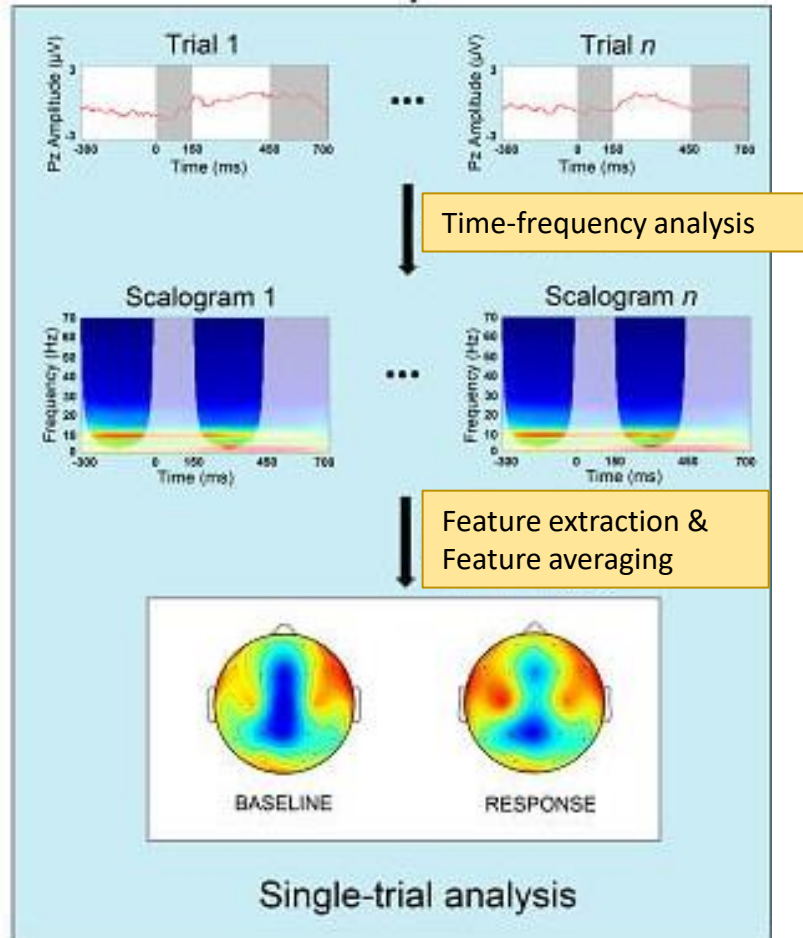
- Capture **trial-by-trial variability** → factors like **fatigue**, **different attention** or **emotion** along the experiment have influence on the subject performance
- Evaluate **dynamic processes** of brain activity
- Analyze **rare events** :
 - AEPs suppresses of the unrelated component to the time-locked event markers
 - AEPs can enhance artefacts time-locked with the external event (i.e. ocular/muscular artefacts)
- Enhance of **statistical analysis** power introducing new time-frequency features
- Analyze information at high frequencies not smoothed by averaging → Connectivity studies
- Assess phase-based measures such as PLV, IC,. Cross-Frequency Coupling (CFC) ...

Single trial analysis is very suitable when individual variability, temporal dynamics, high frequency or rare events are of interest.



SINGLE-TRIAL ANALYSIS

Methodology:



1. Single-trial extraction:
2. Time-frequency analysis:
 - Short-Time Fourier Transform (STFT), Hilbert Transform (HT), Wavelet Transform (WT), Stockwell Transform (ST, or S-Transform)
3. Time & frequency resolution limitations:
 - Heisenberg uncertainty principle, or Cone of influence (COI)
4. Feature extraction:
 - Based on magnitude and phase information
 - e.g. Relative power, spectral entropy, median frequency, inter-trial phase coherence (ITPC), phase-locking value (PLV), ...
5. Feature averaging:
 - Over time windows of interest: baseline, early/late response,...
6. Statistical analysis on single-trial or averaged features.

Outline

- EEG recordings
- Event Related Potentials (ERPs)
- **Brain Connectivity**
 - ✓ What is brain connectivity?
 - ✓ EG connectivity
 - ✓ Case studies on EEG connectivity
 - ✓ Graph Theory
 - ✓ Examples



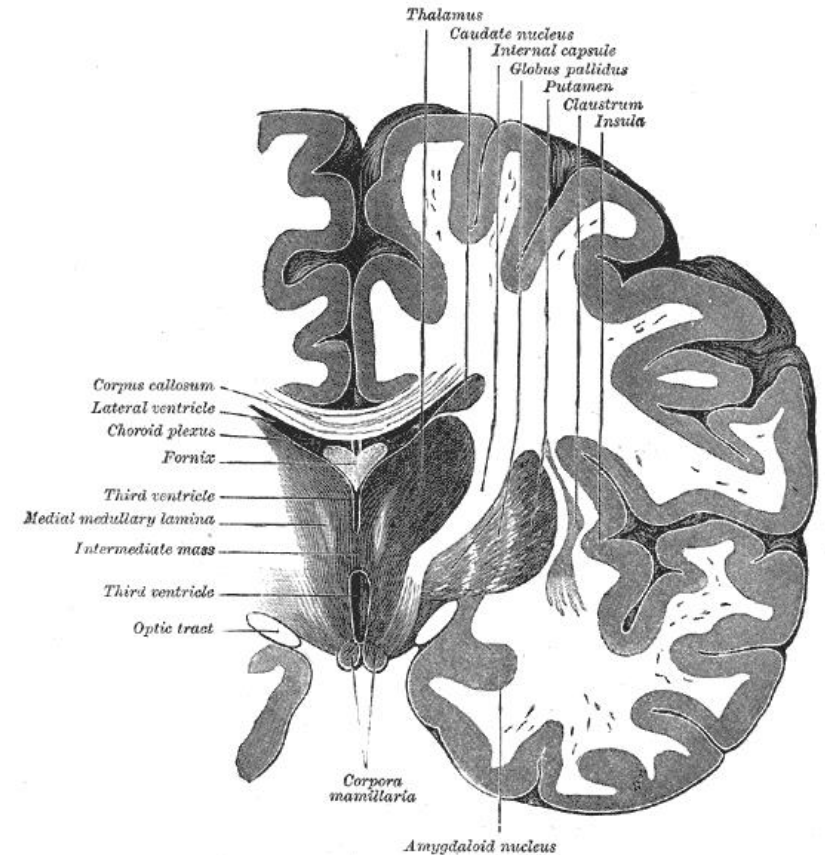
- **What is brain connectivity?**
- **EEG connectivity**
- **Studies on EEG connectivity**
- **Graph Theory**
- **Examples**



What is brain connectivity?

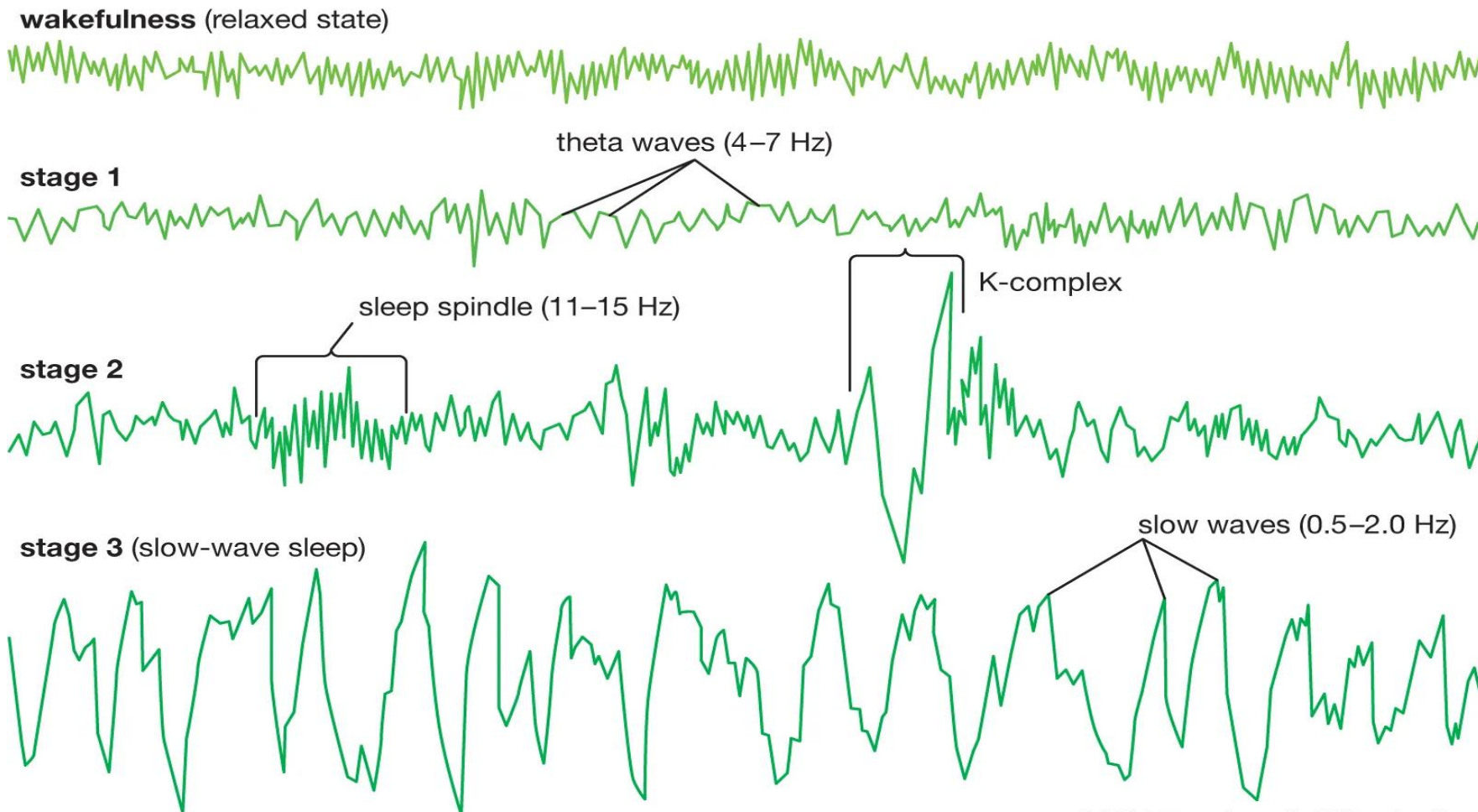
- Brain connectivity spans multiple scales, from microscopic connections between individual neurons to macroscopic networks that connect distinct brain regions
- The coexistence of two mechanisms (segregation and integration) provides very diverse and integrated information that shows a great complexity of patterns.
 - **Segregation:** specialized neurons grouped together to form segregated/separated zones
 - **Integration:** these zones are activated in coordination during different cognitive states

It has been hypothesised that the brain coordinates the flow of information dynamically by changing the strength, pattern, or the frequency with which different brain areas engage in oscillatory synchrony.



What is brain connectivity?

Brain connectivity is not static! Its patterns change over time



© 2013 Encyclopædia Britannica, Inc.



What is brain connectivity?

Our brain Brain connectivity is not static! Its patterns change over time

- Changes as we age
- Is shaped by our experiences, environment, genetics, etc.



0 – 3 explosive growth
4 – 11 pruning/refining
12 – 18 consolidation



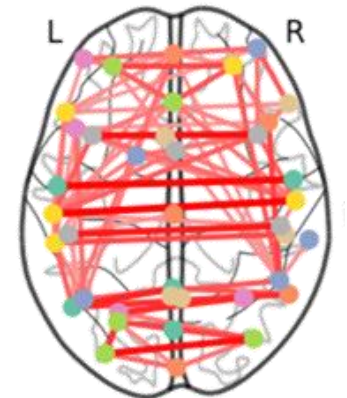
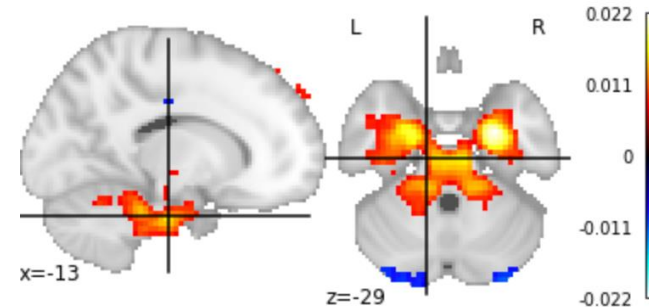
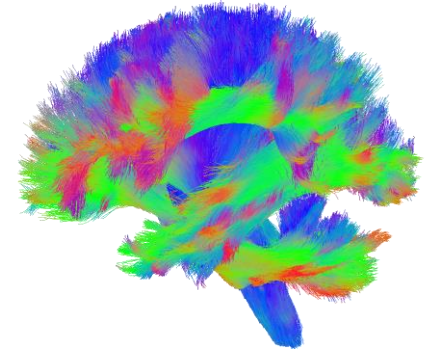
Refining and strengthening
(integration and efficiency)



Loss of neural connections
(especially white matter
tracts)

Types of brain connectivity?

- **Anatomical connectivity**
 anatomic connexions
 physical pathways
 between neurons
- **Functional connectivity**
 statistical relationships-
 dependencies across
 different brain regions
- **Effective connectivity**
 cause-effect interactions
 between brain regions



- What is brain connectivity?
- **EEG connectivity**
- Studies on EEG connectivity
- Graph Theory
- Examples



EEG connectivity

Different Approaches

linear



nonlinear

time domain



information-theoretic
domain

frequency domain

dynamic



static

pairwise



multivariate

model-free

model-based



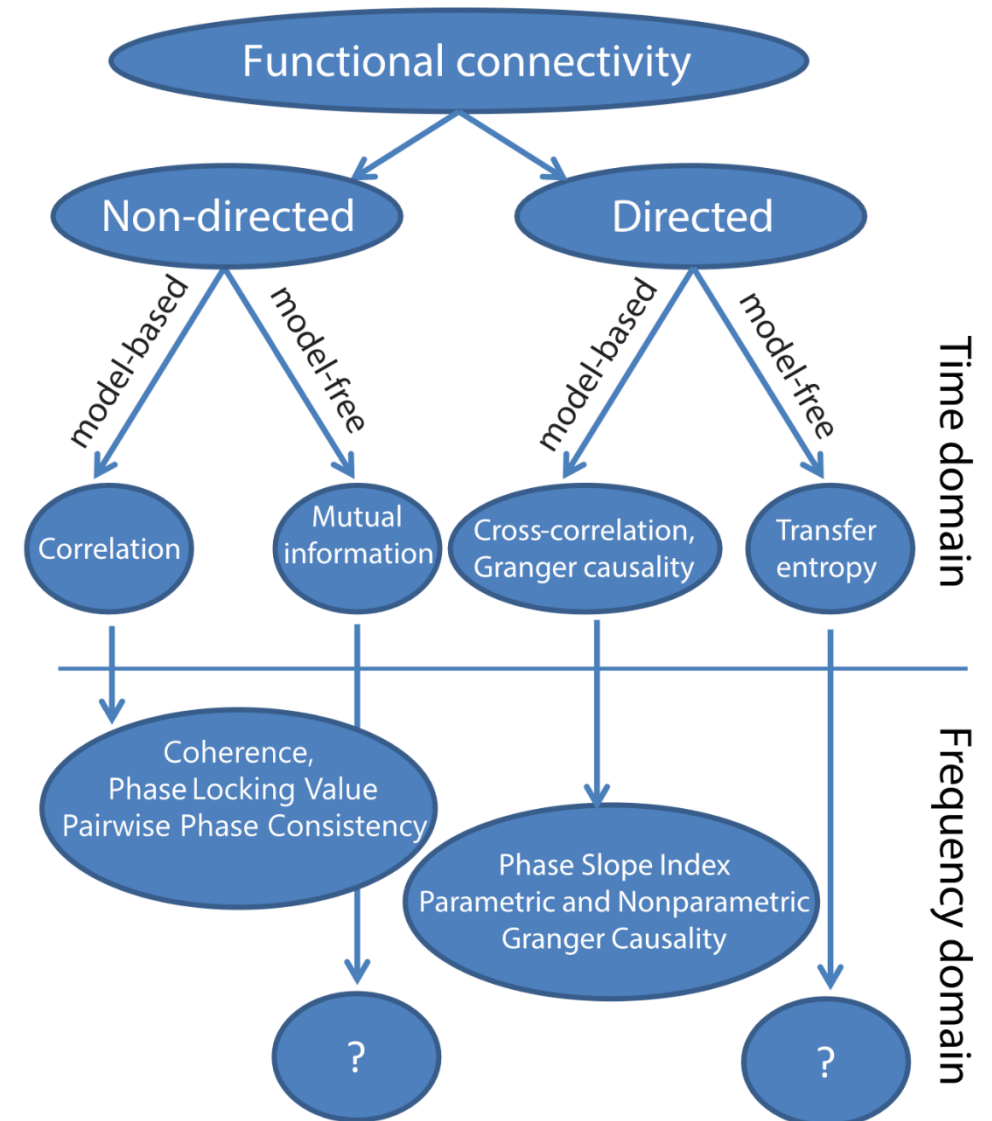
EEG connectivity

A Tutorial Review
of Functional Connectivity Analysis Methods
and Their Interpretational Pitfalls

[Bastos & Schoffelen 2015](#)

A Tutorial Review
of Connectivity Analysis in EEG Data:
State of the Art and Emerging Trends

[Chiarion et al 2015](#)



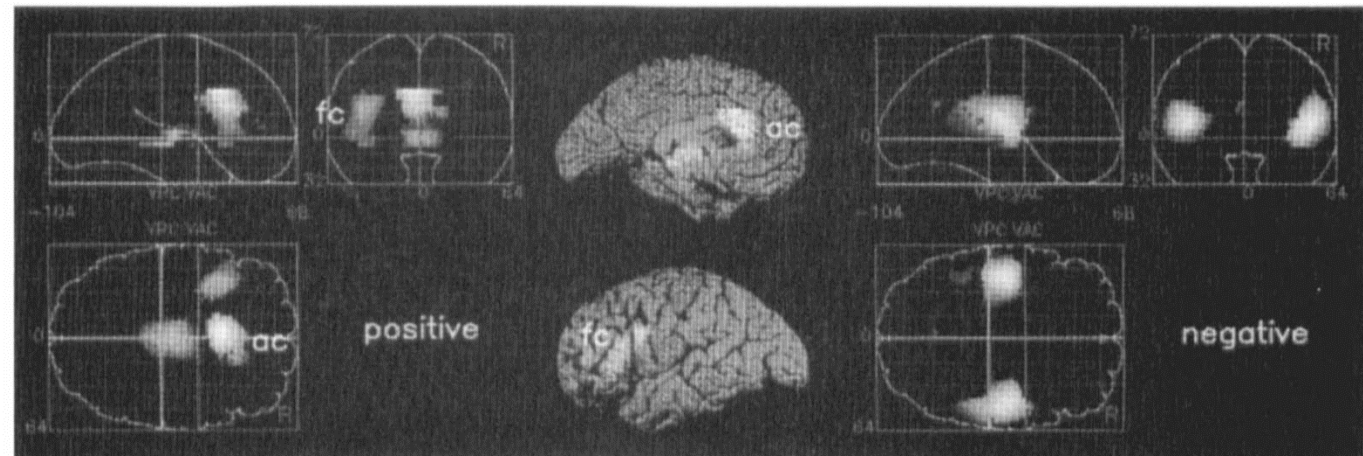
EEG connectivity

Cross-correlation

the concept of **FC** was used by **Karl Friston** on neuroimaging data

assessed via **correlation** or **covariance** (time)

statistical connections between the **dynamic activity** of neural units in **different anatomical locations**



[Friston et al, 1993](#)

EEG connectivity

Coherence/Coherency

Coherence is the frequency domain equivalent to the **time domain cross-correlation function**

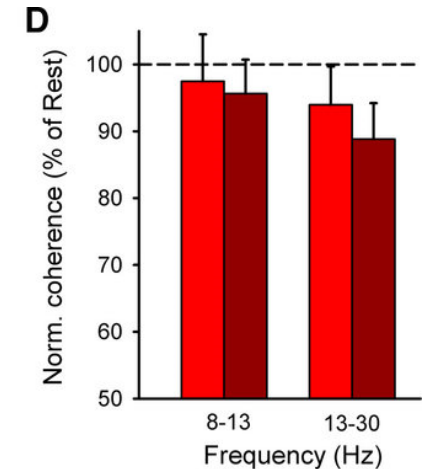
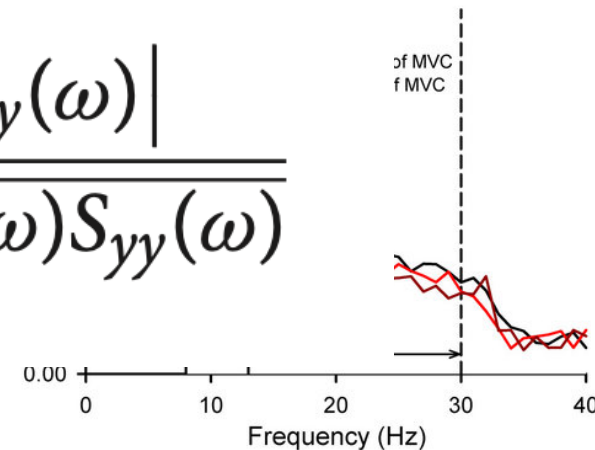
$$coh_{xy}(\omega) = \frac{\left| \frac{1}{n} \sum_{k=1}^n A_x(\omega, k) A_y(\omega, k) e^{i(\varphi_x(\omega, k) - \varphi_y(\omega, k))} \right|}{\sqrt{\left(\frac{1}{n} \sum_{k=1}^n A_x^2(\omega, k) \right) \left(\frac{1}{n} \sum_{k=1}^n A_y^2(\omega, k) \right)}}$$

EEG connectivity

Coherence/Coherency

COH estimates the similarities in the frequency content of two signals combining both amplitude and phase synchrony information

$$coh_{xy}(\omega) = \frac{|S_{xy}(\omega)|}{\sqrt{S_{xx}(\omega)S_{yy}(\omega)}}$$



Close relatives

phase-slope index (PSI)

imaginary part of the coherency (IC)

[Nolte et al., 2008](#)

[Nolte et al., 2004](#)



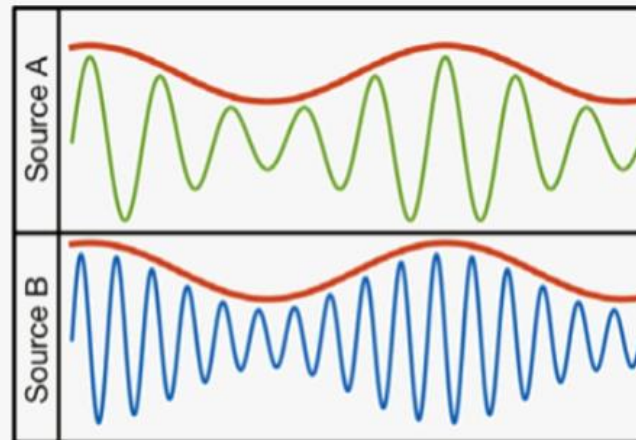
EEG connectivity

Amplitude envelope correlation

Estimates the correlation based on the amplitude of the time series

Three-steps procedure:

- 1- Orthogonalization of each time series
- 2- Computation of power envelopes



- 3- Calculation of Pearson correlation between *log*-transformed power envelopes

EEG connectivity

Phase Synchronization

Quantifies the relationship
between rhythms

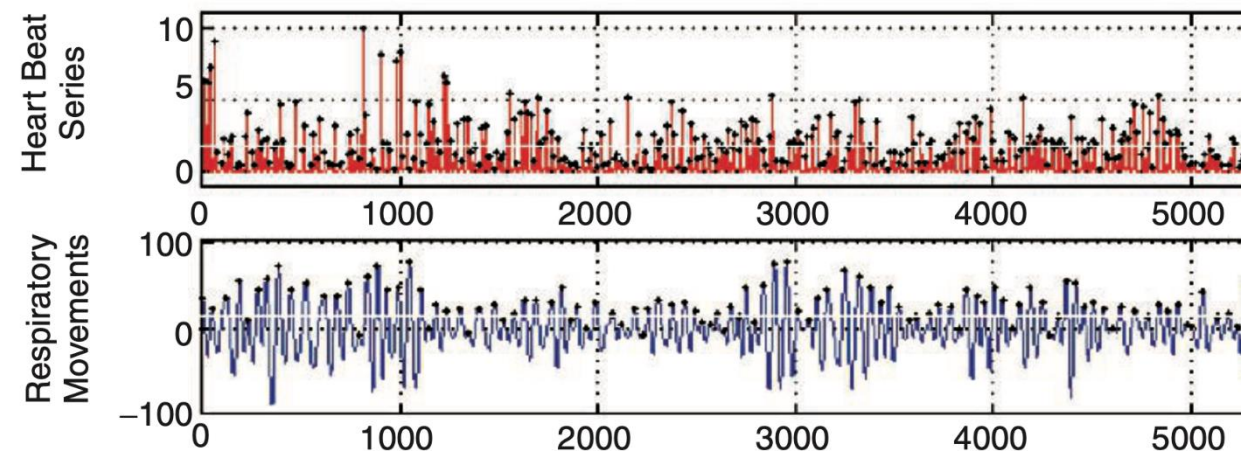
instantaneous phase
extracted from signals

$$|n\phi_1 - m\phi_2| < \textit{const}$$

**not affected by
instantaneous amplitude**

suitable tool for analysing the
interaction between brain units,
especially when the **interaction is too
weak to be detected by other measures**

[Rosenblum et al., 1996](#)



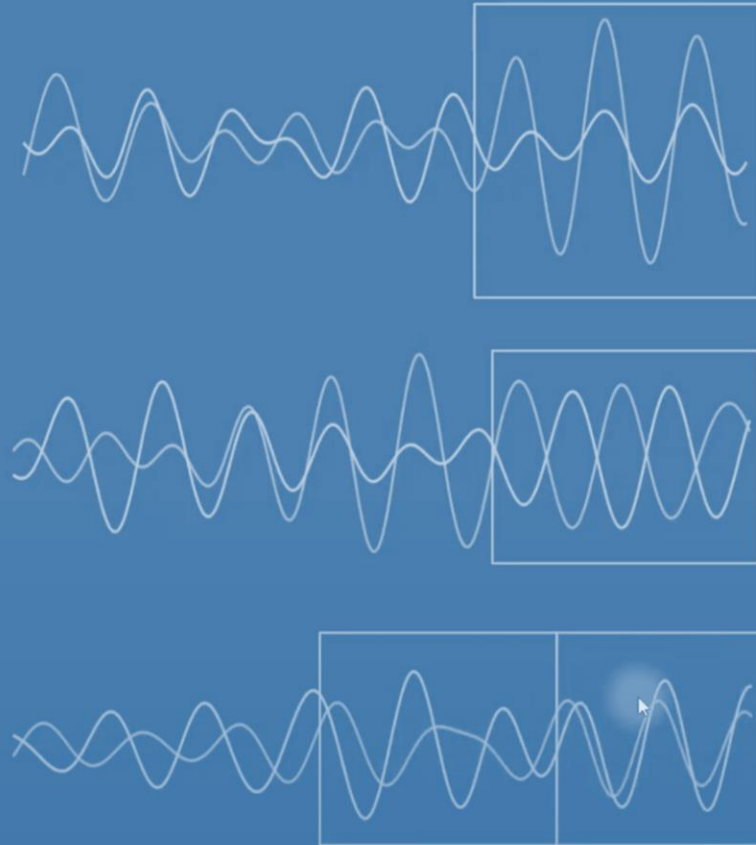
[Hoyer et al., 2001](#)



EEG connectivity

Phase Synchronization

Intuitive
concept of
phase
synchronization

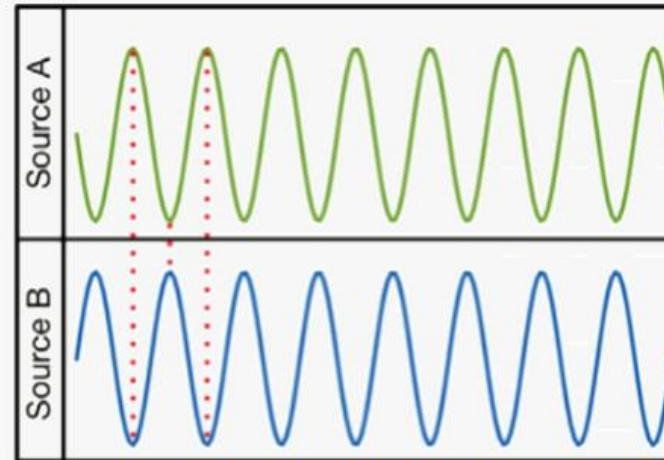


- Timing is important (not amplitude)
- *Consistency* in phase difference, not relative phase, is important (but relative phase is relevant)
- Synchronization is dynamic over time (by changes in frequency)

EEG connectivity

Phase Synchronization/Synchronization likelihood

Phase-based connectivity metrics



SL estimates the likelihood of a system which is at the same state at two different times, and another system will also be in the same state at these times

PLI quantifies the asymmetry of the phase difference distributions of two time series (proposed to overcome SL limitations)

$$PLI_{X,Y} = |\langle \text{sign} \sin(\Delta\phi_{X,Y}) \rangle|$$

Ruiz-Gómez 2022



EEG connectivity

Phase Locking Value

Same as coherence, but normalizing signals
(unit amplitude in the Fourier domain)

$$plv_{xy}(\omega) = \frac{\left| \frac{1}{n} \sum_{k=1}^n 1_x(\omega, k) 1_y(\omega, k) e^{i(\varphi_x(\omega, k) - \varphi_y(\omega, k))} \right|}{\sqrt{\left(\frac{1}{n} \sum_{k=1}^n 1_x^2(\omega, k) \right) \left(\frac{1}{n} \sum_{k=1}^n 1_y^2(\omega, k) \right)}}$$
$$= \left| \frac{1}{n} \sum_{k=1}^n e^{i(\varphi_x(\omega, k) - \varphi_y(\omega, k))} \right|$$

PLV looks for latencies at which the phase difference between the signals varies little across trials

[Lachaux et al., 1999](#)

Close relatives

Phase Lag Index (PLI)

[Stam et al., 2007](#)

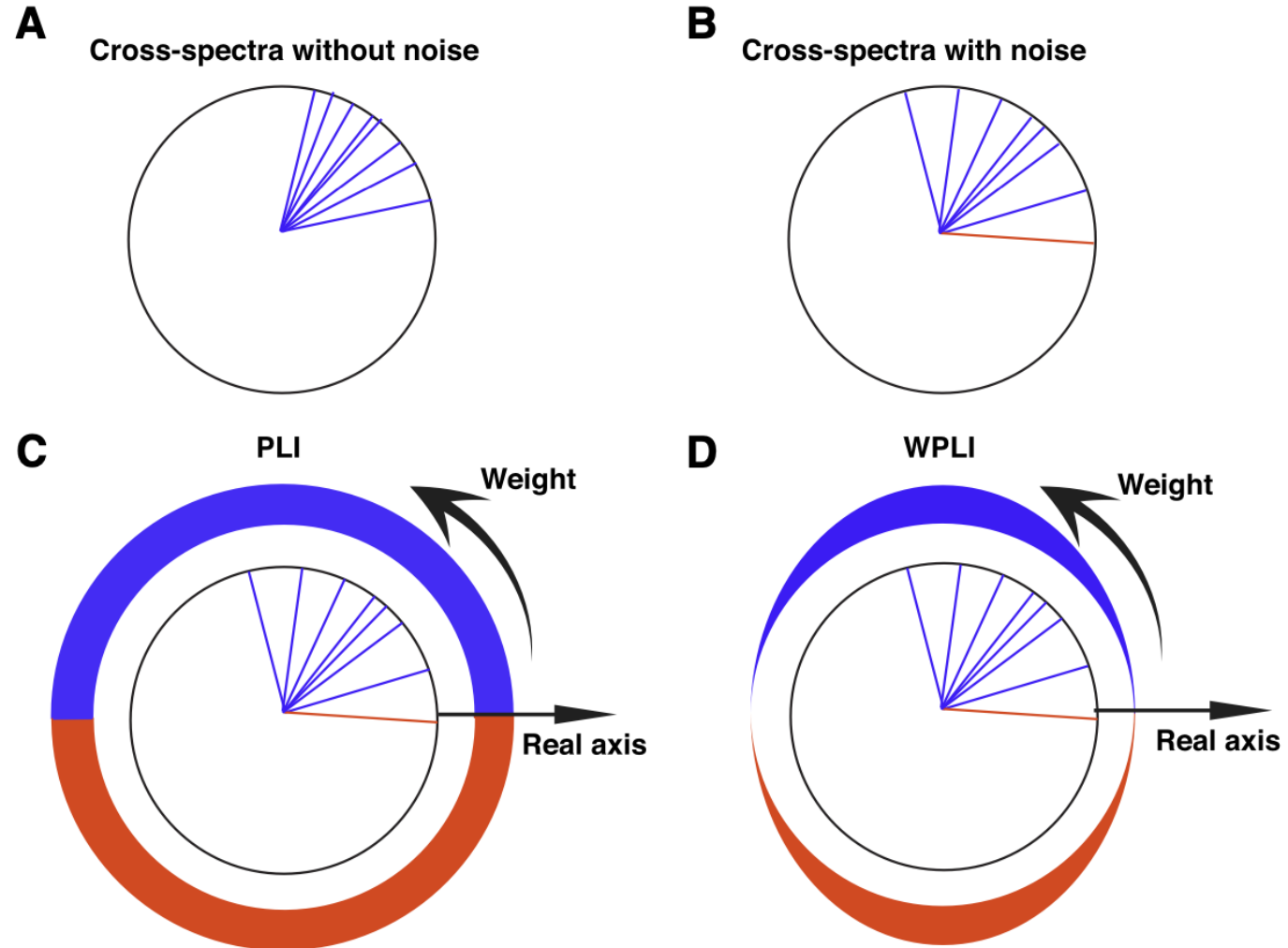
Weighted Phase Lag Index (wPLI)

[Vink et al., 2011](#)



EEG connectivity

Phase Lag Index



[Vink et al., 2011](#)

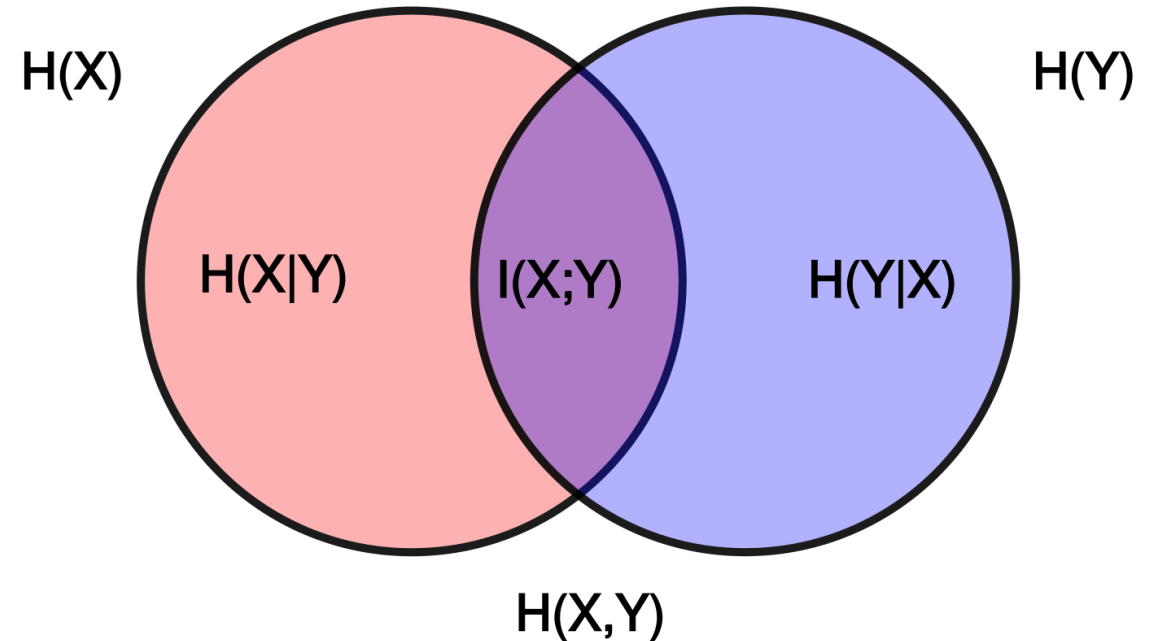
EEG connectivity

Mutual Information

$$H(X) = - \sum_x p(x) \log(p(x))$$

$$H(X, Y) = - \sum_{x,y} p(x, y) \log(p(x, y))$$

$$\begin{aligned} MI_{xy} &= I(X, Y) = H(X) + H(Y) - H(X, Y) \\ &= \sum_x \sum_y p(x, y) \log \left(\frac{p(x, y)}{p(x)p(y)} \right) \end{aligned}$$

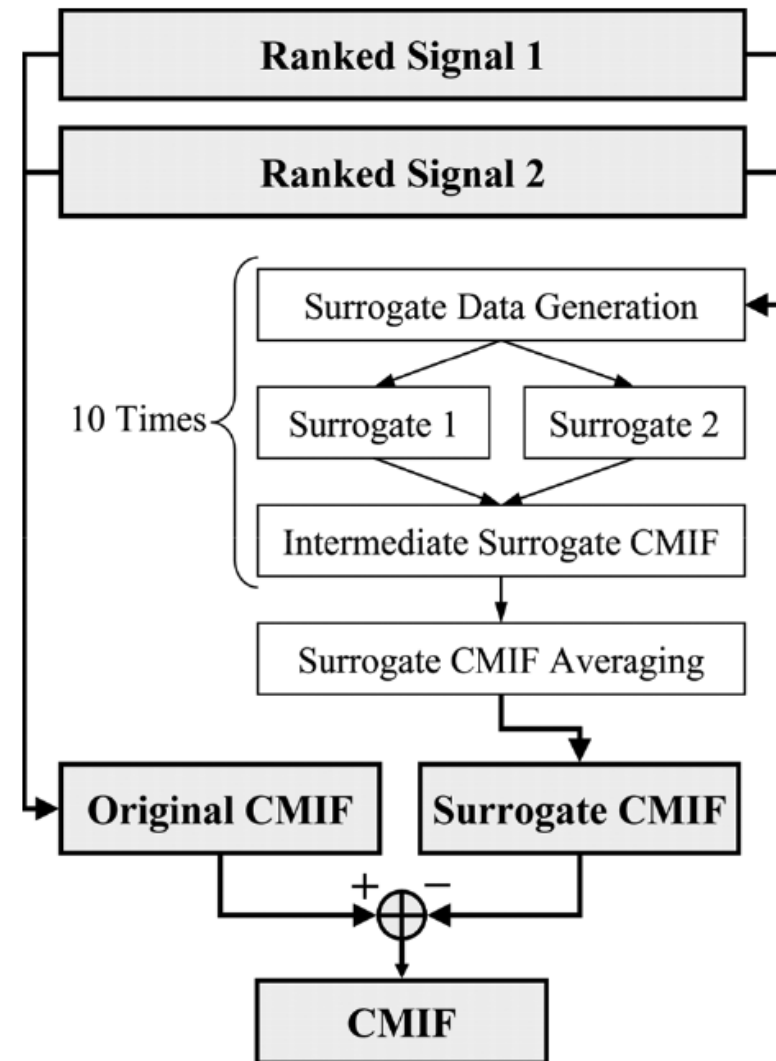


[Kraskov et al., 2004](#)

EEG connectivity

Mutual Information

- CMI permits to evaluate the **non-linear interactions separately by surrogate data (SD)**
- SD conserves all the original data statistical properties but the property of interest.
- CMIF is calculated from original data and SD (many times) and, then, subtracted to get the final CMIF which measures the non-linear coupling/connectivity

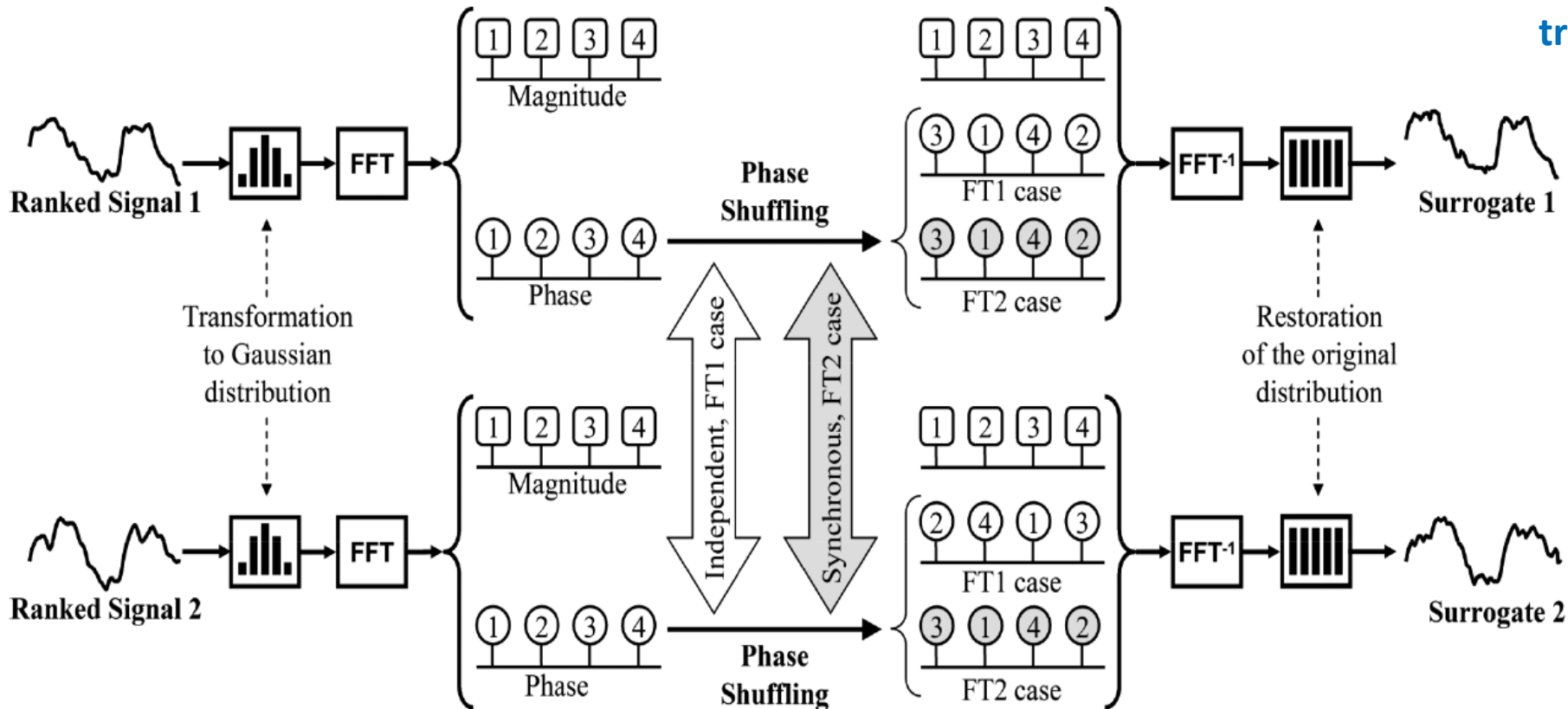


EEG connectivity

Mutual Information

Amplitude adjusted Fourier transform method (AAFT):

1. Preserving the magnitudes of the FT in order to conserve first and second order statistics (linear properties)
2. changing randomly the phases of the FT to remove nonlinear properties; and
3. transforming back to the time domain.



EEG connectivity

Granger Causality/Transfer Entropy

What about **directionality/causality**?

X Granger-causes Y if predicting *Y based on past Y and past X* performs better than *predicting solely on past Y*

[Granger 1969](#)

Transfer entropy is a version of mutual information operating on conditional probabilities

[Schreiber 2000](#)

Granger causality and transfer entropy are equivalent for Gaussian variables

[Barnett et al., 2009](#)

$$TE_{x \rightarrow y} = \sum_{\mathbf{x}_{n+1}} p(\mathbf{y}_{n+1}, \mathbf{y}_n, \mathbf{x}_n) \log \left(\frac{p(\mathbf{y}_{n+1}, \mathbf{x}_n, \mathbf{y}_n) p(\mathbf{y}_n)}{p(\mathbf{x}_n, \mathbf{y}_n) p(\mathbf{y}_{n+1}, \mathbf{y}_n)} \right)$$

[Alonso et al., 2015](#)



- What is brain connectivity?
- EEG connectivity
- **Studies on EEG connectivity**
- Graph Theory
- Examples



Drug Effect: alprazolam

Mutual Information

- Linear and nonlinear components present opposite trends

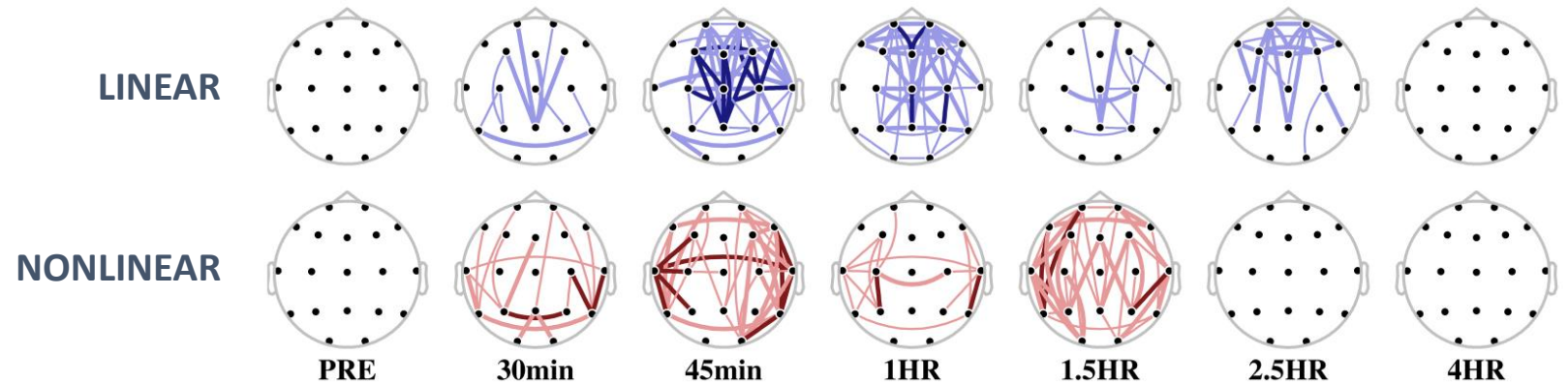
Objective

Describe short-term changes caused by alprazolam

Results

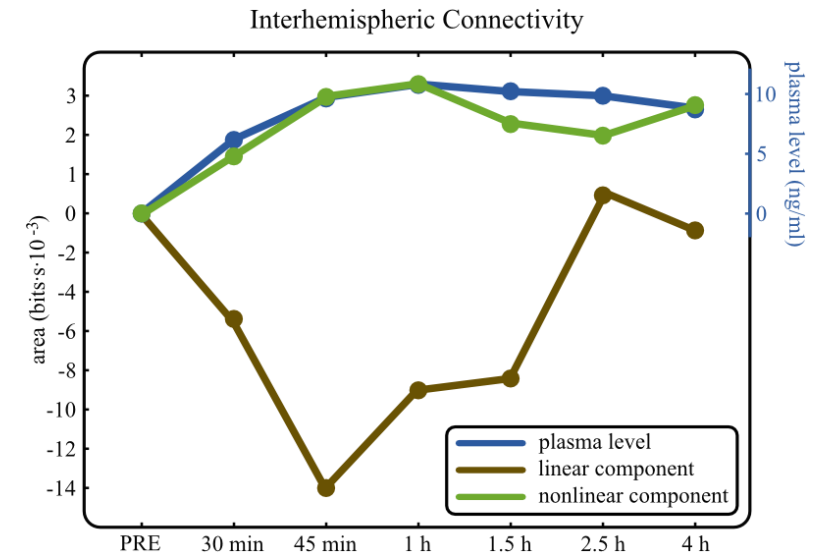
Alprazolam induced significant changes in EEG connectivity in comparison with placebo.

Linear changes were negatively correlated and nonlinear changes were positively correlated with drug plasma concentrations; the latter showed higher correlation coefficients.



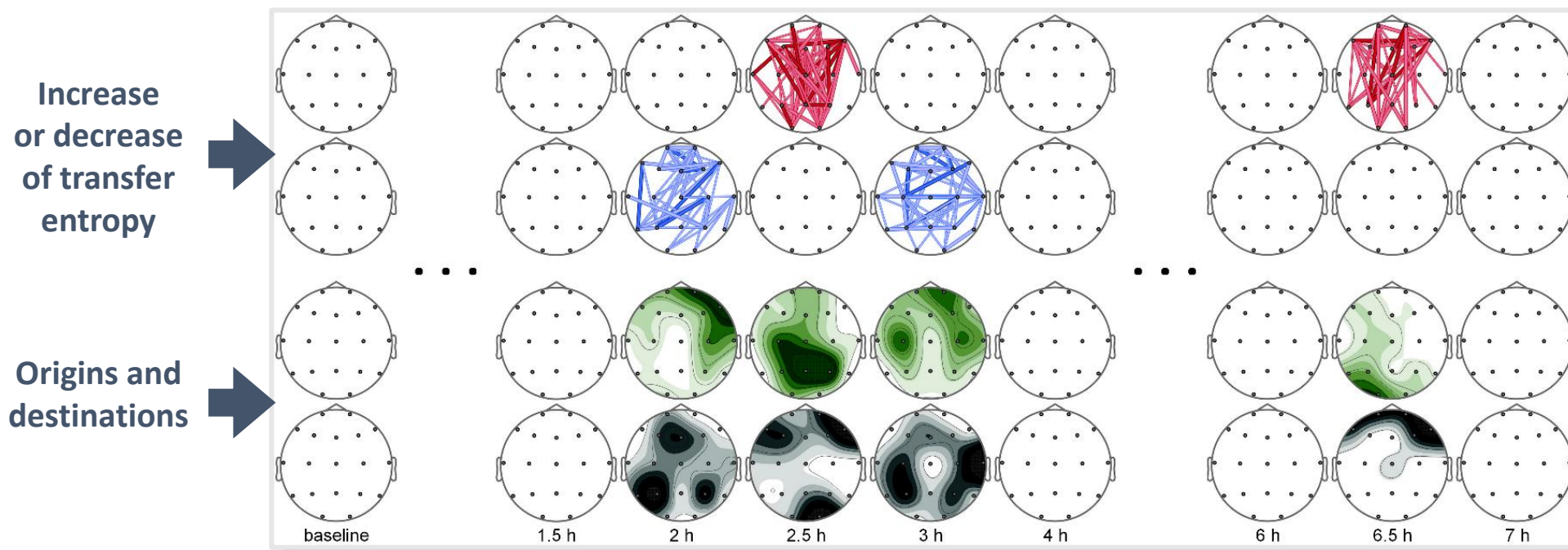
High correlation with plasma measurements

[Alonso et al., 2010](#)



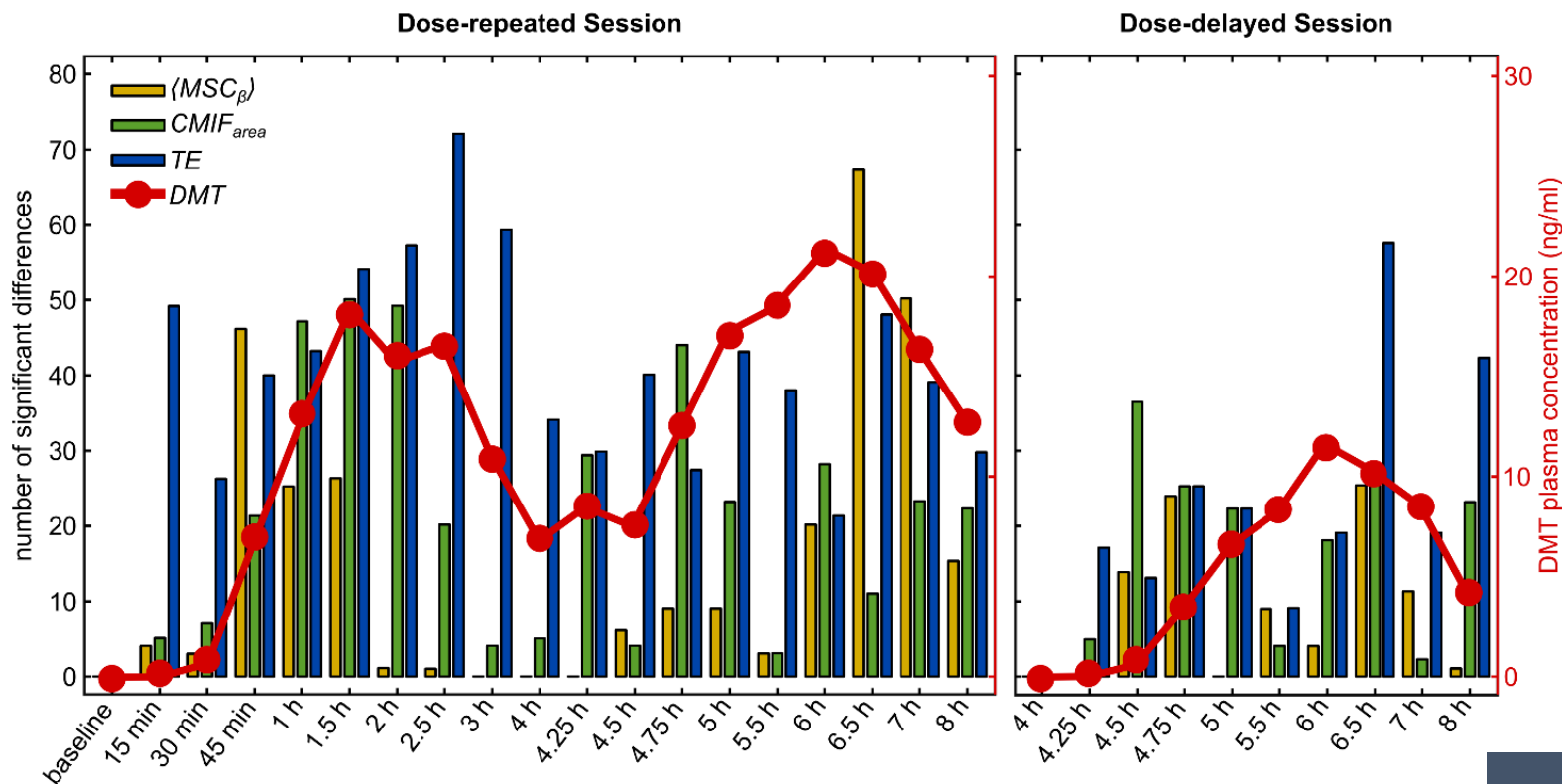
Drug Effect: Ayahuasca

Transfer Entropy



Drug Effect: Ayahuasca

Transfer Entropy



Correlation Coefficients



Measure	Dose-delayed	Dose-repeated
$\langle MSC_{\beta} \rangle$	0,728	0,688
$CMIF_{area}$	0,759	0,722
TE	0,834	0,881

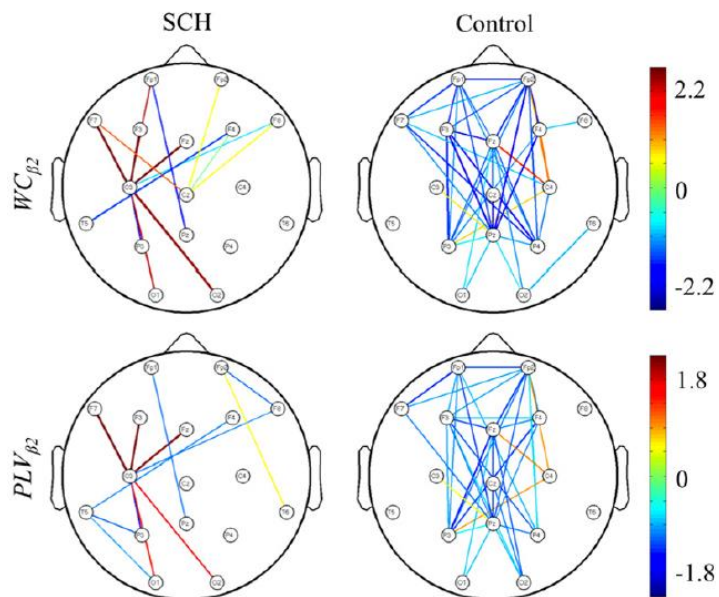


Schizophrenia

Coherence, PLV

Objective

To explore the coupling patterns of brain dynamics during an auditory oddball task in schizophrenia (comparing between after and before the stimulus)

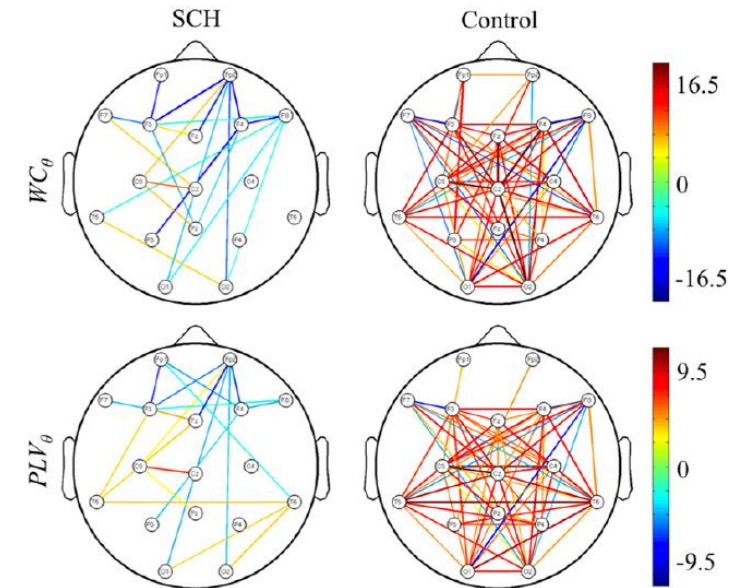


[Bachiller et al., 2015](#)

Results

SCH patients fail to change their coupling dynamics between stimulus response and baseline when performing an auditory cognitive task
 Different behaviour is observed in controls

This may reflect impaired communication among neural areas.



Rett Syndrome

Coherence, Mutual Information

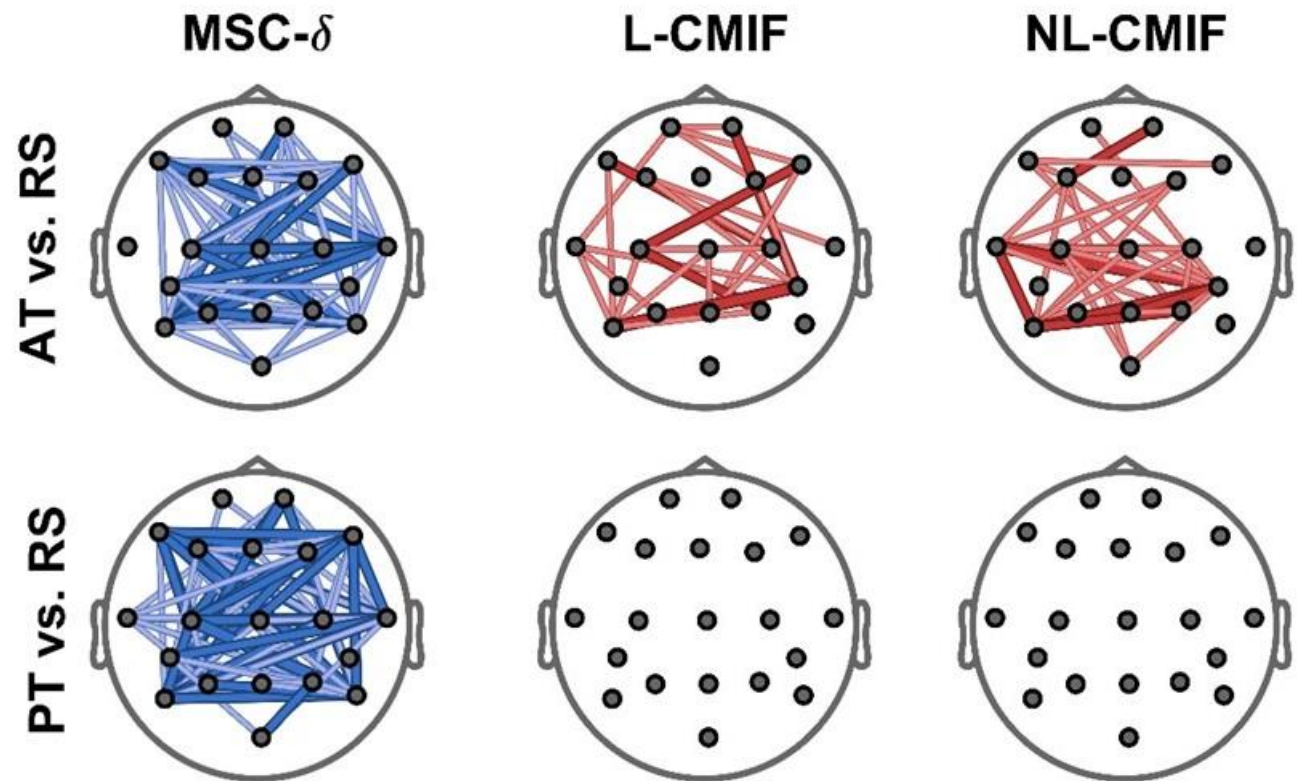
Objective

investigate the effect of different types of repeated cognitive stimulation in RTT patients on EEG brain connectivity

Results

Active Task (AT) leads to increase of nonlinear couplings (suggesting a nonlinear functional structure consequence of active stimulation).

Gaming activities may elicit greater attention and increased functional connectivity among brain regions.



- **What is brain connectivity?**
- **EEG connectivity**
- **Studies on EEG connectivity**
- **Graph Theory**
- **Examples**



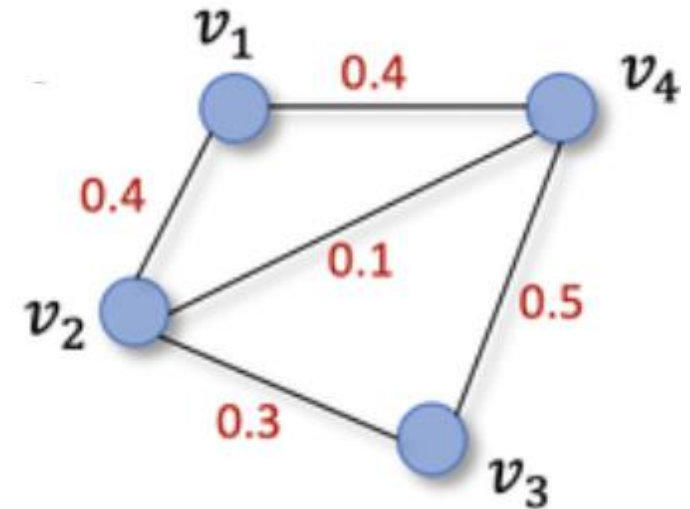
What is a network

A **mathematical representation** of a real-world complex system, such as the brain

Defined by:

- **Nodes (vertices):** *represent brain regions, electrodes...*
- **Links (edges) between pairs of nodes:** *represent anatomical, functional, or effective connectivity*

All networks are represented by their **adjacency (connectivity) matrices**. Rows and columns denote nodes, matrix entries denote links.



	v_1	v_2	v_3	v_4
v_1	0	0.4	0	0.4
v_2	0.4	0	0.3	0.1
v_3	0	0.3	0	0.5
v_4	0.4	0.1	0.5	0

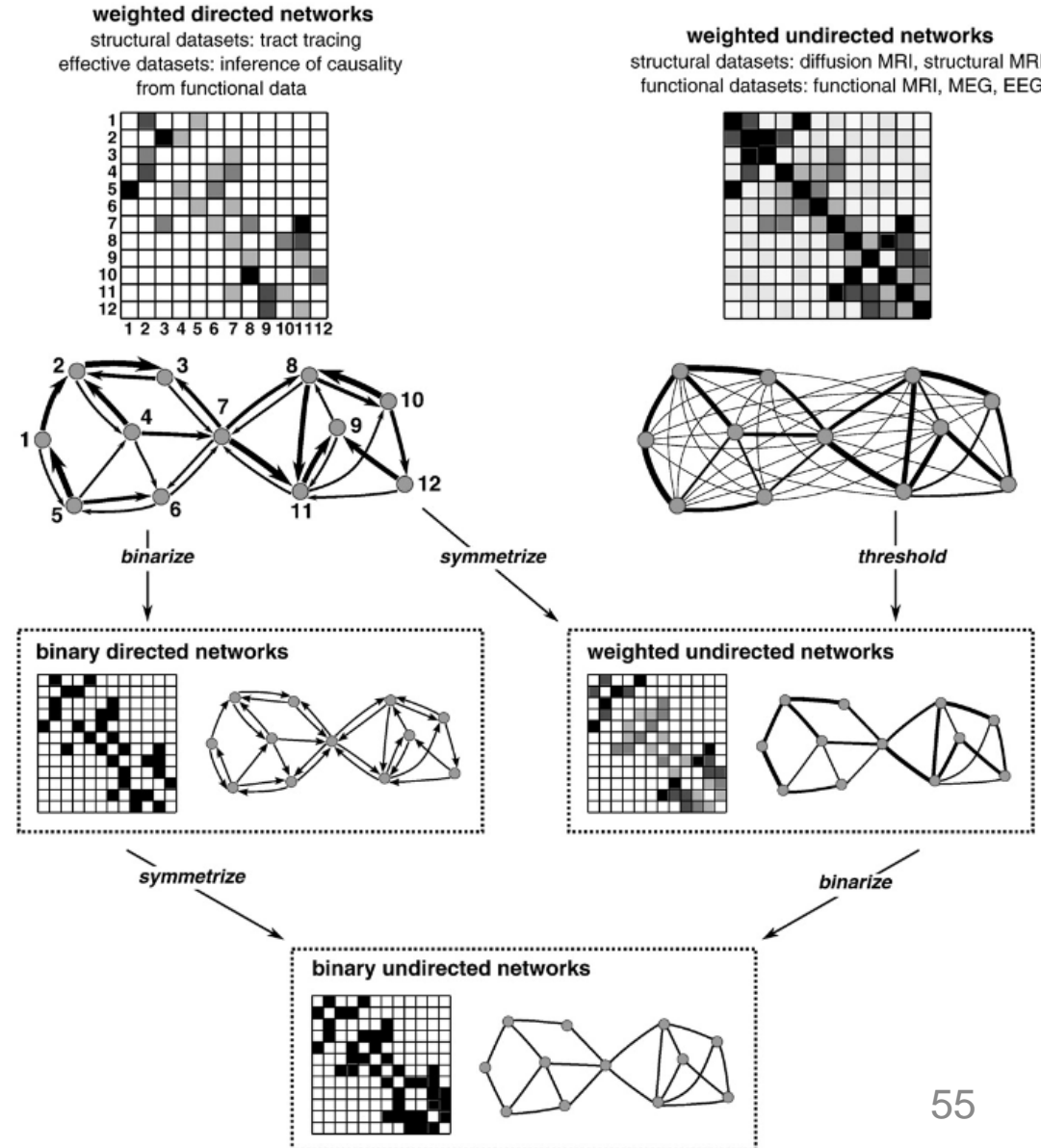
Types of networks

Depending on the **weight** of the links:

- Weighted networks:** links have information about connection strengths
- Binary networks:** just denote the presence or absence of connections

Depending on the **directionality** of the links:

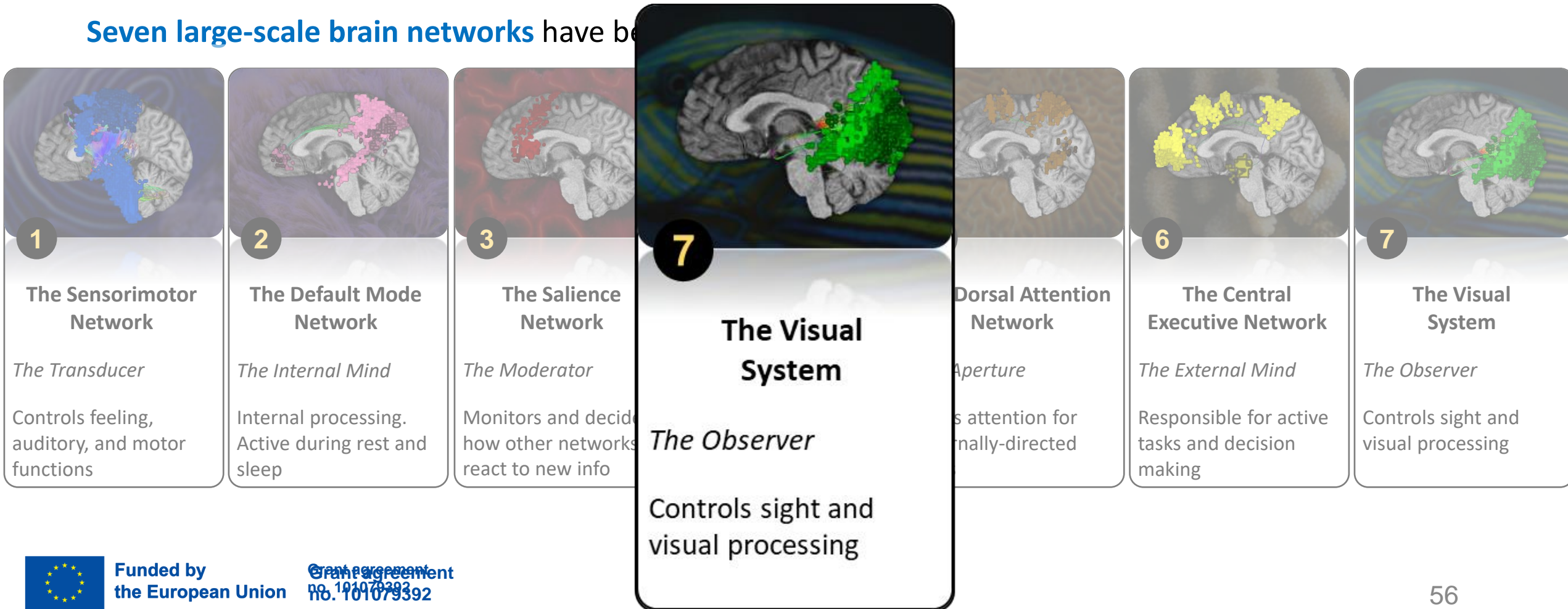
- Directed networks:** no symmetric adjacency matrices; show anatomical or causal directionality (tract tracing studies)
- Undirected networks:** symmetric adjacency matrices (other neuroimaging techniques: EEG, MEG, fMRI...)



Brain networks

Different major networks **control brain function** both during task processing and while at rest

Seven large-scale brain networks have been identified



Graph Theory parameters

An individual **graph theory parameter** may **characterize** one or several aspects of global and/or local brain connectivity

Basic concepts and notation:

N is the set of all nodes in the network.

n is the number of nodes

L is the set of all links in the network.

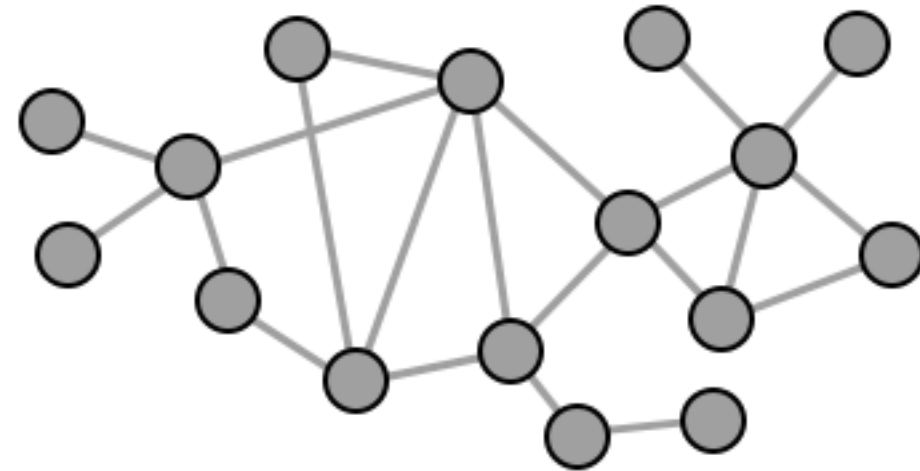
l is the number of links

(i, j) is a link between nodes i and j

$a_{i,j}$ is the connection between nodes i and j

for binary networks, $a_{i,j} = 1$ when link (i,j) exists, $a_{i,j} = 0$ otherwise

for weighted networks, $a_{i,j} = w_{i,j}$ and $0 < w_{i,j} < 1$



Rubinov and Sporns, 2010. 'Complex network measures of brain connectivity: uses and interpretations'

Brain Connectivity Toolbox for MATLAB (brain-connectivity-toolbox.net)

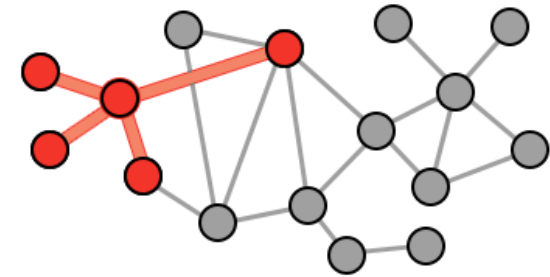


Graph Theory parameters

1. **Measures of centrality:** based on node degree, quantify the total “wiring cost” of the network

Global strength (average node degree):

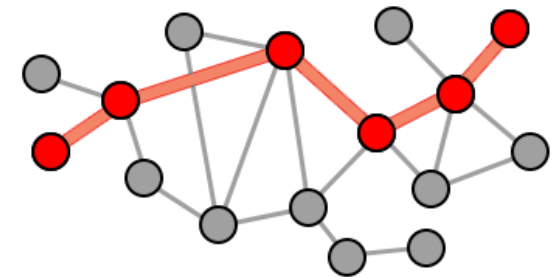
$$s = \frac{1}{N} \sum_{i \in N} s_i = \frac{1}{N} \sum_{i \in N} \sum_{j \in N} w_{ij}$$



2. **Measures of functional integration:** average shortest path length between all pairs of nodes in the network. Quantify the ability to rapidly combine specialized information from distributed brain regions (global connectivity)

Characteristic path length:

$$L = \frac{1}{n} \sum_{i \in N} L_i = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \neq i} d_{ij}}{n - 1}$$



Graph Theory parameters

3. Measures of functional segregation: based on

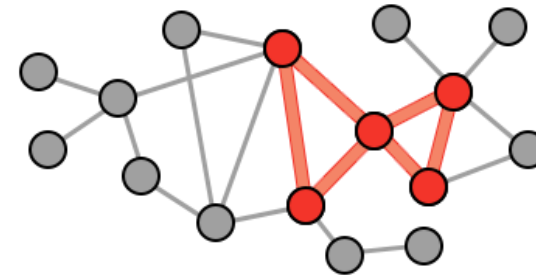
triangle counts, quantify

- The presence of information hubs based on the number of triangles
- the ability for specialized processing to occur within densely interconnected groups of brain regions (local connectivity)

Fraction of node's neighbours that are also neighbours of each other

Clustering coefficient:

$$C = \frac{1}{n} \sum_{i \in N} C_i = \frac{1}{n} \sum_{i \in N} \frac{2t_i}{k_i(k_i - 1)}$$



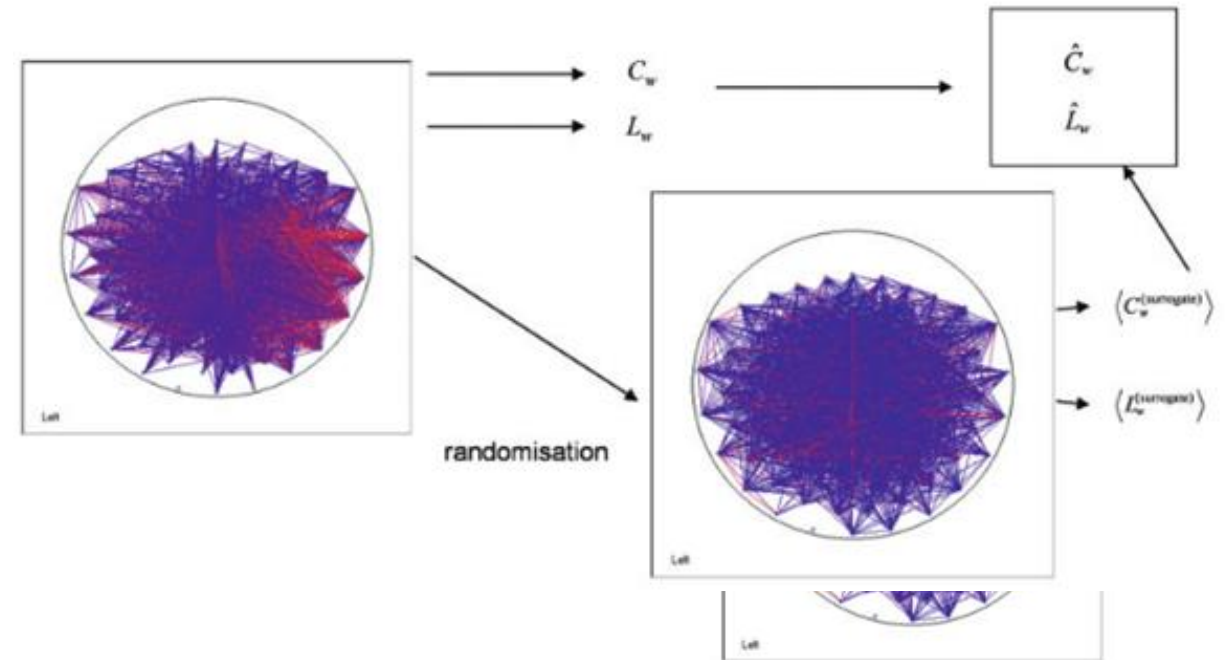
Higher transitivity/clustering coefficient: greater number of connections within the module (forming triangles)

Normalization Procedure

By definition, **these metrics depend** on edge weights and network structure but also on **network size**

To obtain measures that are independent of network size, a **randomization procedure** should be carried on:

1. Generate a set of **surrogate random networks** derived from the original networks by randomly reshuffling the edge weights preserving the basic characteristics of the original network (size, density, and degree distribution)
2. Compute the desired parameter in the surrogate networks (at least 50 or more)
3. Obtain the **parameter ratio** by dividing the original value and the mean value of the random graphs



- **What is brain connectivity?**
- **EEG connectivity**
- **Studies on EEG connectivity**
- **Graph Theory**
- **Examples**

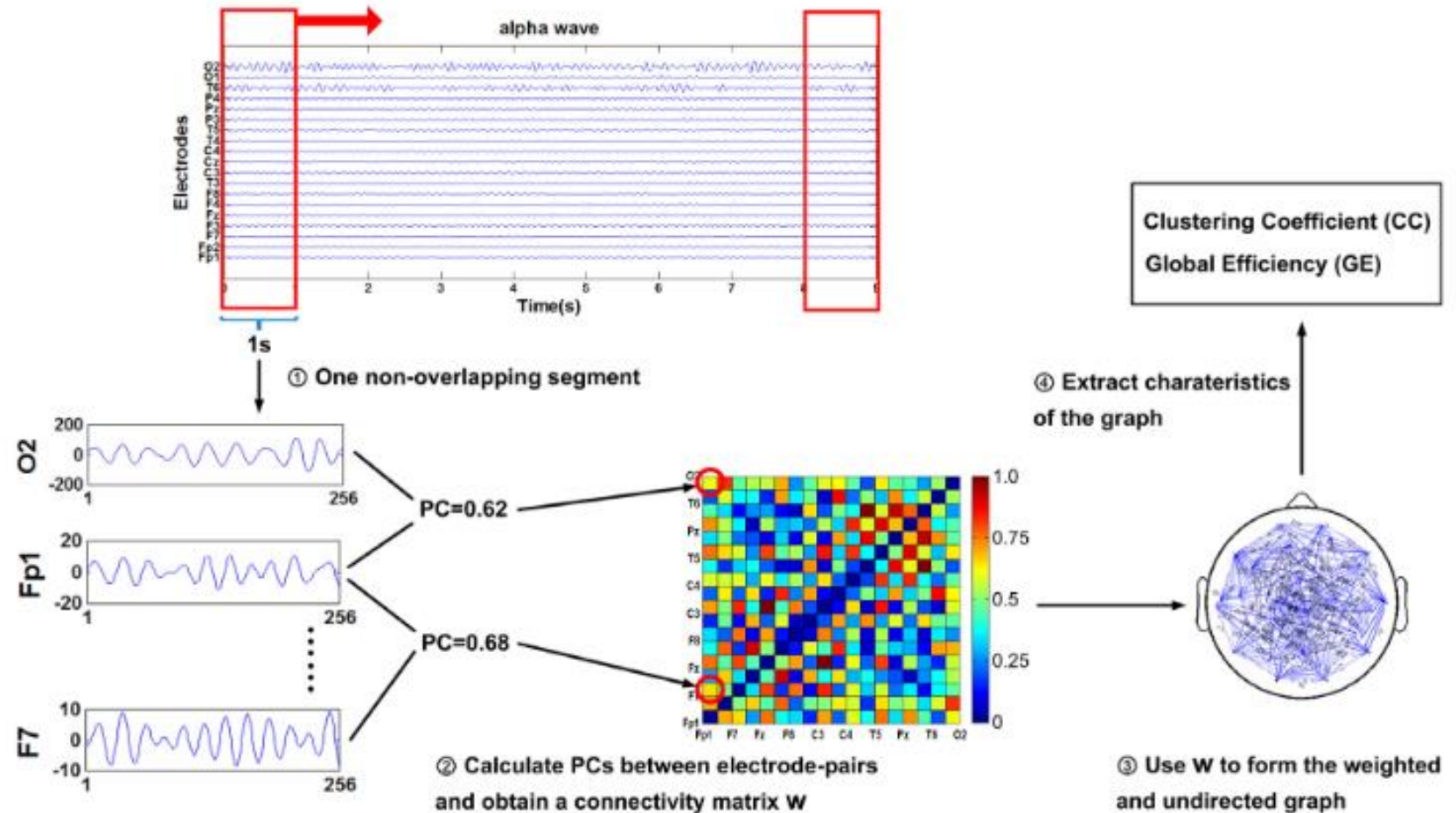


Alzheimer's disease and MCI (I)

Chen J. et al., 2019. 'Topological reorganization of EEG functional network is associated with the severity and cognitive impairment in Alzheimer's disease'

Resting state EEG

1. Connectivity: Phase Coherence (PC)
2. Graph metrics: average clustering coefficient (aver_CC) and global efficiency (GE)

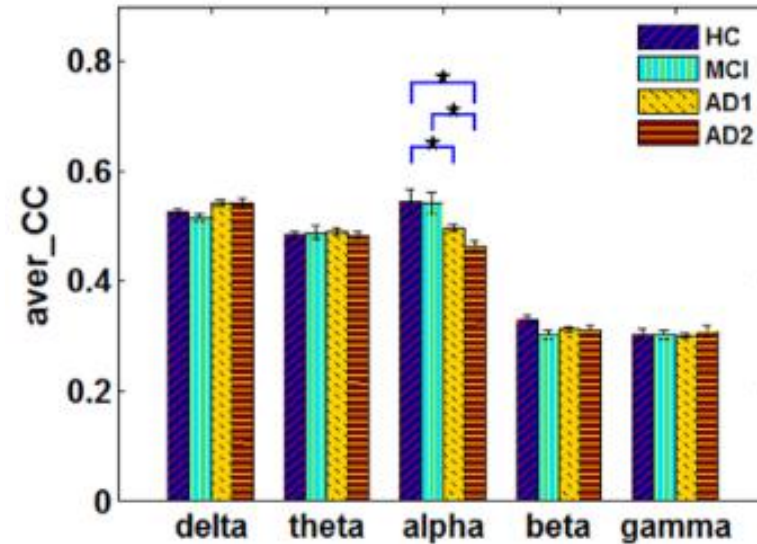


Alzheimer's disease and MCI (I)

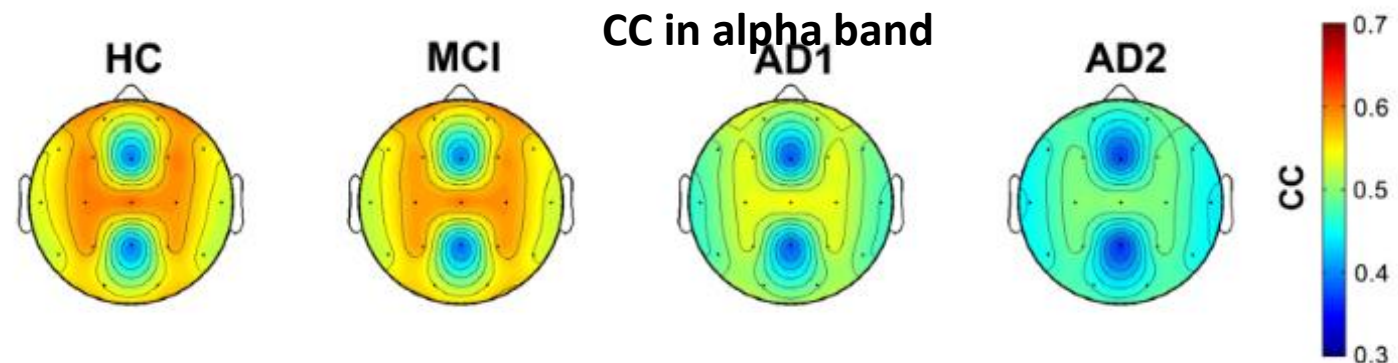
Chen J. et al., 2019. 'Topological reorganization of EEG functional network is associated with the severity and cognitive impairment in Alzheimer's disease'

Resting state EEG (eyes closed)

1. Connectivity: Phase Coherence (PC)
2. Graph metrics: average clustering coefficient (aver_CC)



MCI: mild cognitive impairment
AD1: mild AD
AD2: moderate to severe AD



Schizophrenia

Gomez-Pilar et ál., 2017. 'Functional EEG network analysis in schizophrenia: Evidence of larger segregation and deficit of modulation'

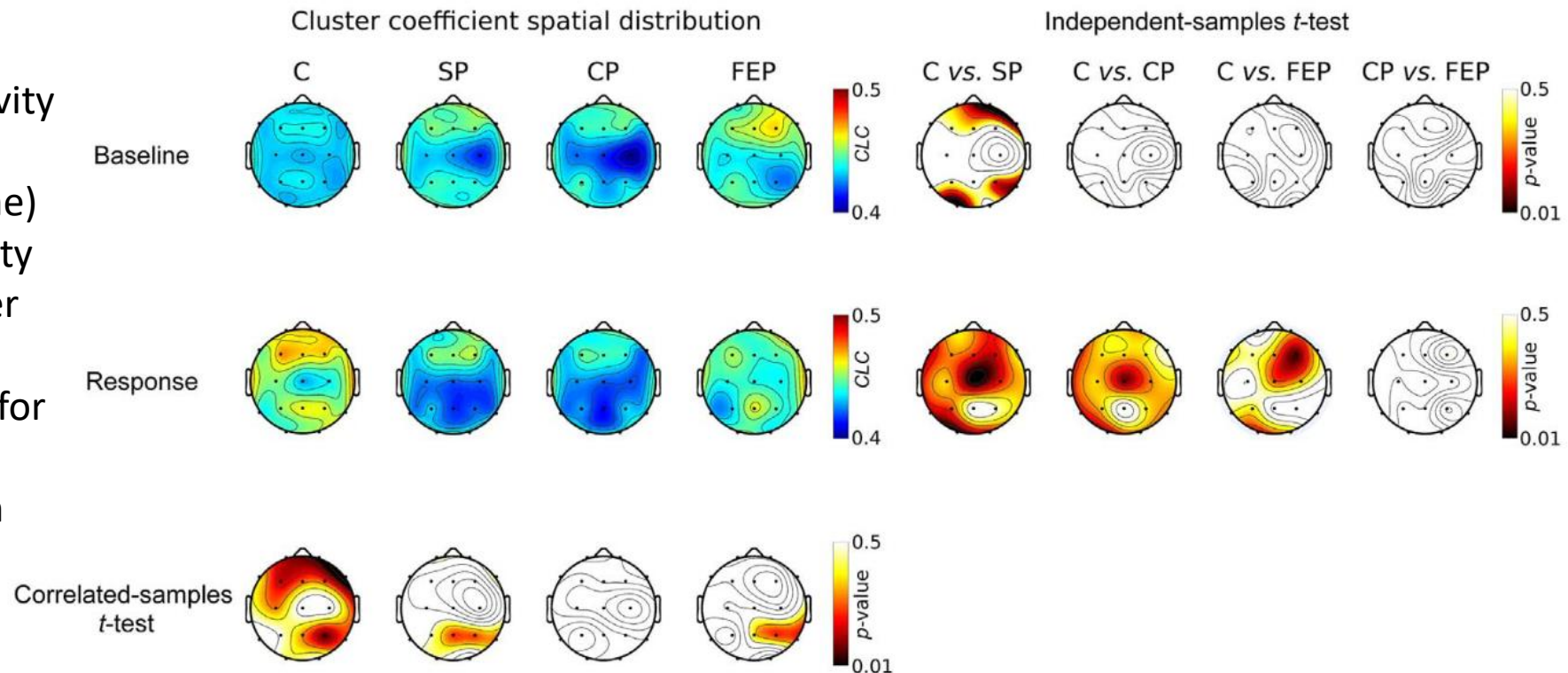
Auditory odd-ball 3-stimulus paradigm (P300) EEG

1. Connectivity: event-related Coherence (ERC) from CWT
2. Graph metrics: clustering coefficient (CLC), path length (PL)

C: controls
 SP: schizophrenia Patients
 FEP: first episode patients
 CP: chronic patients

Results:

- More segregated cortical activity prior to stimulus onset for patients (higher CLC in baseline)
- Less segregated cortical activity in response for patients (lower CLC in response)
- Complex cognitive capacities for patients (larger integration activity between distant brain regions is needed)



Alzheimer's disease and MCI (II)

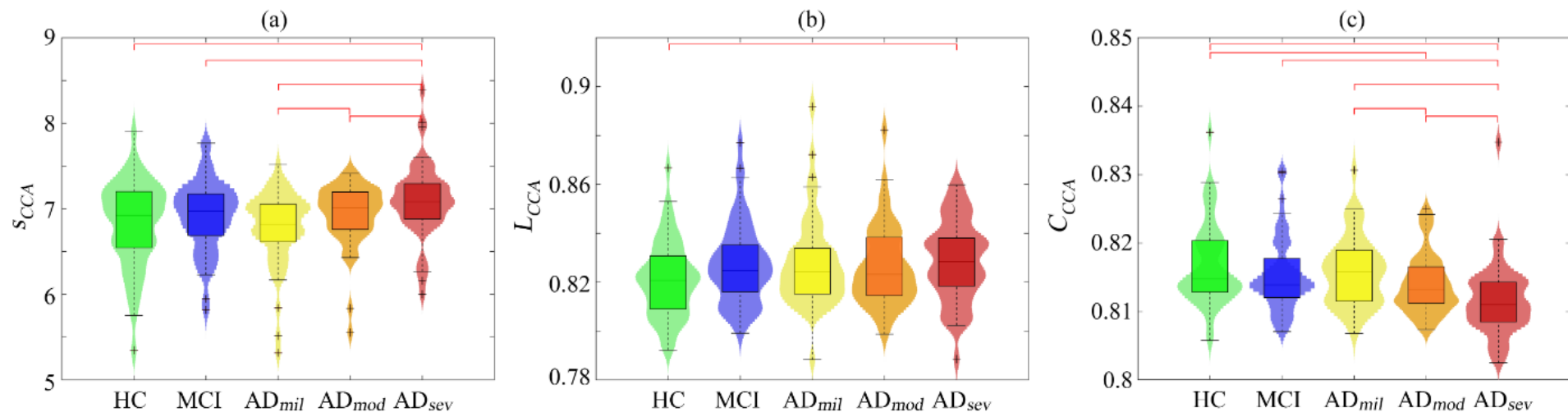
Ruiz-Gómez SJ et ál., 2021. 'A new method to build multiplex networks using Canonical Correlation Analysis for the characterization of the Alzheimer's disease continuum'

Resting state EEG

1. Connectivity: PLI
2. Graph metrics: global strength (s), characteristic path length (L) and clustering coefficient (C)

Results:

- Lower integration in AD networks (higher L) compared to HC subjects
- Decreases in global segregation for the AD group (lower C)



Schizophrenia

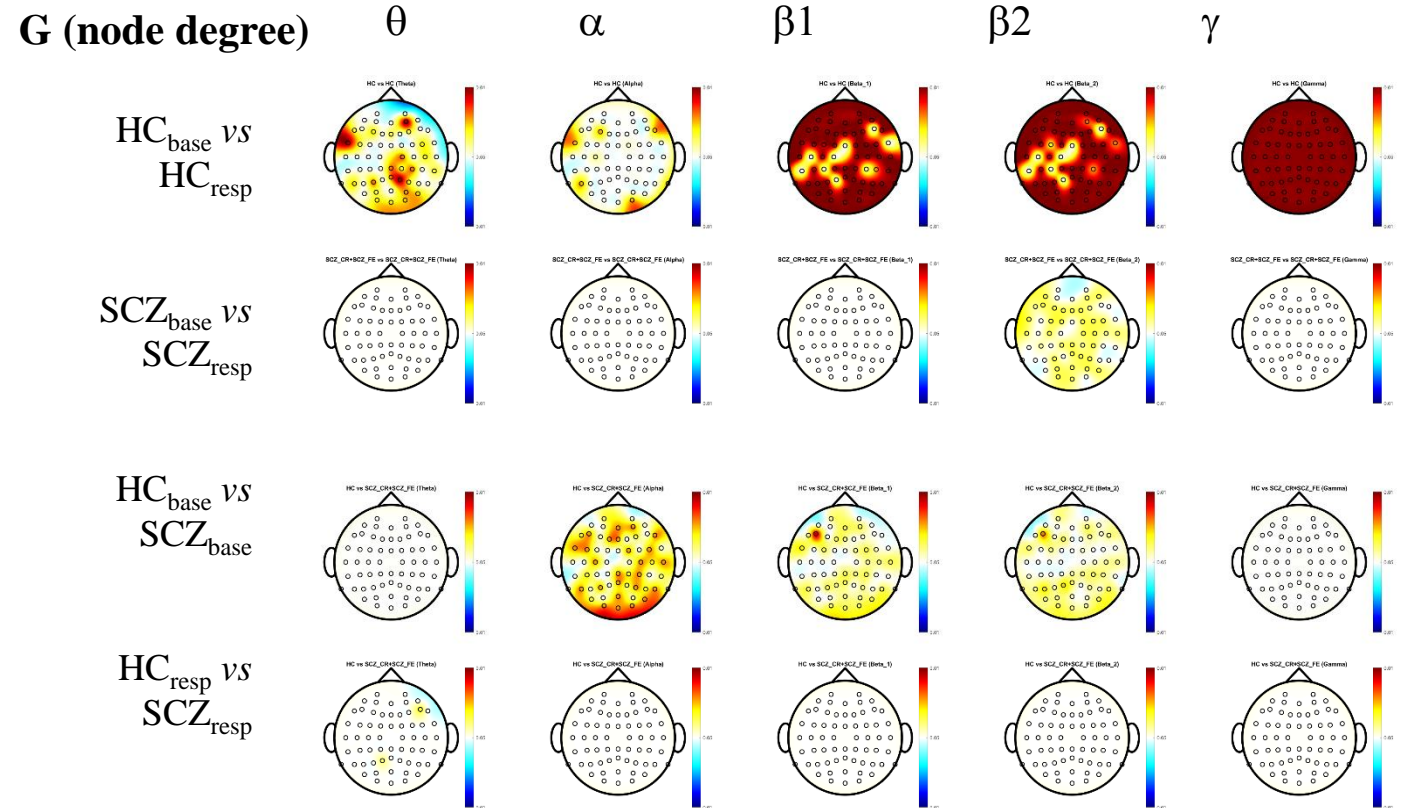
Ruiz-Gomez and Mijancos, 2025

TMS: Repetitive Single Pulses

1. Connectivity: PLV from CWT coefficients
2. Graph metrics: Global strength (G) and path length (L)

Results:

- Baseline: SCZ networks are more connected: higher values of G and lower values of L
- Response: more similar networks between SCZ and HC. The cerebral response to the TMS stimulus is different for each group

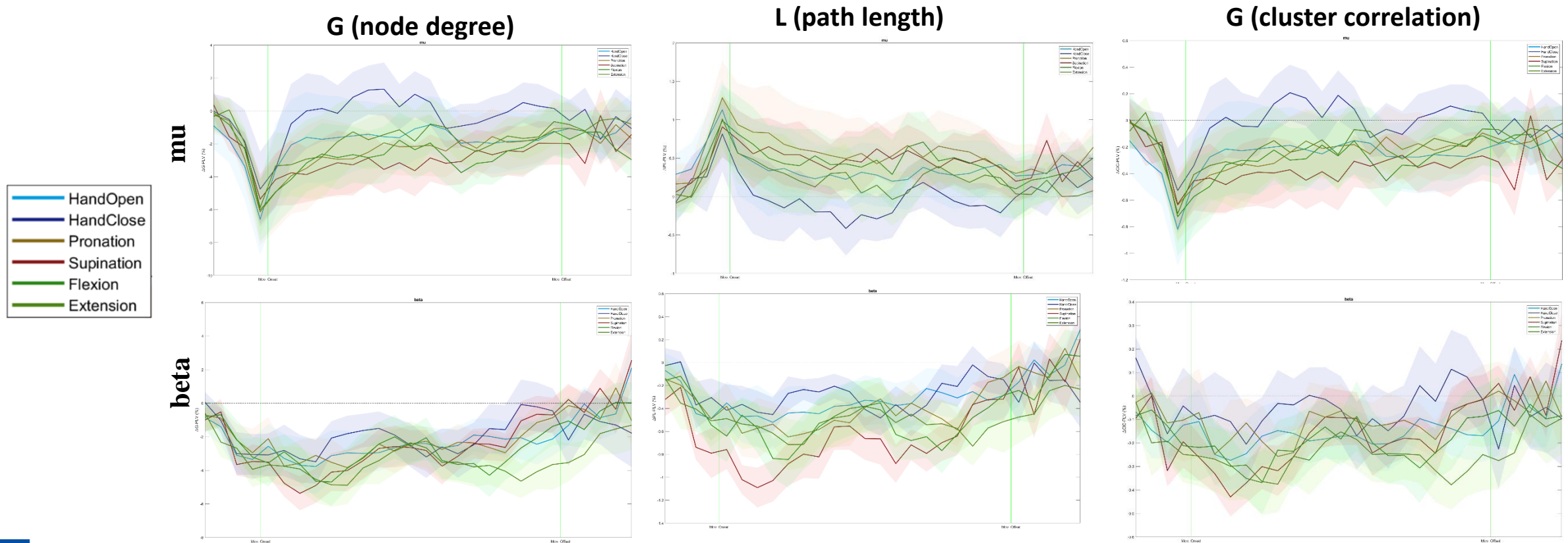


Motor execution

Ruiz-Gomez and Borràs, 2025

Six different movements performed during few seconds repetitively.

1. Connectivity: PLV from CWT coefficients
2. Graph metrics: Global strength (G), Cluster correlation (C) and path length (L)



Thanks!

BIOsignal Analysis for Rehabilitation and Therapy (BIOART) Group



Funded by
the European Union

Grant agreement
no. 101079392