Elaborazione di Immagini - Laurea in Bioinformatica
Prof. G. Menegaz

EEG SIGNAL PROCESSING

2. Signal Processing

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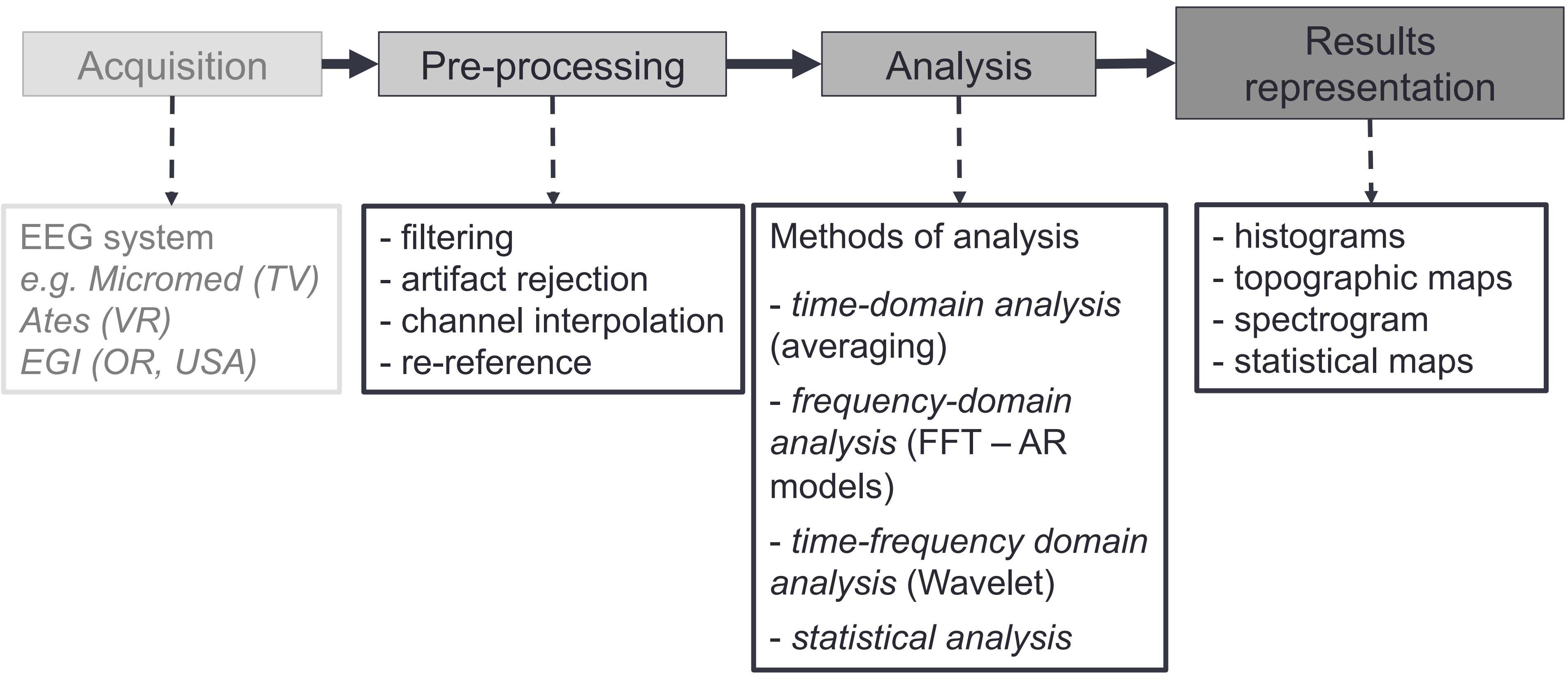
EEG signal processing



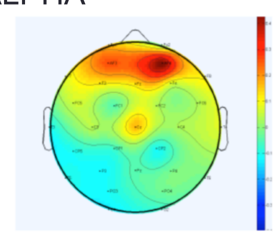
Representation of data

Topographical maps

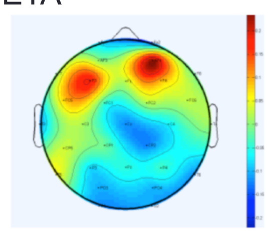
→ plot EEG data on a map of the brain. Data is interpolated between electrodes.

ERP maps → potential changes

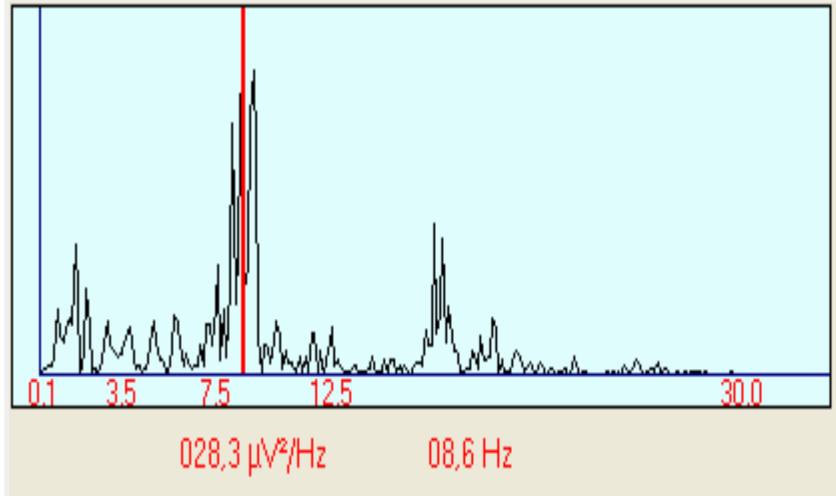
ALPHA



BETA

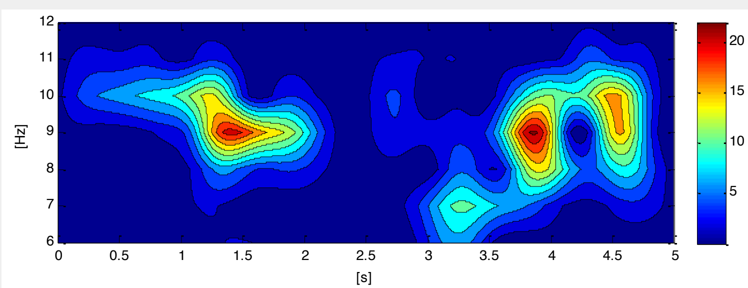


Spectral maps → frequency changes



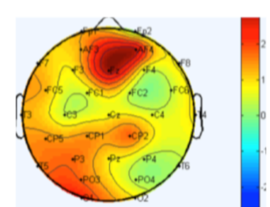
Time-frequency maps

→ time-frequency changes

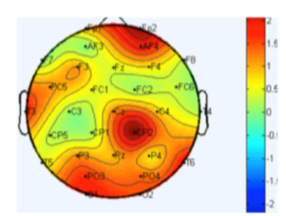


Statistical maps

→ statistical comparisons (e.g. conditions, techniques)



t-map ALPHA

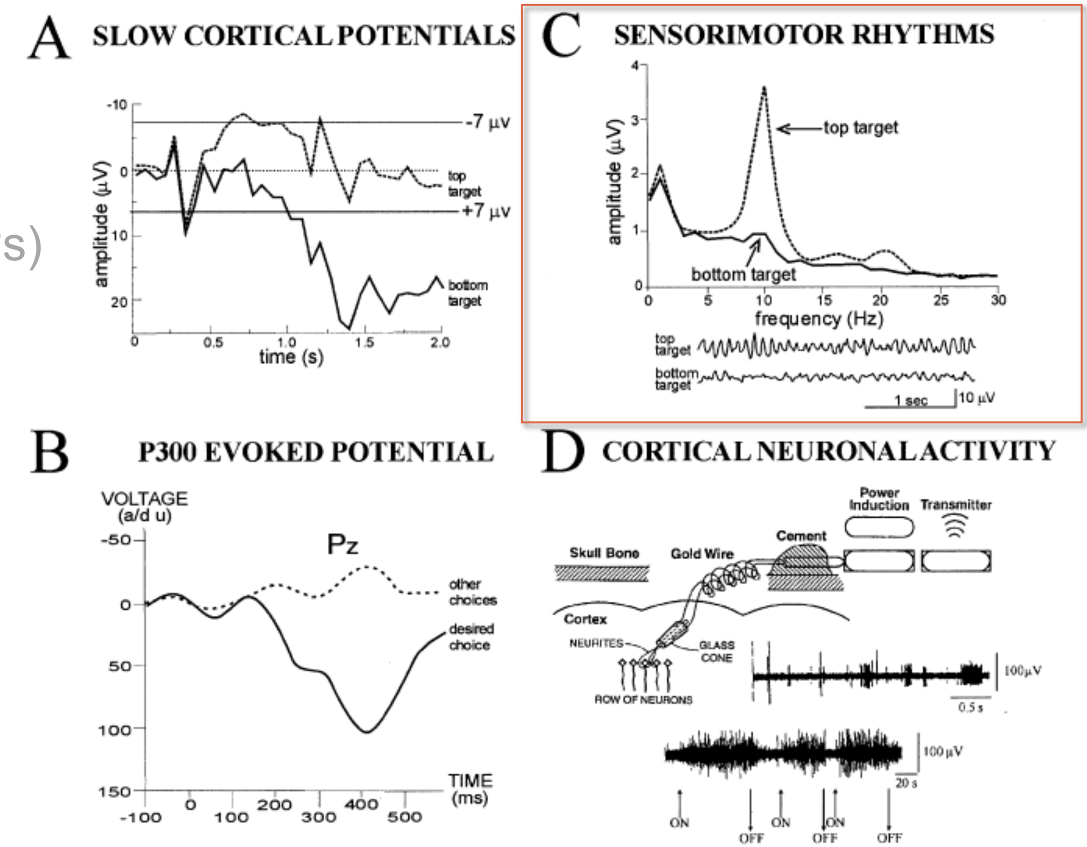


t-map BETA

EEG-based BCI: control signal types

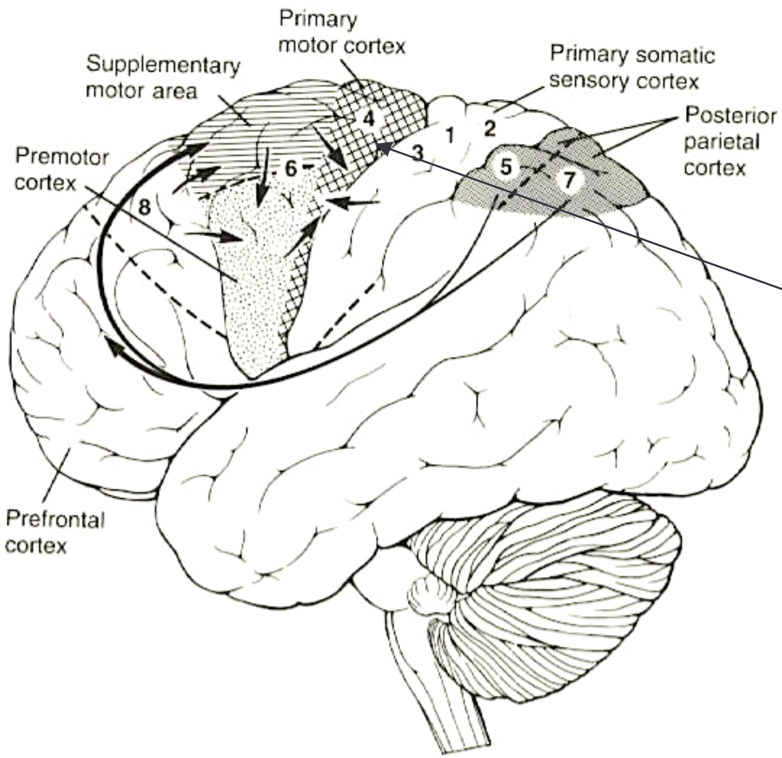
EEG-based BCIs can be grouped into 4 categories:

- slow cortical potentials (SCPs)
- event-related desynchronization/ synchronization (ERD/ERS)
- P300 component of event related potentials (ERPs) / steady state visual evoke potentials (SSVEP)
- cortical neurons, direct brain interfaces



Wolpaw et al. Clinical Neurophysiology 2002

Sensorimotor rhythms: Mu rhythm



Cortical generator
Mu rhythm
(C3, Cz, o C4)

Mu rhythm (8-13 Hz) is localized over primary sensorimotor cortex.

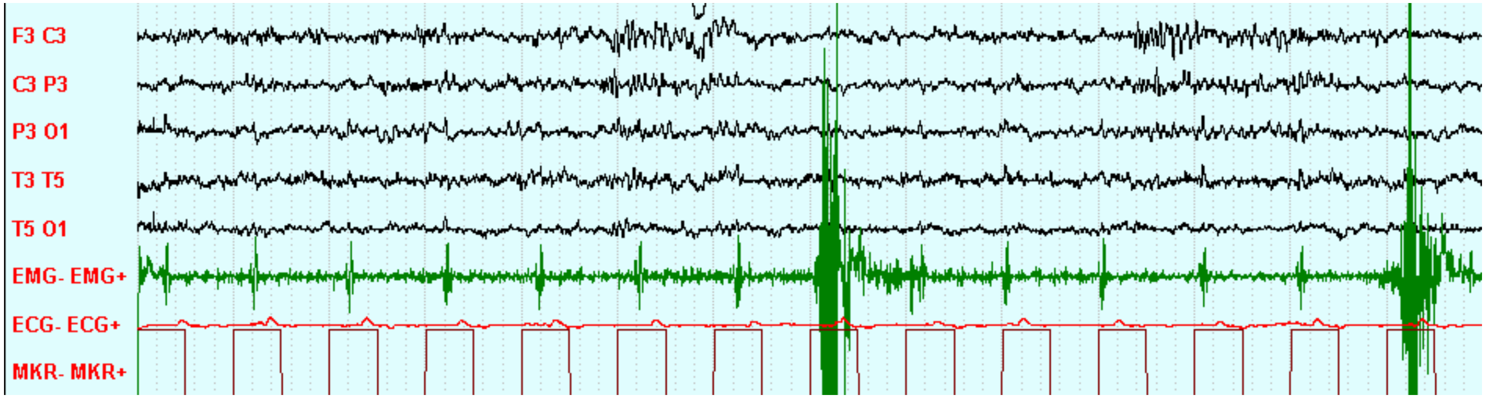
Movement preparation suppresses the cortical activity in alpha (mu rhythm: 8-13 Hz) and beta (13-30 Hz) bands starting before the onset of finger movement.

Mu rhythm and BCI

Mu rhythm is associated with cortical areas that are most directly connected to the brain's normal motor output channels.

Movement or preparation for movement is typically accompanied by a decrease in mu activity over sensorimotor cortex, particularly contralateral to the movement called event-related desynchronization (ERD).

Its opposite, rhythm increase, or event-related synchronization (ERS) occurs in the post-movement period and with relaxation.



Event-related-synchronization/desynchronization

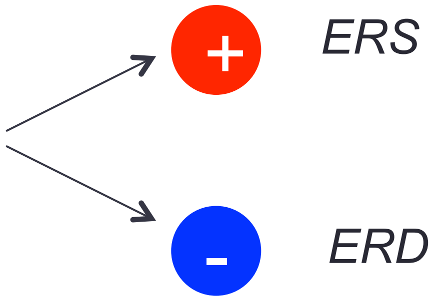
Event related synchronization (ERS)

- reflects a cortical "idling state"
- sincronous activation of the neuronal network
- associated with activity increase (positive values)

Event related desynchronization (ERD)

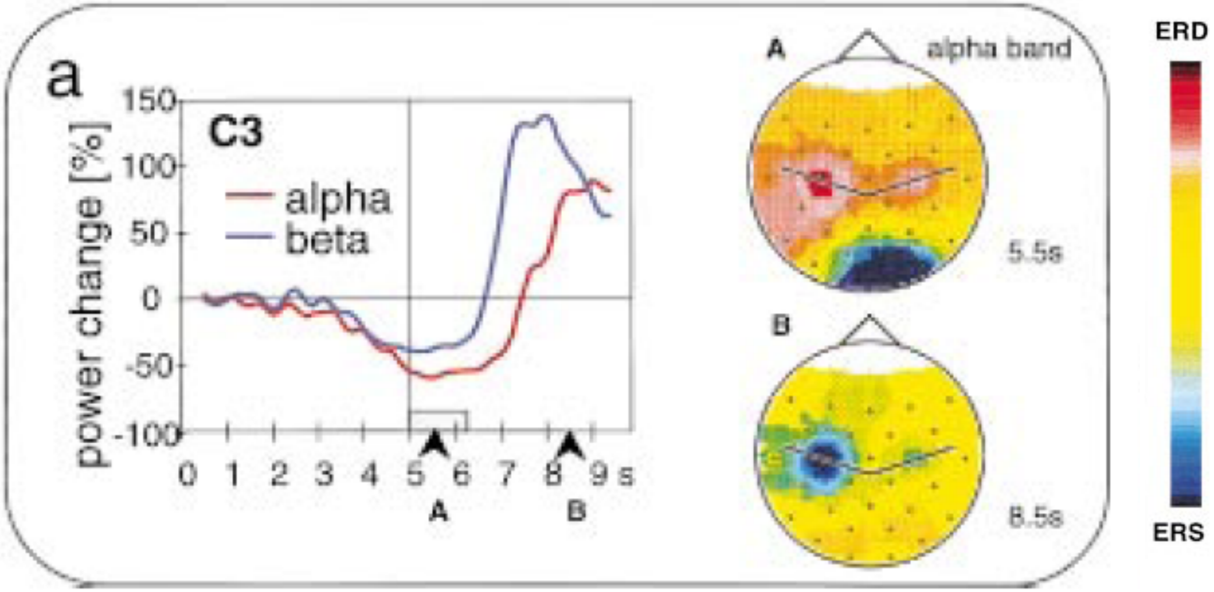
- indicates oscillations in cortical activation
- asincronous activation of the neuronal network
- associated with activity decrease of the underline neuronal population (negative values)

$$ERP_x = \frac{\left(P_{xactivation} - P_{xrest}\right)}{P_{xrest}} \cdot 100$$



Pfurtscheller and Aranibar, 1979; Pfurtscheller and Neuper, 1994

Event-related-synchronization/desynchronization

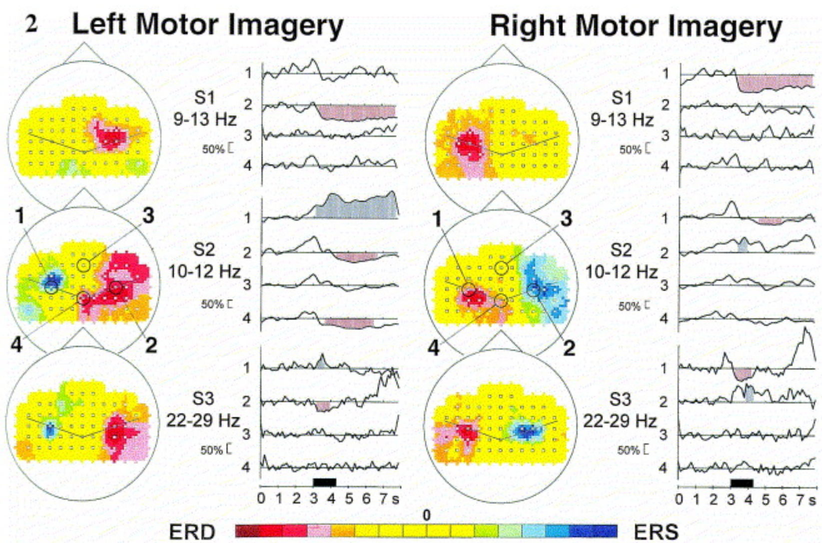


A group study on 9 subjects performing self paced right hand movement

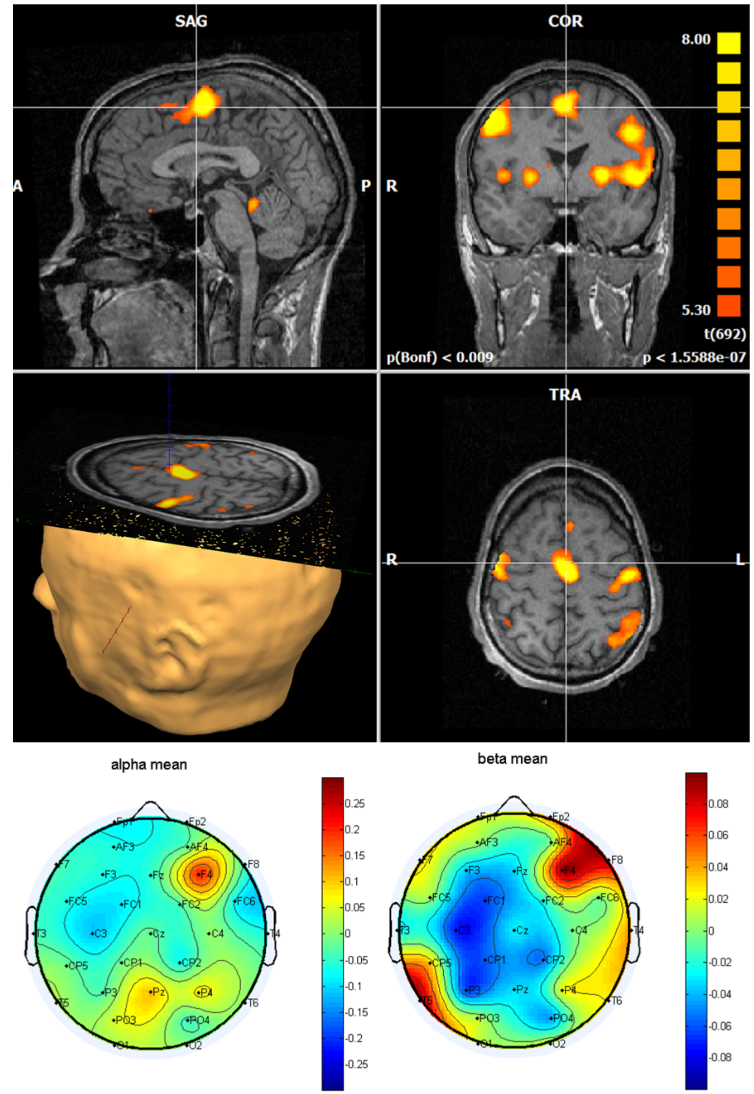
- contralateral alpha ERD localization, occipital alpha ERS localization
- contralateral alpha ERS localization after movement

Pfurtscheller and Lopes da Silva, 1999

Motor imagery



Pfurtscheller and Neuper, 1997



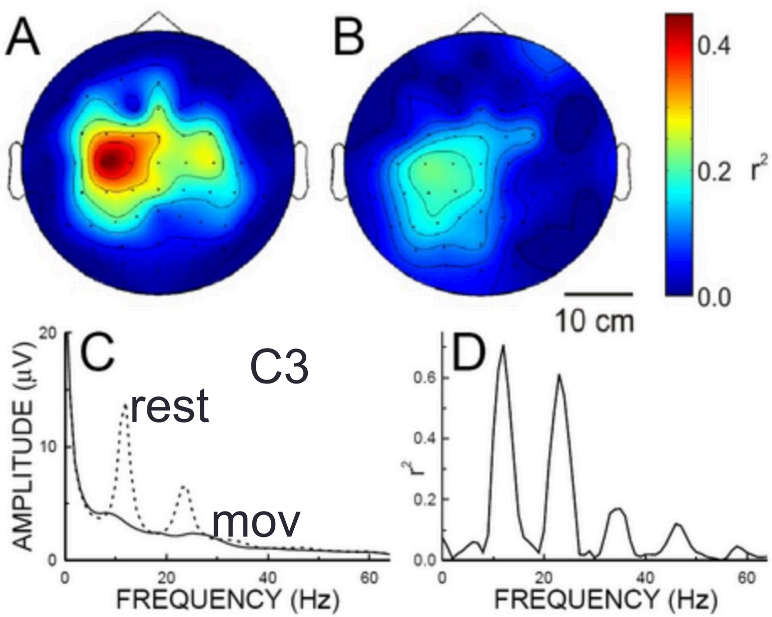
Formaggio et al., Magn. Reson. Imag. 2010

Motor imagery results in ERD and ERS without active movement

Sensorimotor rhythms in BCI

In BCI applications, ERD and ERS occur also with *motor imagery*; they do not require actual movement.

ERD and ERS can occur independent of activity in the brain's normal output channels of peripheral nerves and muscles, and could serve as the basis for a BCI.



Schalk et al. IEEE Trans Biomed Imag, 2004

Actual (A) and imagined (B) right-hand movements vs. rest

Feature extraction: the coefficient of determination

The *coefficient of determination* r^2, is a statistical measure computed over a pair of sample distributions, giving a measure of how strongly the means of the two distributions differ in relation to variance.

In a BCI: r^2 is computed over signals that have been measured under two different task conditions, and represents the fraction of the total signal variance that is accounted for by the task condition.

It is a measure of how well the original task condition ("user intent") may be inferred from a brain signal.

$$r^2 = \frac{\mathrm{cov}(x, y)^2}{\mathrm{var}(x)\mathrm{var}(y)}$$

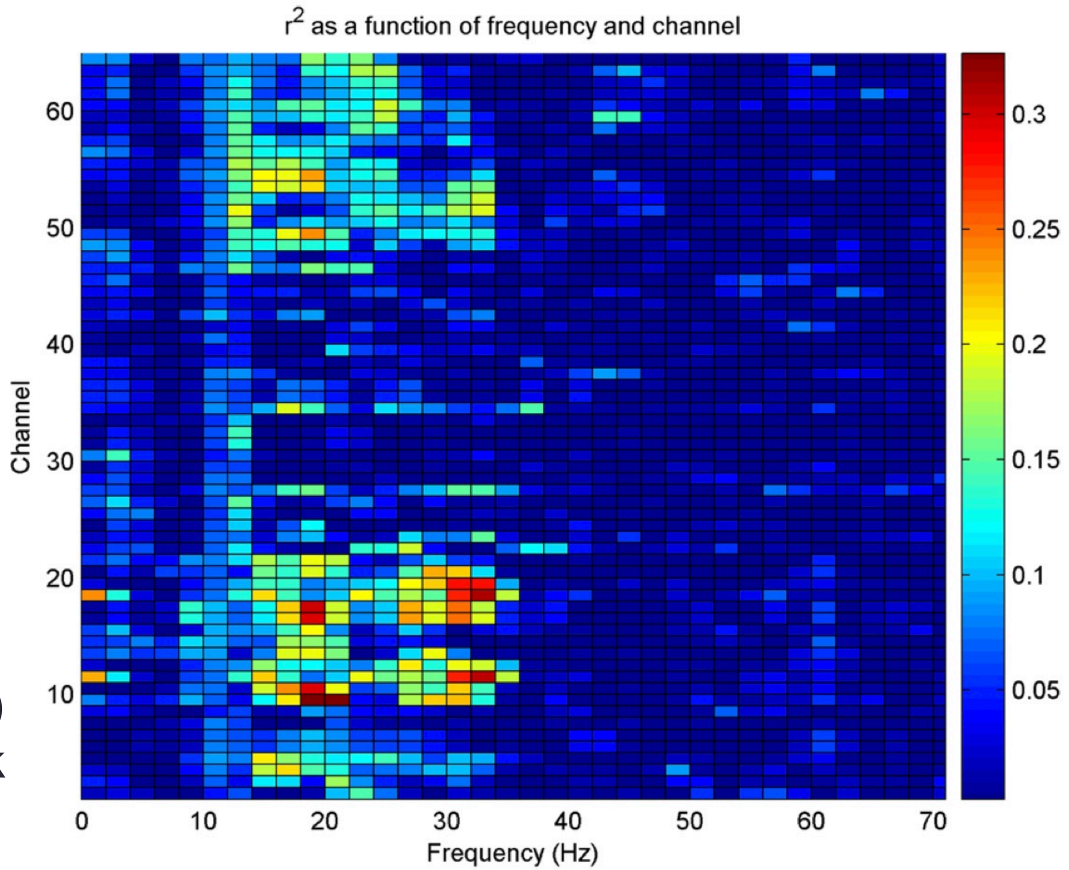
http://www.bci2000.org/wiki/index.php/User_Tutorial:Performing_an_Offline_Analysis_of_EEG_Data

Example: feature extraction map

The horizontal axis corresponds to **frequencies**, and the vertical axis corresponds to individual **channels**.

Color codes represent r^2 values, which are numbers between 0 and 1.

r^2 values provide a measure for the amount to which a particular EEG feature (i.e., amplitude at a particular frequency and location) is influenced by the subject's task (e.g., hand vs. foot imagery).



http://www.bci2000.org/wiki/index.php/User_Tutorial:Performing_an_Offline_Analysis_of_EEG_Data

Example: BCI based on sensorimotor rhythm

Tetraplegic patient attempts left or right hand movements and tries to move the circle from the middle of the screen to the target

Example: Modulation of ERD in robot-assisted hand performance

Aims

- to evaluate the modification of cortical activity during voluntary active movement, passive robot-assisted movement, and motor imagery performed under unimanual and bimanual protocols

- a better knowledge of cortical modifications after robotic therapy could inform the design and development of stroke rehabilitation protocols

Equipment

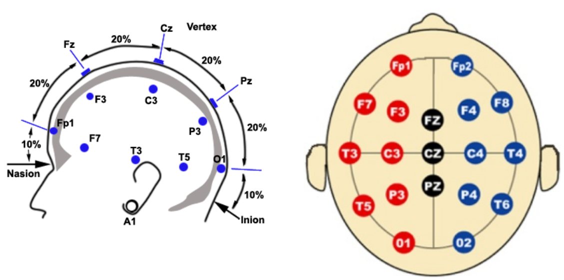
Bi-Manu-Track arm trainer works on more distal arm movements, practicing bilateral elbow prosupination and wrist flexion (Hesse et al., 2003).

Material and methods

8 subjects 3M/5W
Age: 26.12 ± 2.64 (range: 22-31)

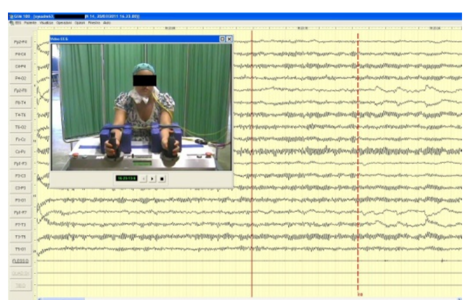
EEG cap 21 channels

(SEI EMG s.r.l, Padova, Italy)



Video EEG system

(Ates Medica Device, Verona, Italy)



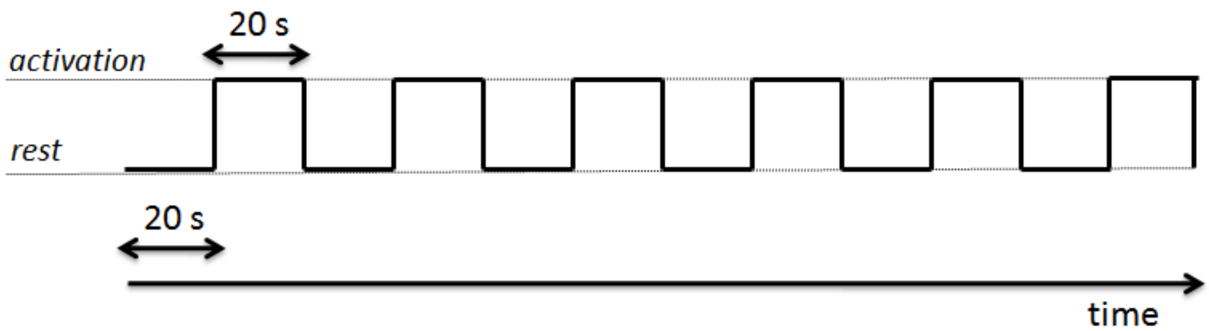
Bi Manu Track®

(Reha-stim Co, Berlin)

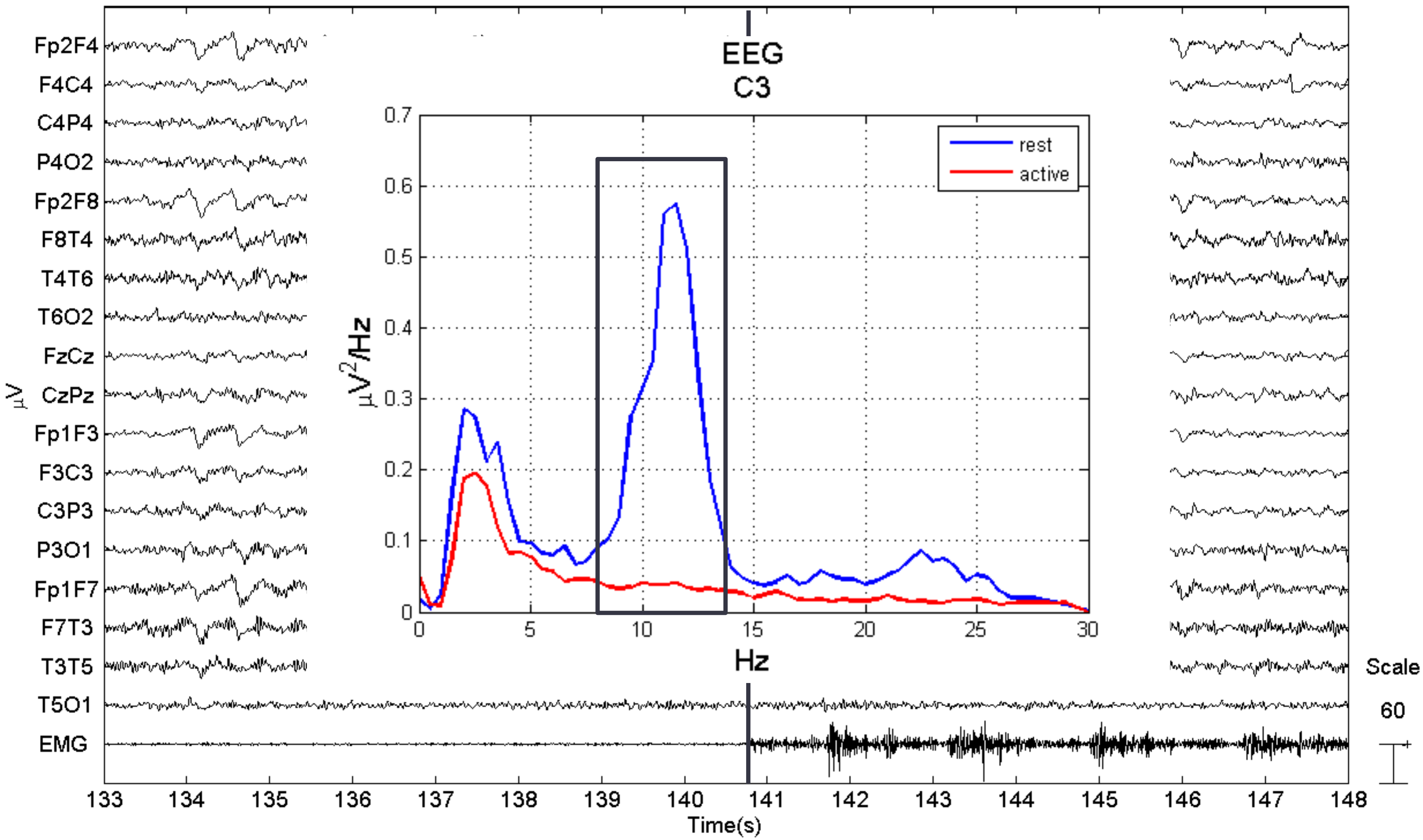
Data acquisition

Design protocol:

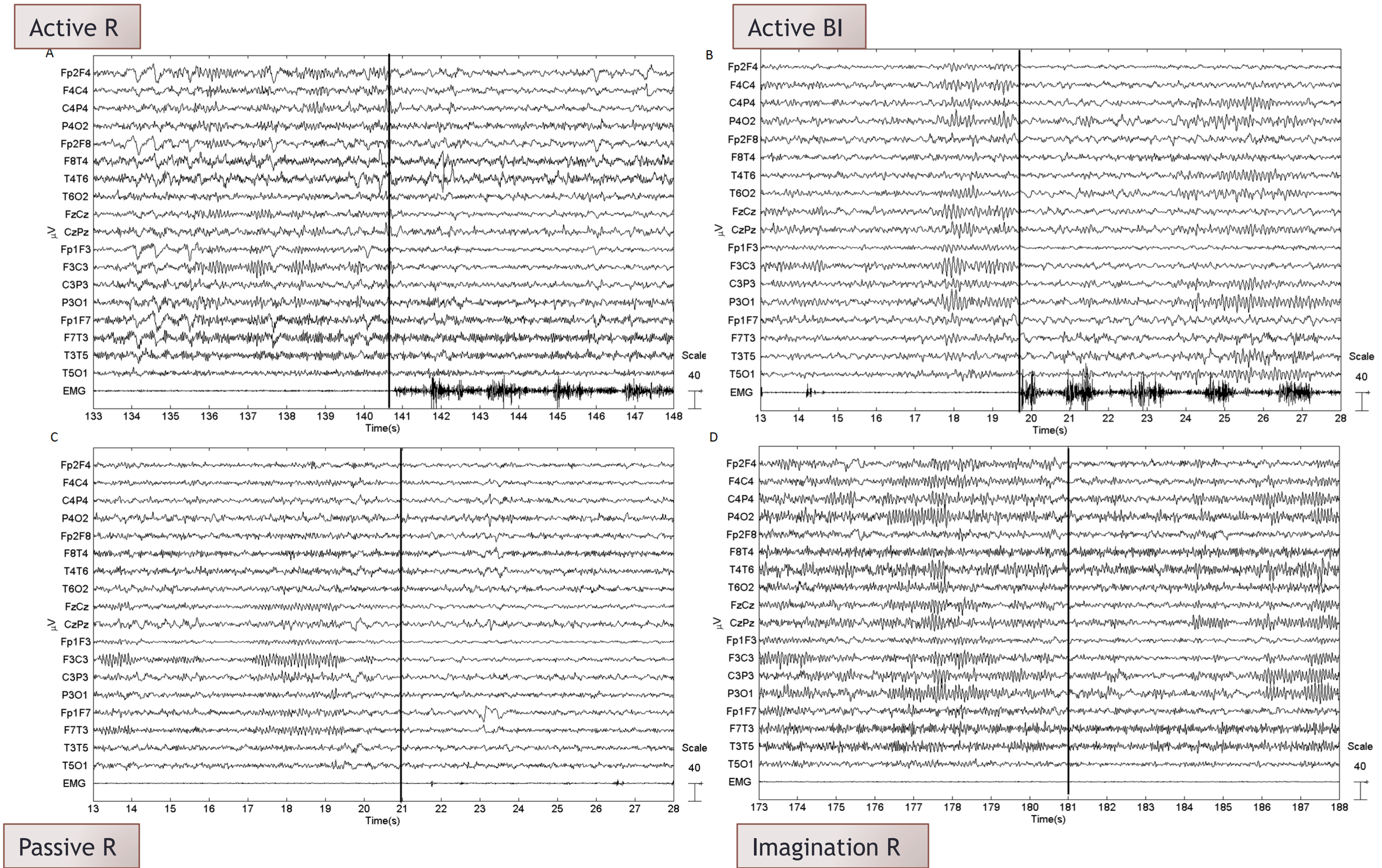
- active movement with the right/left hand
- bimanual active movement
- passive movement with the right/left hand (right/left hand moved by the BMT)
- bimanual passive movement (both hands moved by the BMT)
- active – passive movements (the right/left hand drives the left/right hand in a mirror-like fashion)
- imagination of movement with the right/left hand
- imagination of bimanual movement



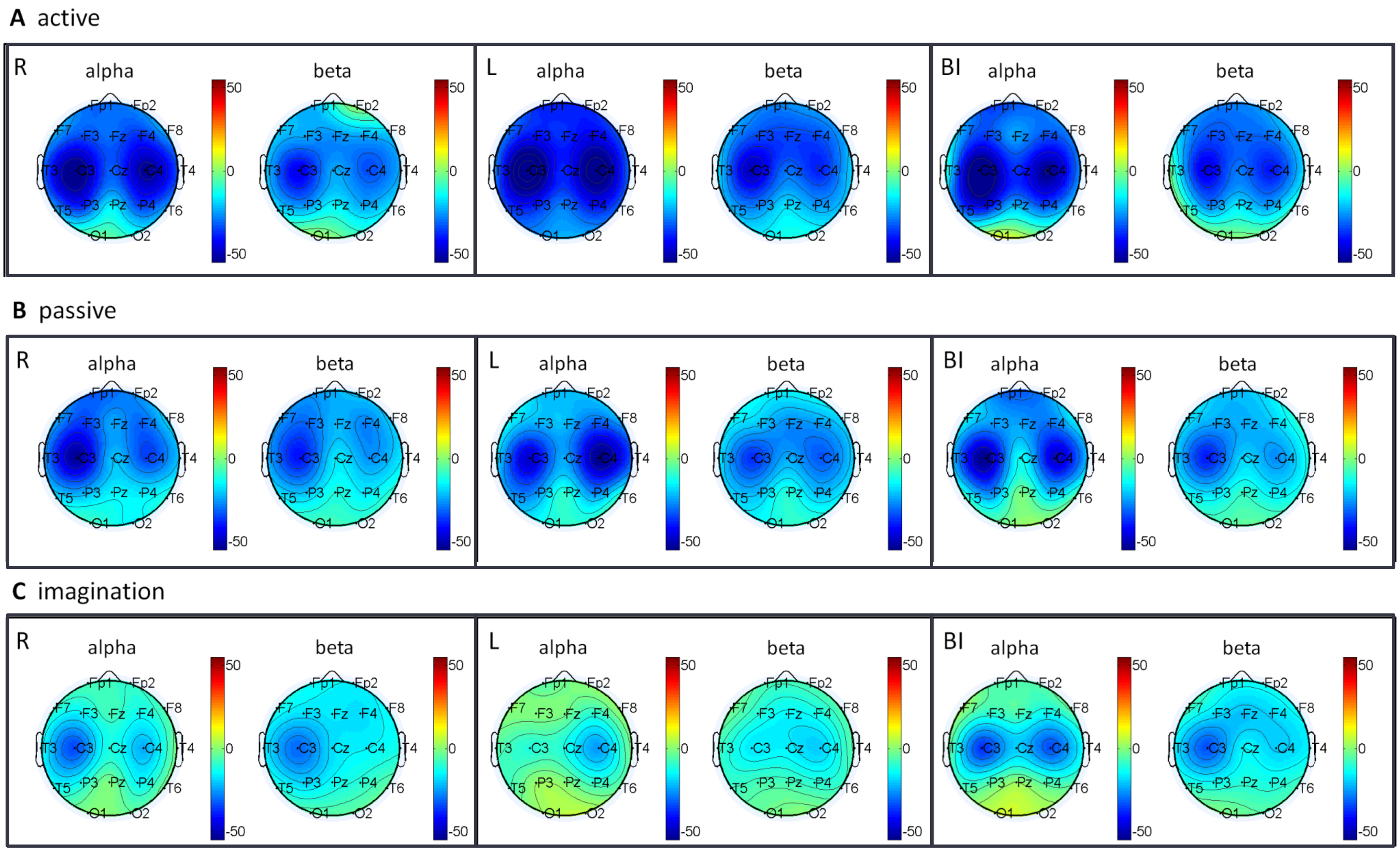
EEG during task



EEG during task



Results


A active
B passive
C imagination
R
L
Bl
alpha
beta
50
0
-50
Fp1
Fp2
F7
F3
Fz
F4
F8
T3
C3
Cz
C4
T4
T5
P3
Pz
P4
T6
O1
O2

Conclusions

- This study suggests new perspectives for neurological assessment by evaluating cortical oscillatory activity in stroke patients presenting with motor deficit.
- We are evaluating stroke patients under the same experimental conditions in order to study their cortical responses before and after rehabilitation therapy.

EEG-based BCI: control signal types

EEG-based BCIs can be grouped into 4 categories:

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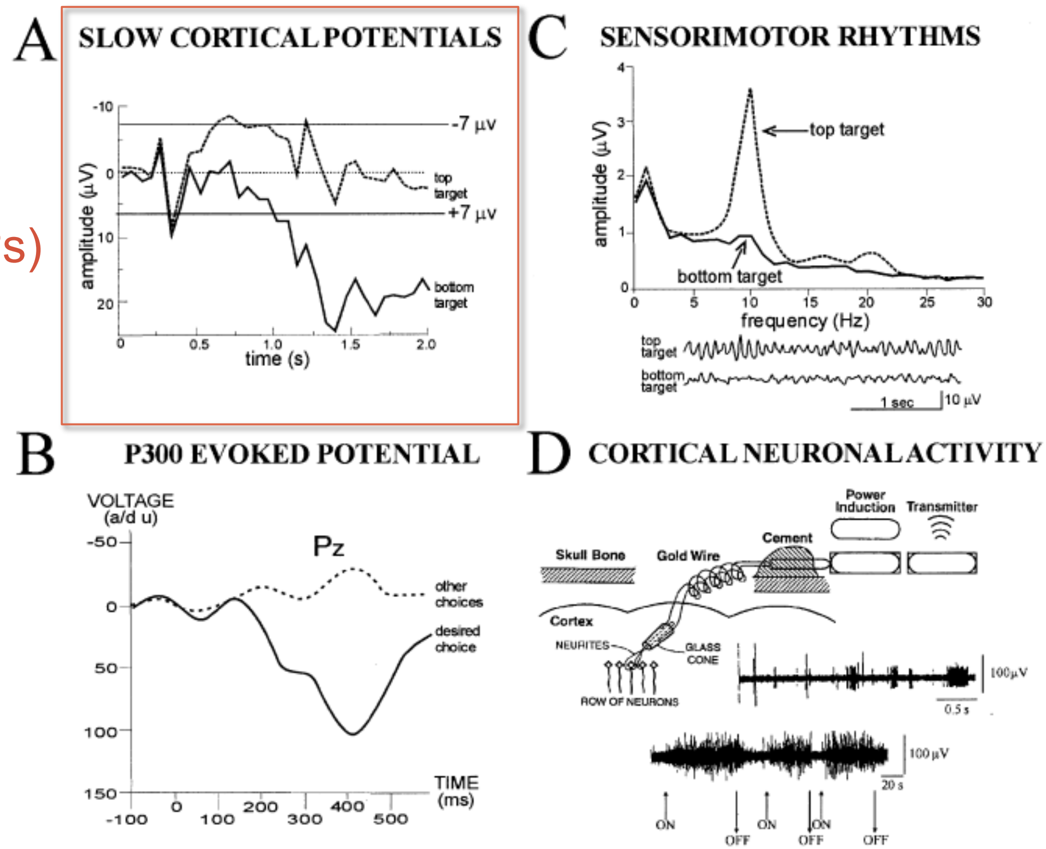
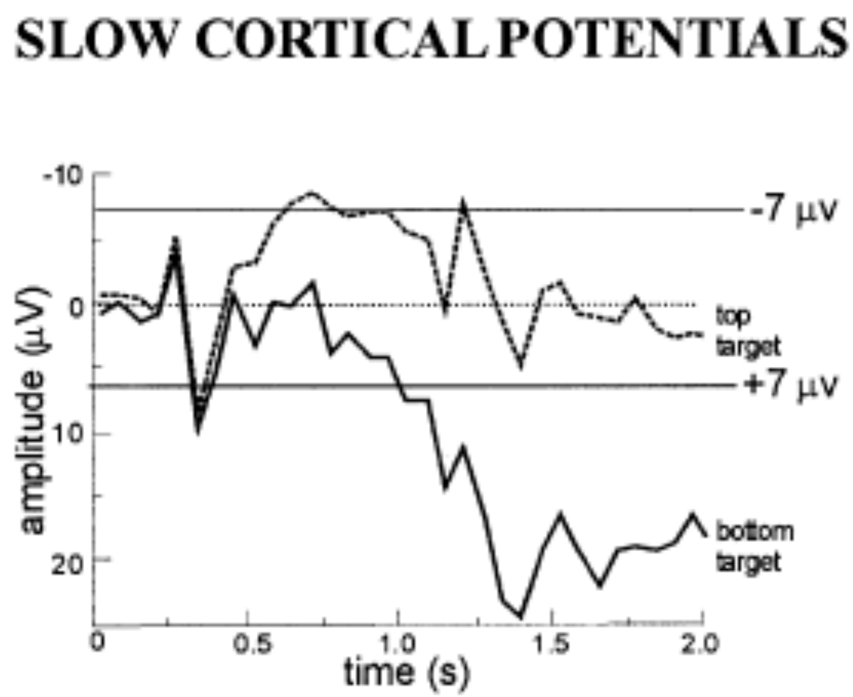


Wolpaw et al. Clinical Neurophysiology 2002

SCP-based BCI

Slow cortical potentials (SCPs) are the voluntary production of negative and positive potential shifts (below 1 Hz)

- they can occur from 300 ms to over several seconds.
- negative values are usually associated with movements and other functions involving cortical activations, while positive values detect reductions of such activities



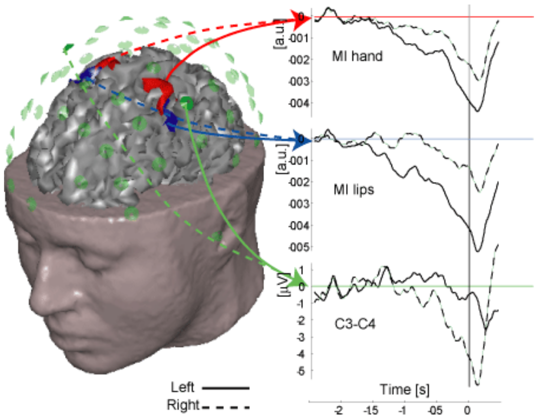
Wolpaw et al. Clinical Neurophysiology 2002
Thilo Hinterberger et al., TBME 2003

SCP-based BCI

The **Thought-Translation-Device (TTD)** is an EEG-based brain computer communication system which has been developed to re-establish communication in severely paralyzed patients.

- the device relies on the self-regulation of SCPs.
- the user can learn to self-control their SCPs when they are provided with *visual or auditory feedback* of their brain potentials and when potential changes in the desired direction are positively reinforced.
- in the TTD the vertical position of a feedback cursor reflects the amplitude of an SCP shift.
- after a patient has achieved reliable control over his \her SCP shifts, the responses can be used to select items presented on a computer screen.

- first successful device end 1990’s
- intensive training was necessary to gain control over the SCP waves



Patient using thought translation device to write a letter

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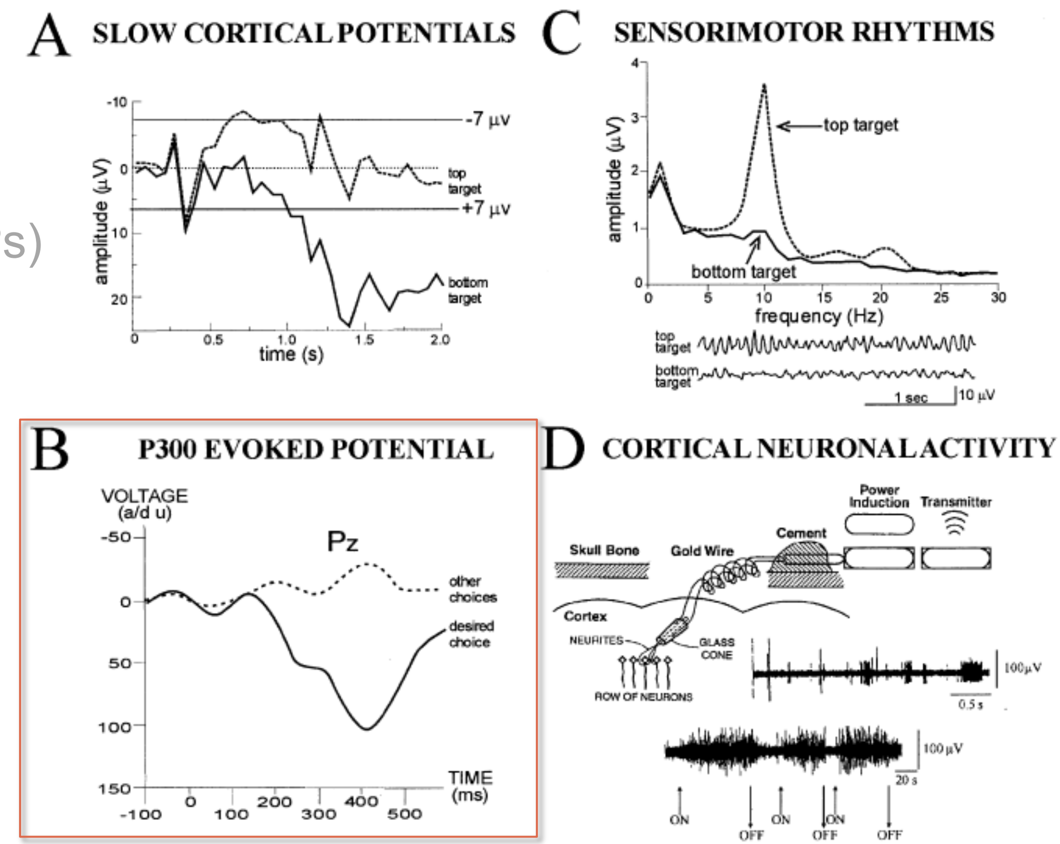


Wolpaw et al. Clinical Neurophysiology 2002

Evoked potential and BCI

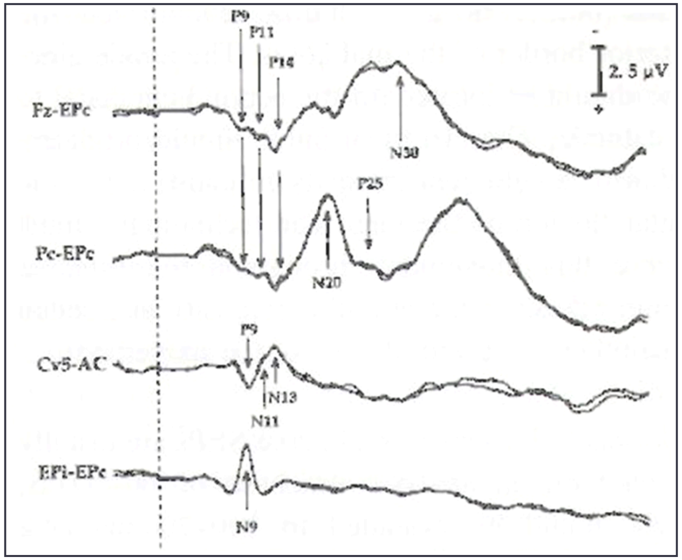
Evoked potentials (EPs) are the measurement of brain responses to specific cognitive, sensory or motor events.

One of the main approaches towards BCI is based on EPs.

Evoked potential (EP)

An evoked potential is an electrical potential recorded from the nervous system in response to stimulation of specific sensory nerve pathways.

Evoked potential amplitudes ranging from less than a μV to several μV.

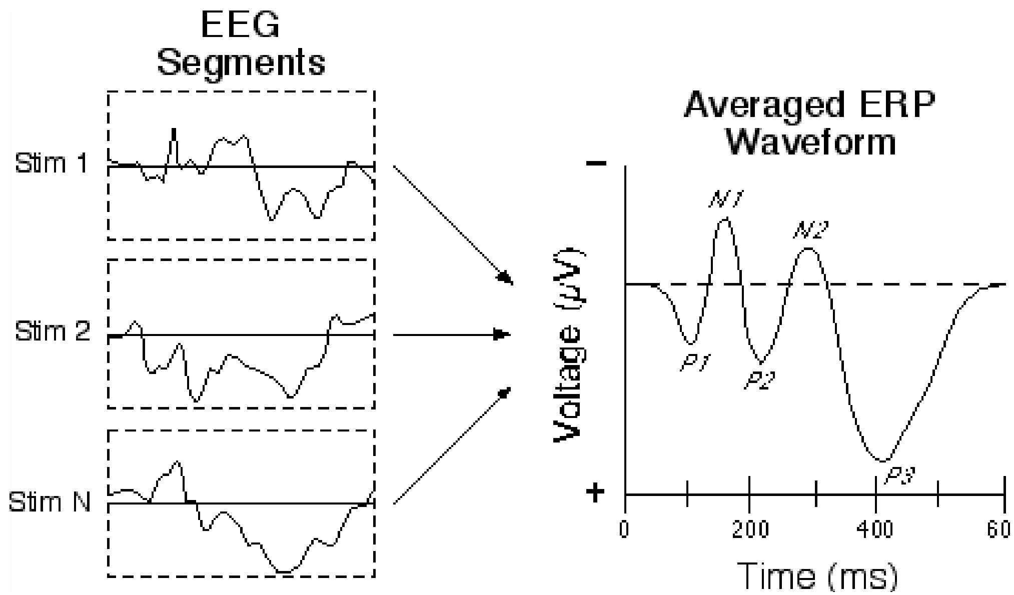


Evoked potential (EP)

$$y(t) = u(t) + v(t)$$

EP

noise
(EEG)

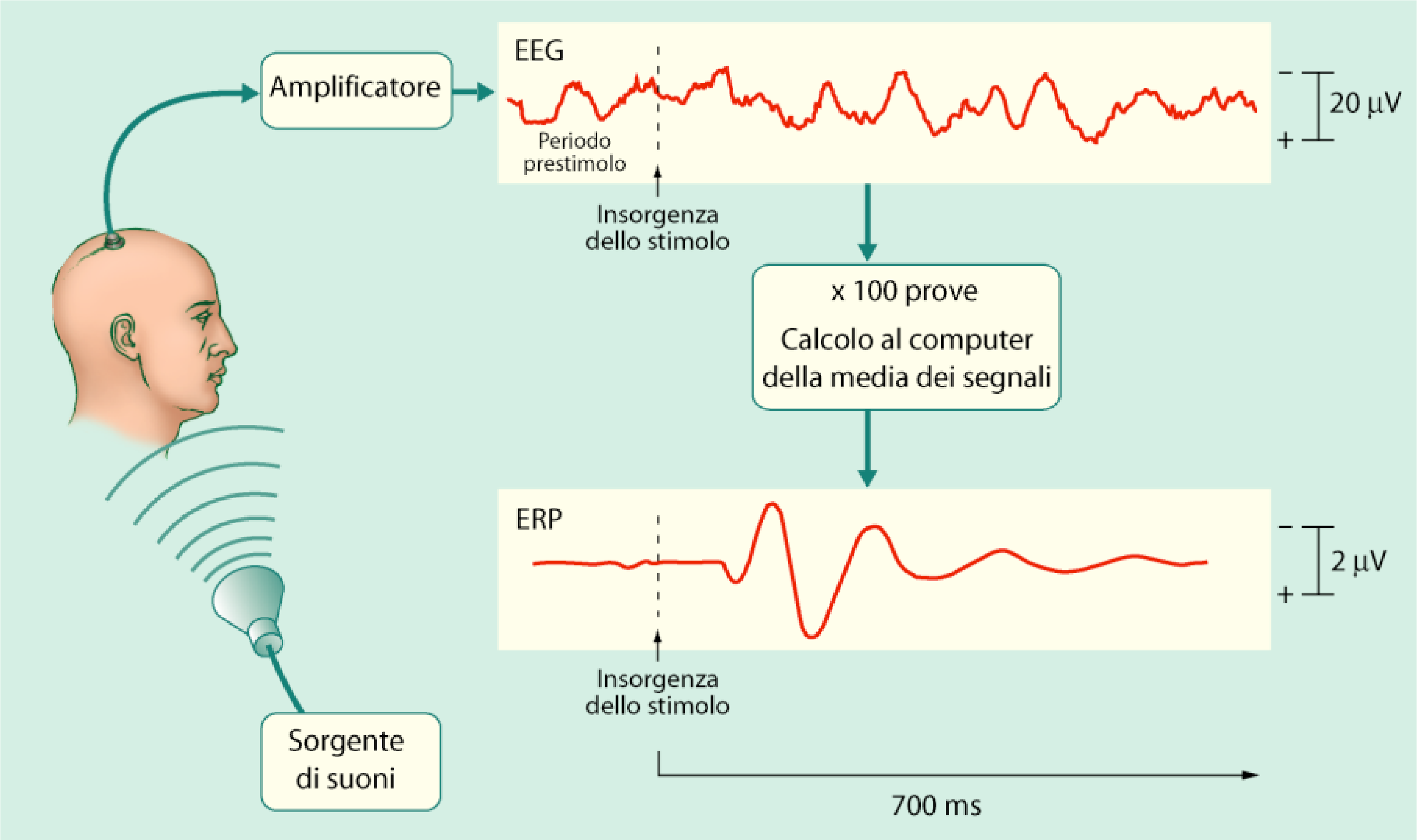


To solve these low-amplitude potentials against the background of ongoing EEG and external noise, **signal averaging** is usually required.

The signal is time-locked to the stimulus and most of the noise occurs randomly, allowing the noise to be averaged out with averaging of repeated responses.

$$\hat{u}(t) = \frac{1}{N}\sum_{i=1}^{N} y_i(t)$$

Evoked potential (EP): signal averaging

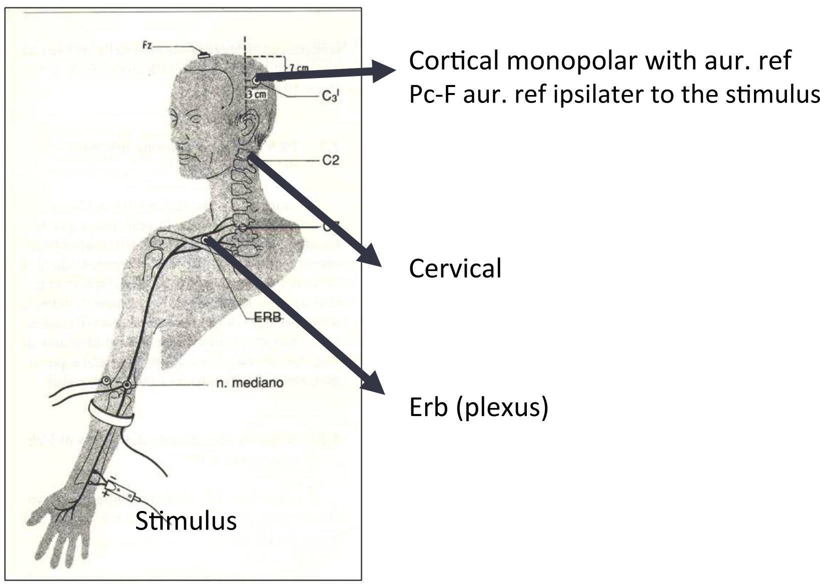


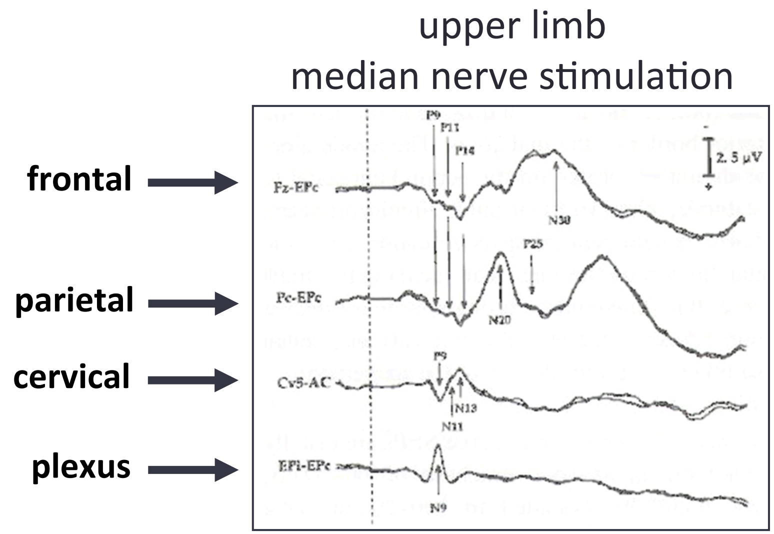
Types of EP

According to the type of stimulation different brain circuits are activated.

The most common evoked potentials are **sensory** and **motor** evoked potentials.

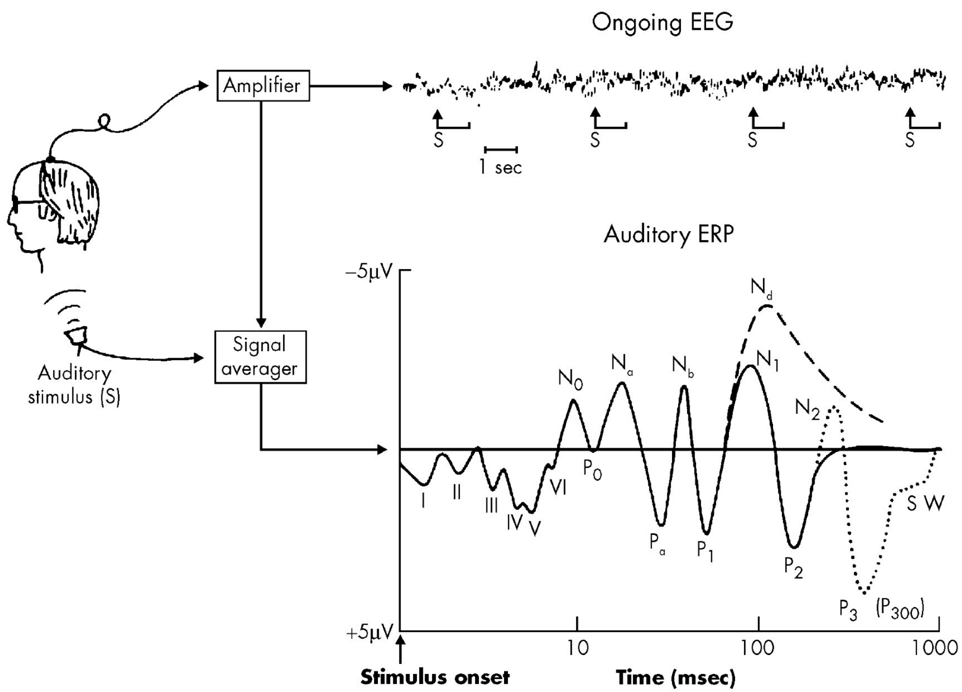
The sensory evoked potentials depending on the kind of the external stimulus are categorized as: *visual, auditory and somatosensory.*





Auditory evoked potential

Idealized waveform of computer-averaged auditory ERP elicited to brief sound.

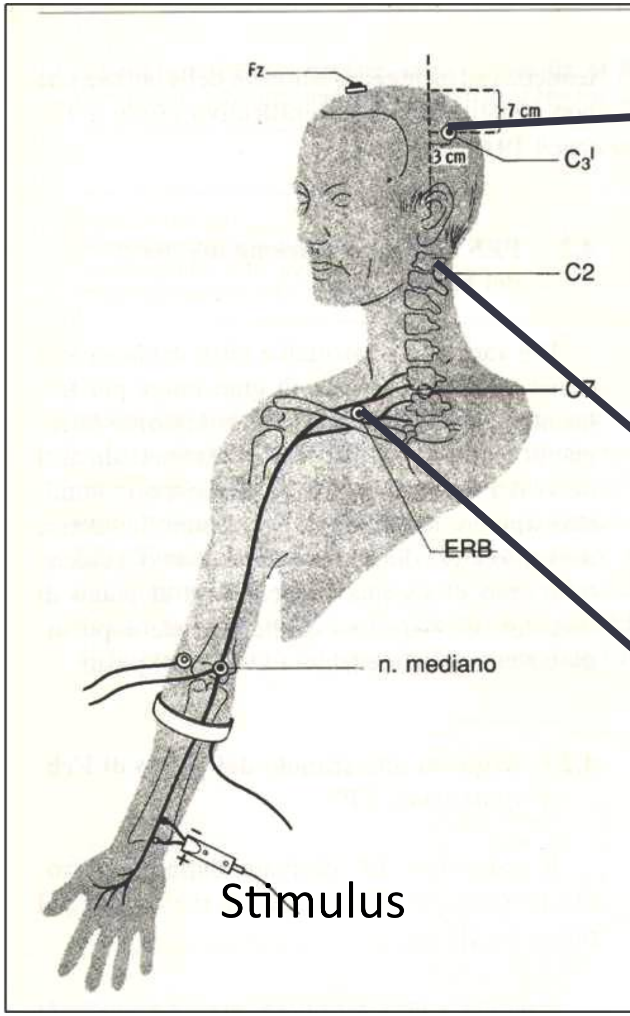


Kuperberg et al., PsychNeuroImage 2004

Visualization of:

- early brain-stem responses (waves I–VI)
- the mid latency components (N0, P0, Na, Pa, and Nb)
- the “vertex potential” waves (P1, N1, and P2)
- the task-related endogenous components (Nd, N2, P3, and slow wave [SW])

Somatosensory evoked potential (SSEP)



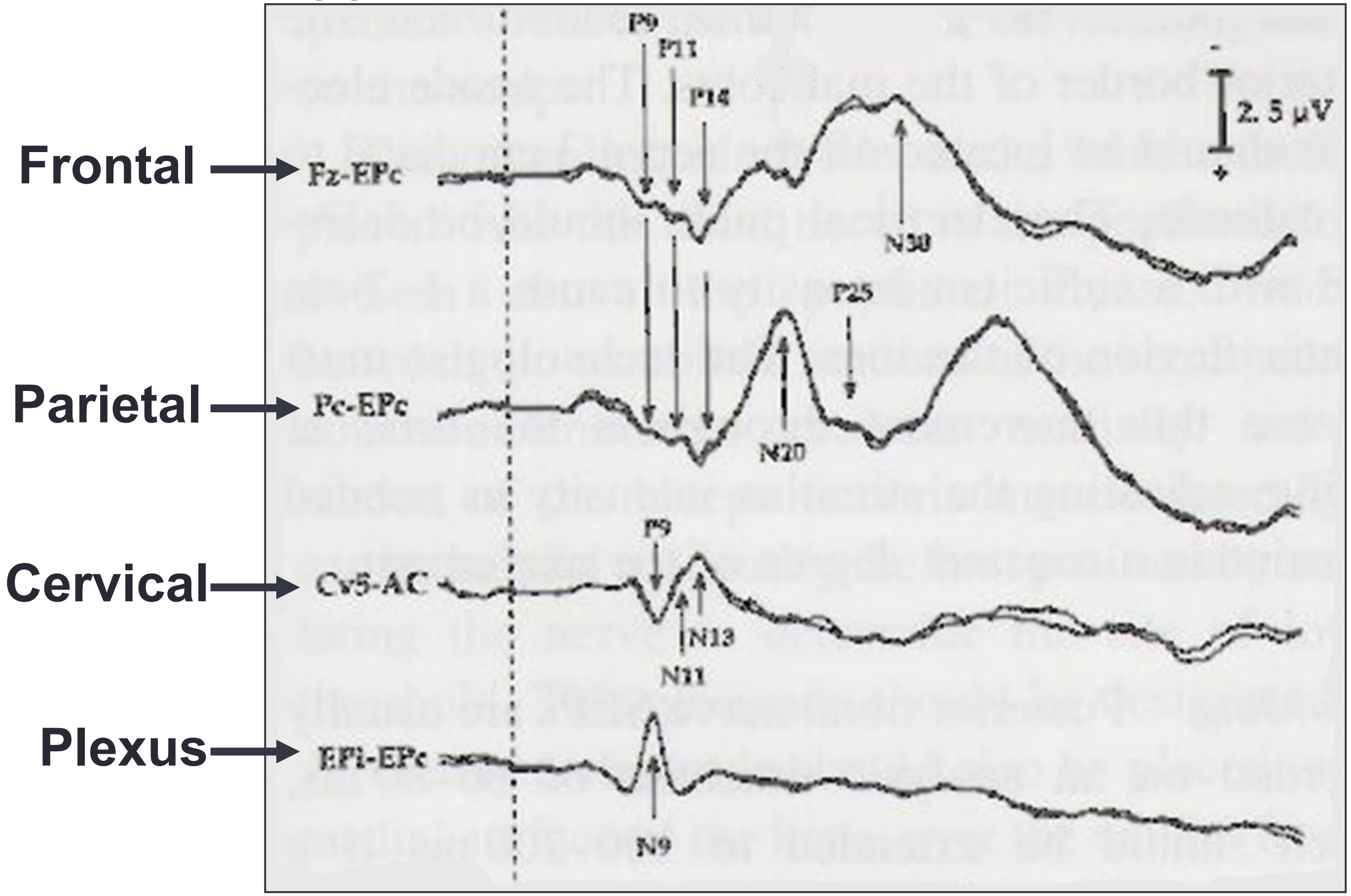
Cortical monopolar with aur. ref
Pc-F aur. ref ipsilater to the stimulus

Cervical

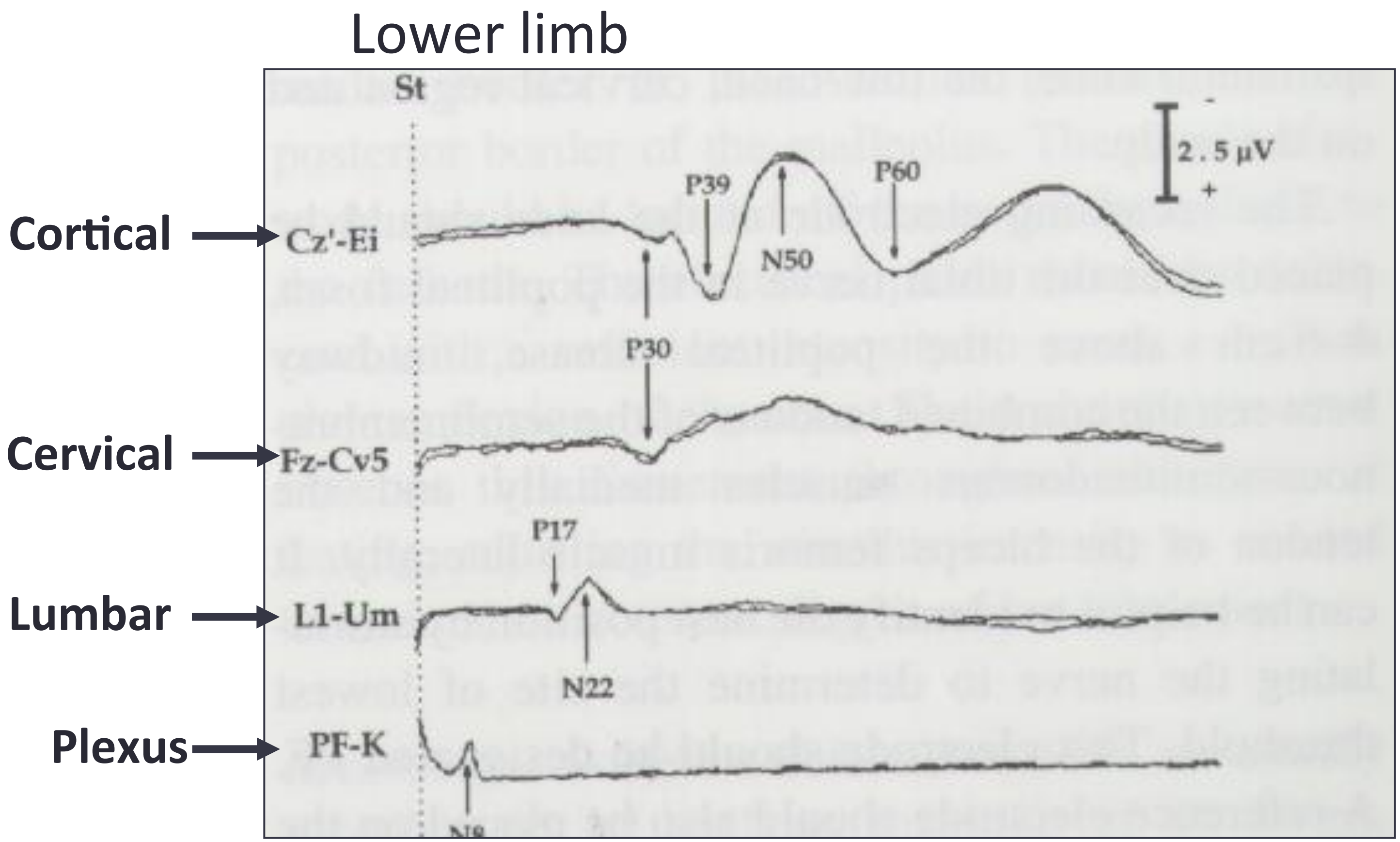
Erb (plexus)

Somatosensory evoked potential (SSEP)

Upper limb – median nerve stimulation

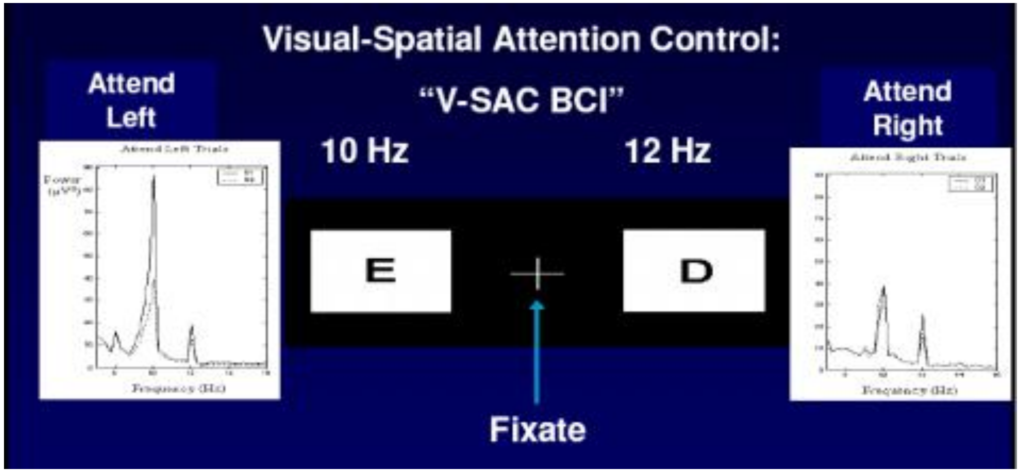


Somatosensory evoked potential (SSEP)



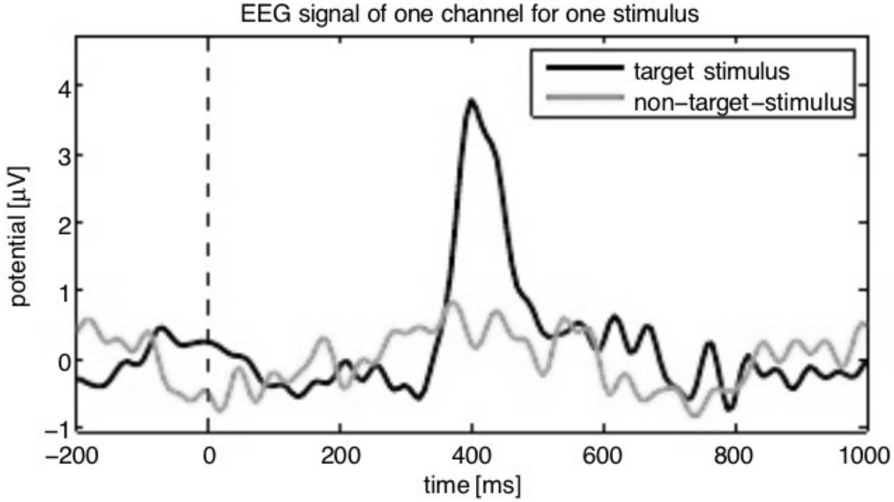
SSVEP-based BCI

- Steady State Visual Evoked Potentials (SSVEP) derived from the occipital cortex
- focusing attention to visual stimuli different frequency shows up in the EEG frequency bands
- reliable and high transfer rate, but some prerequisites (eyes)



P300-based BCI

Since the 1960s, it has been known that presentation of infrequent stimuli evokes a positive deflection in the EEG over parietal cortex about 300 ms after stimulus presentation: the "P300" or "oddball" potential.



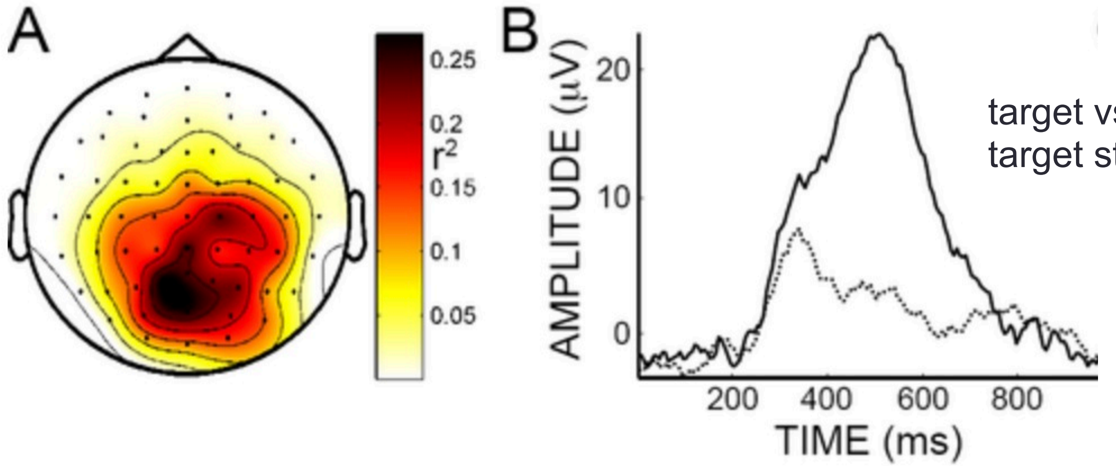
Martinovic et al. NeuroFocus Press Release 2011

The P300 component of EPs has often been used as an electrophysiological cue to control BCIs owing to its association with categorical stimulus-evaluation processes

- P300 is a major peak
- P300 is independent from the type of stimulus: it can either be *visual, auditory* or *somatosensory*.

P300-based BCI

- the spatial amplitude distribution of the P300 potential is symmetric around Cz
- the P300 is mostly detected at the parietal lobe, optimally with electrodes attached at Pz position, which is a centered on the median line at the top of the head
- it is characterized in a stimulus locked record by a positive deflection of the EEG signal between 300 and 450 ms after stimulus onset
- temporally, a typical P300 response has a width of 150-200 ms, and a triangular shape
- it is robust and has a high amplitude after averaging (5−20 μV)



http://www.bci2000.org/wiki/index.php/User_Tutorial:Introduction_to_the_P300_Response

Example: P300-based BCI

The P300 Speller: using brain activity to spell word

A user focuses attention successively on alphabetic characters he/she wishes to communicate, and the computer detects the P300 that is elicited when matrix-elements containing the chosen character are presented.

1988 Farwell and Donchin

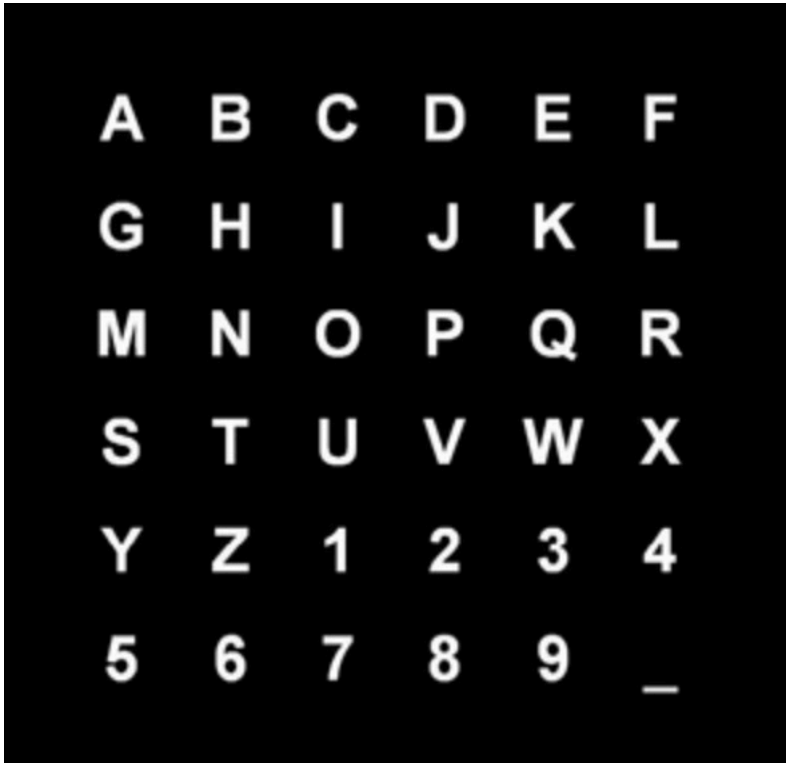
Example: P300-based BCI

The rows and columns in this matrix flash successively and randomly at a rapid rate (e.g. eight flashes per second).

The user selects a character by focusing attention on it and counting how many times it flashes.

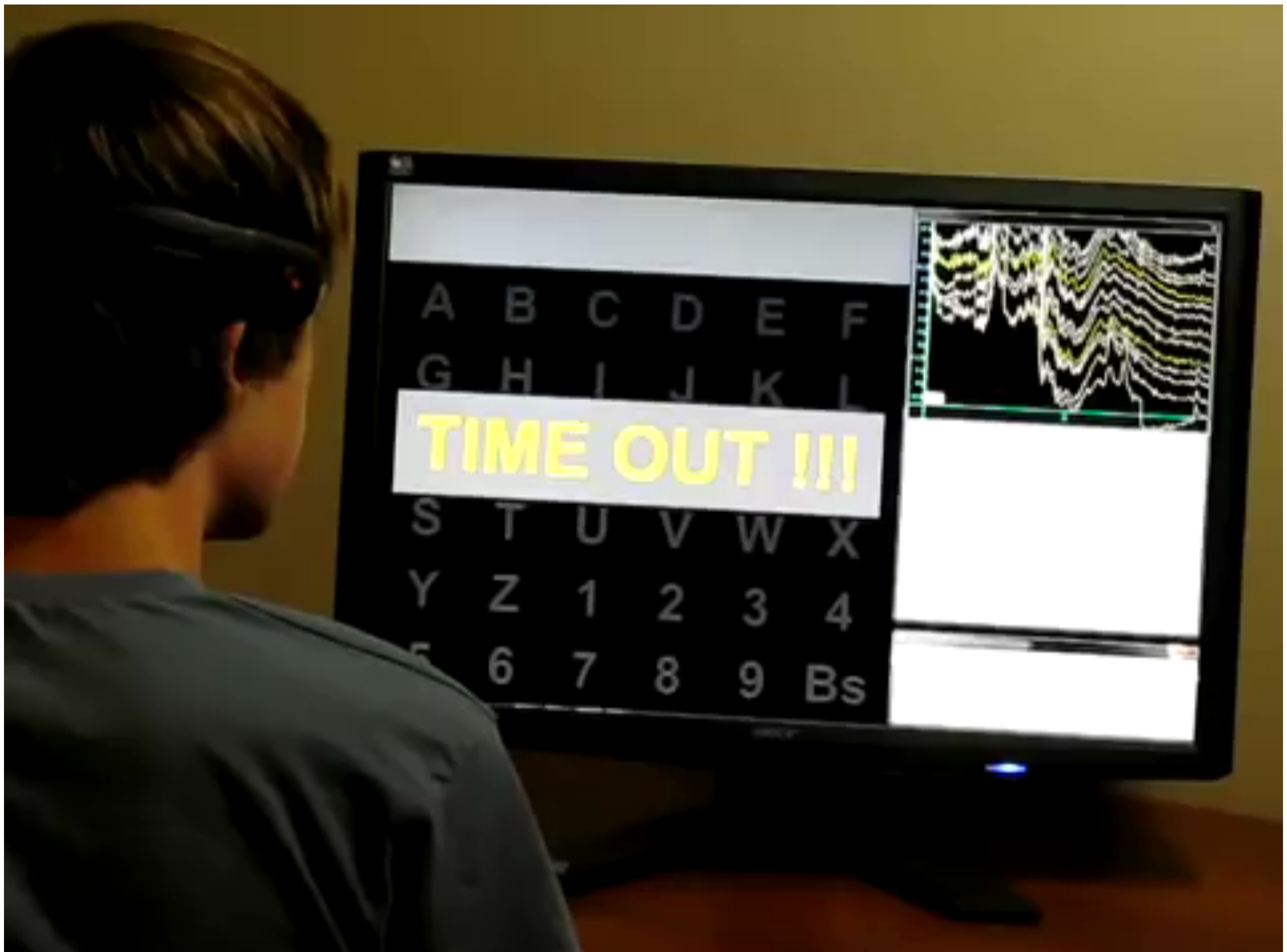
The row or column that contains this character evoke a P300 response, whereas all others do not.

After averaging several responses, the computer can determine the desired row and column (i.e., the row/column with the highest P300 amplitude), and thus the desired character.



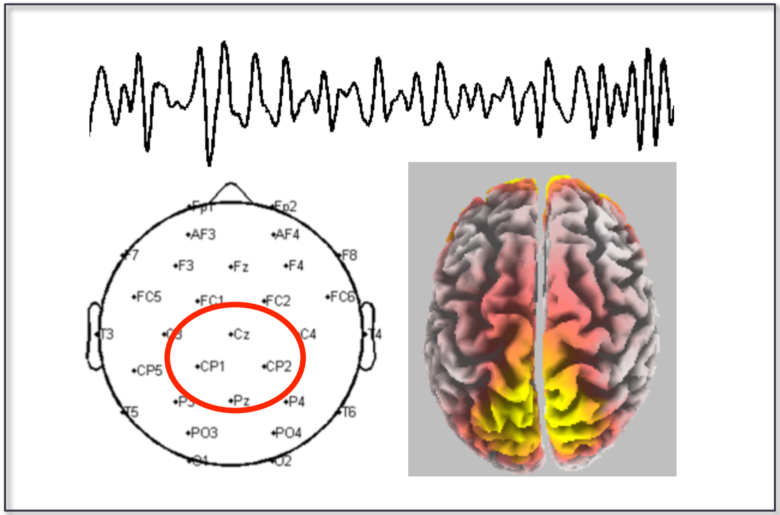
http://www.bci2000.org/wiki/index.php/User_Tutorial:Introduction_to_the_P300_Responsex

Example: the P300 Speller
Using brain activity to spell word



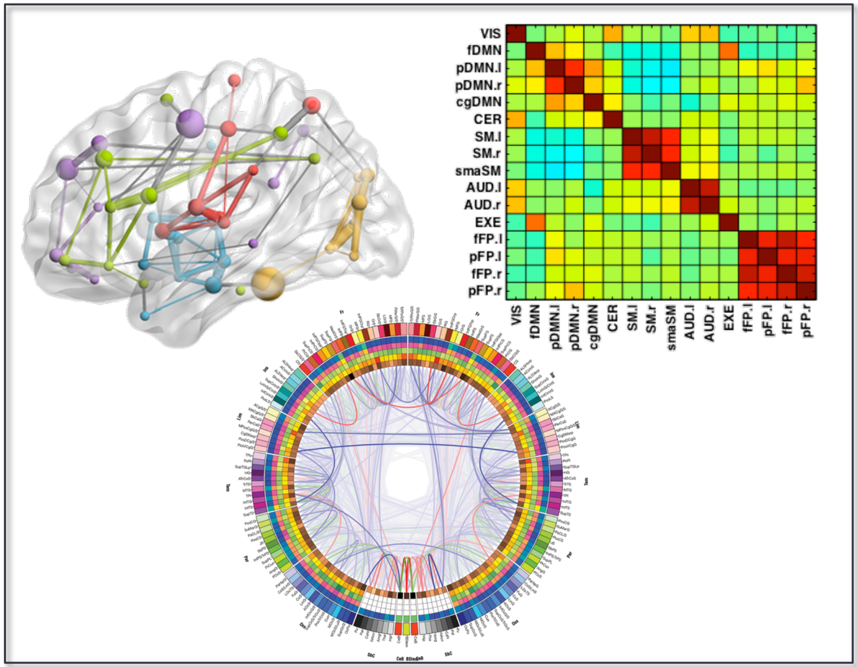
Emotiv_Bci2000_Video.Mp4

From Localization to connectivity



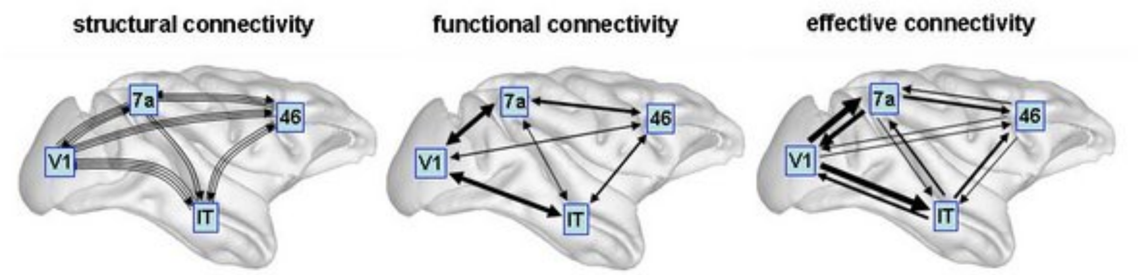
- Source localization of cortical generator
- Regional activations/ deactivation

- Communications between brain regions
- Estimate the changes of connectivity strength from a baseline to a task
- Network organization



Brain Connectivity

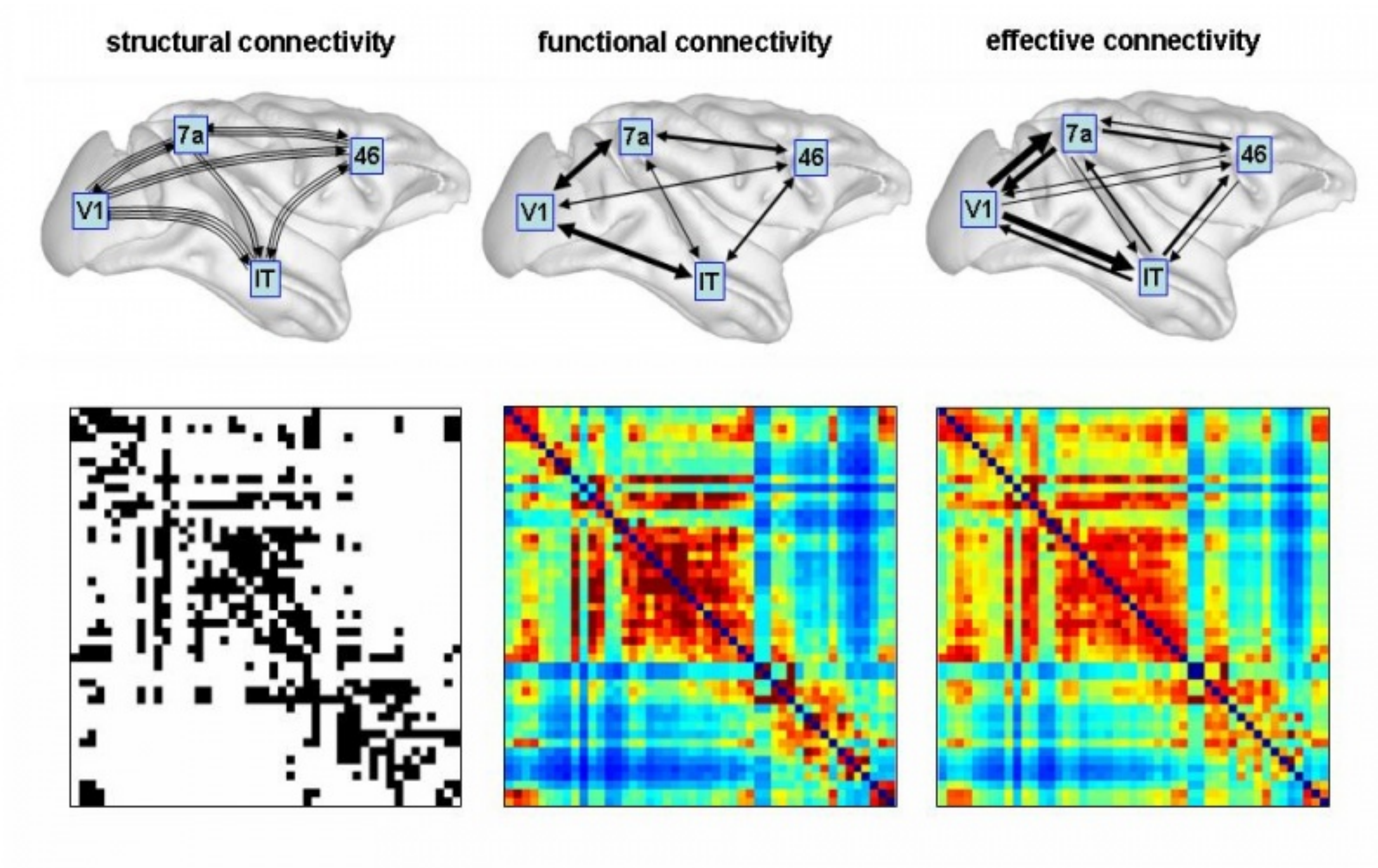
The **Brain Connectivity** describes how units within the nervous system are connected and can refers to a pattern of anatomical connections, of statistical dependencies or of causal interactions between distinct individual neurons, neuronal populations, or anatomically segregated brain regions (Horwitz, 2003)



- **anatomical/structural connectivity**
  = presence of axonal connections
- **functional connectivity**
  = statistical dependencies between regional time series
- **effective connectivity**
  = causal (directed) influences between neurons or neuronal populations

Sporns 2007, Scholarpedia

Brain Connectivity



Functional vs. Effective Connectivity

Functional Connectivity

- temporal correlation between spatially remote areas

⇨ Involves the estimation of **covariance properties** **no causation**

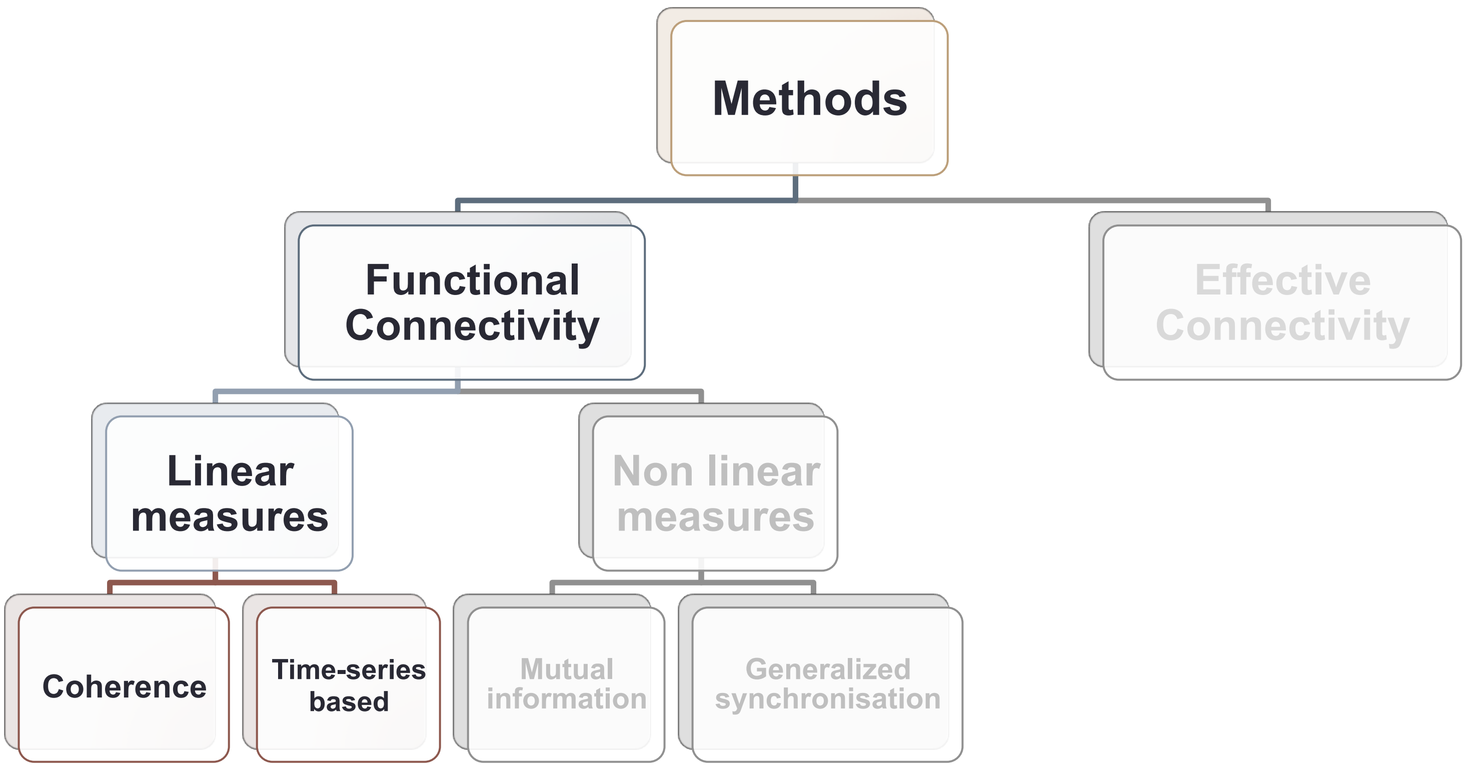
Effective Connectivity

- the influence one neuronal system exerts over another
- the mechanism of coupling
- how the dependencies are expressed

⇨ Captures **causal relationship**

Friston et al., 1993
Friston, 1994
Horwitz, 2003

Methods to estimate Functional Connectivity



Frequency based methods

Coherence is a measure of degree of association or coupling of frequency spectra between different times series

Coherence
(or Magnitude-Square Coherence)

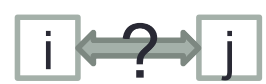
$$|Coh_{ij}(f)|^2 = \frac{|S_{ij}(f)|^2}{S_{ii}(f)S_{jj}(f)}$$

where *Coh* (*f*) is a coherence function, *f* is frequency, $S_{ii}(f)$ and $S_{jj}(f)$ are Fourier transforms of EEG signal in two different channels, and $S_{ij}(f)$ is the cross-spectrum.
Range [0, 1]:

$|Coh_{ij}(f_0)|^2 = 0$ ⇨ frequency components of both signals are not correlated

$|Coh_{ij}(f_0)|^2 = 1$ ⇨ frequency components of the signals are fully correlated

$|Coh_{ij}(f)|^2 = |Coh_{ji}(f)|^2$ ⇨ symmetry ⇨ undirectionality



Walter, 1968
Lopes da Silva 1991
Nunez, 1981
Pfurtscheller and Andrew, 1999

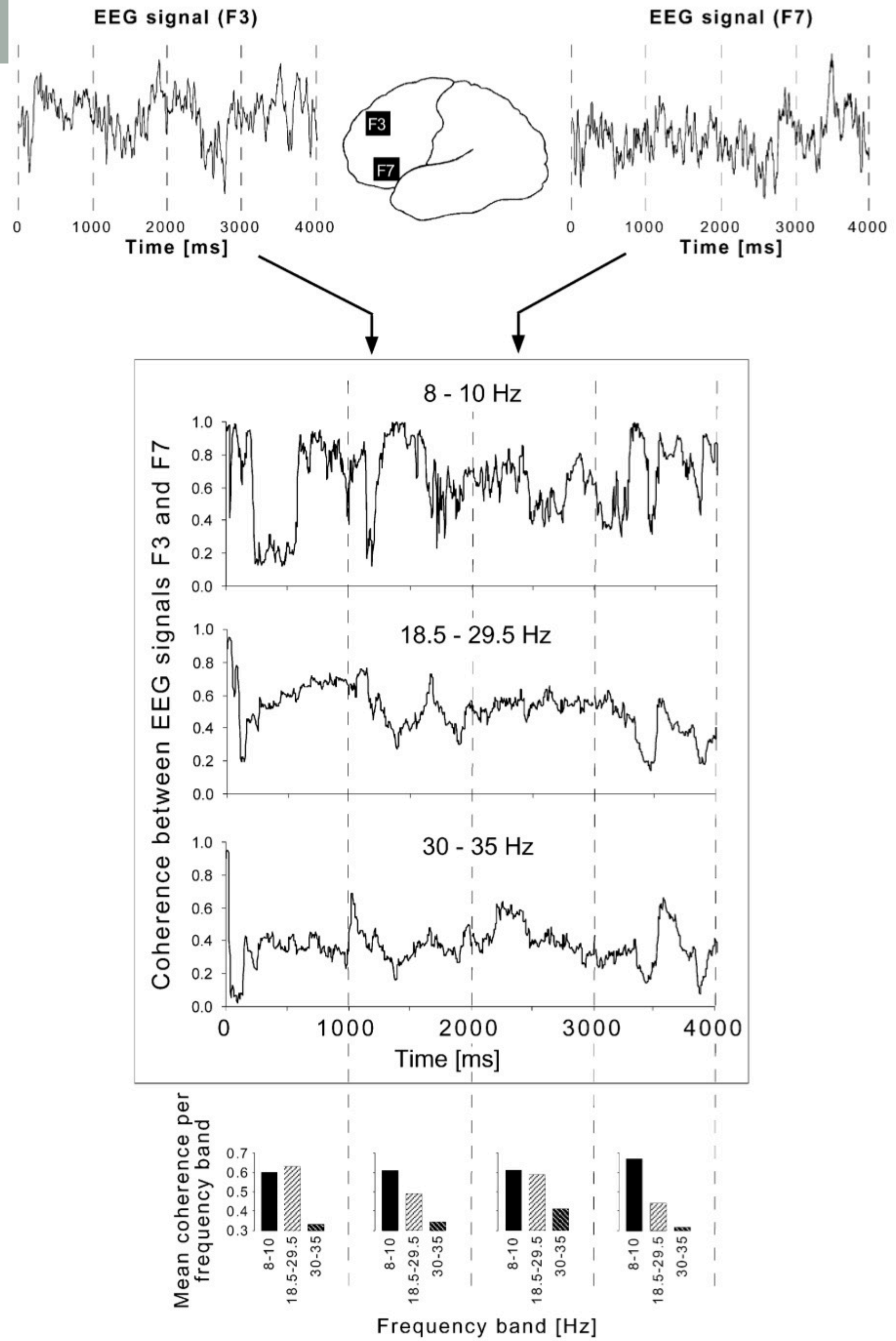
Application (EEG)

Coherence

Example for coherence analysis between two signals

EEG signals at F3 and F7

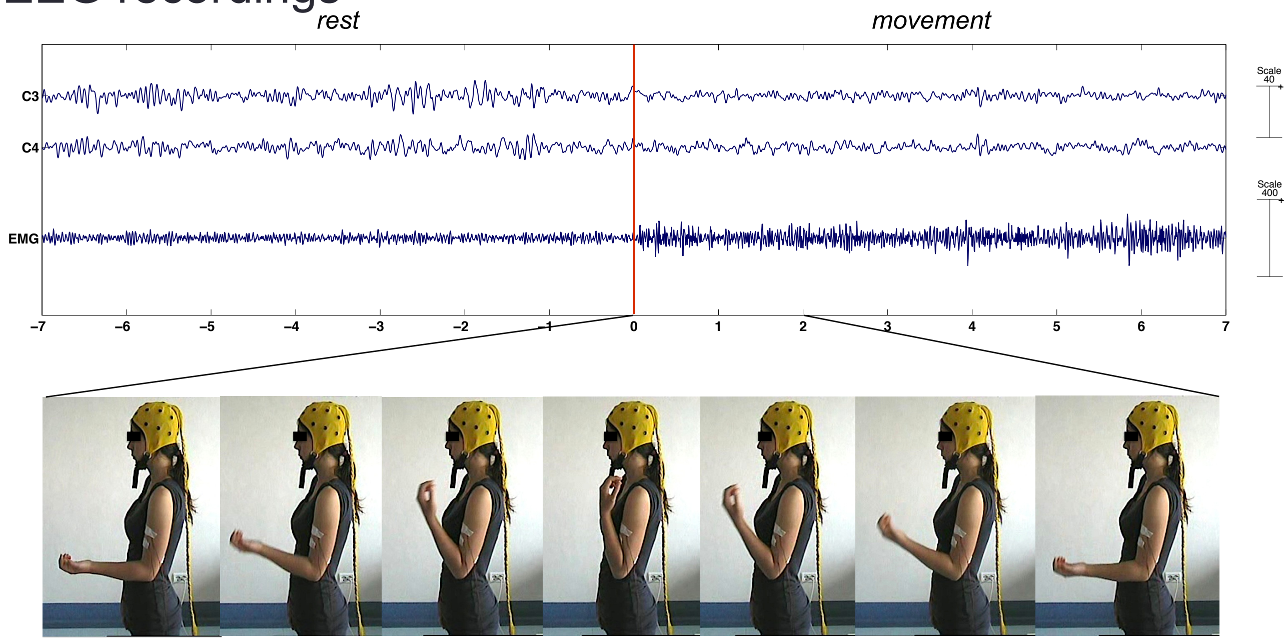
Each frequency band showed specific coherence values dependent on the time interval investigated.



Weiss and Muller, 2003

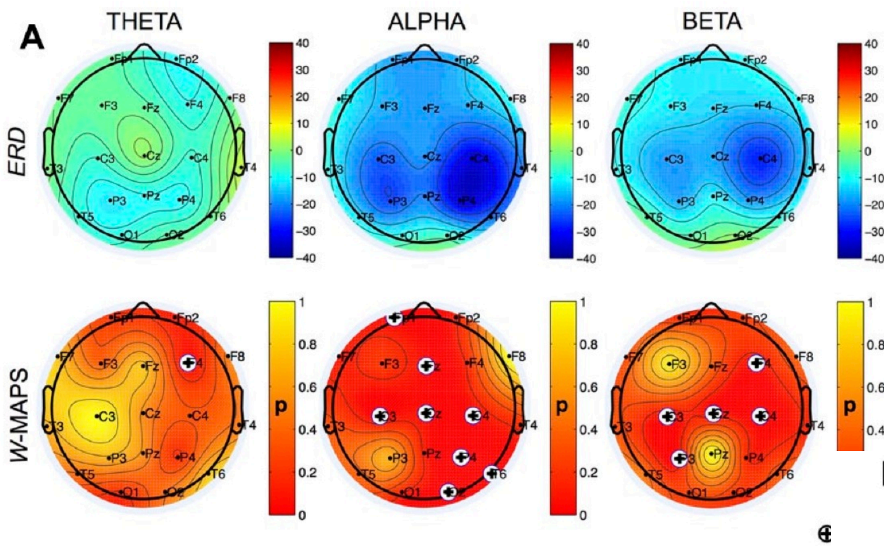
Application (EEG)
Coherence

The aim is to investigate the task related changes in brain activity and functional connectivity by applying event-related desynchronization (ERD), and coherence to EEG recordings



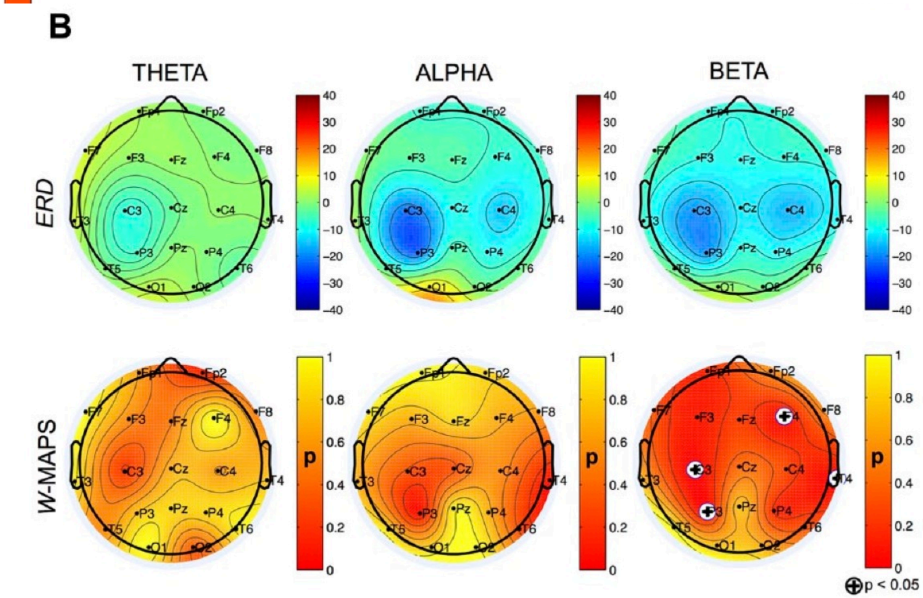
Synchronous video-EEG GEM 100 digital mobile system

Application (EEG)
ERD



left arm movement (LAM)

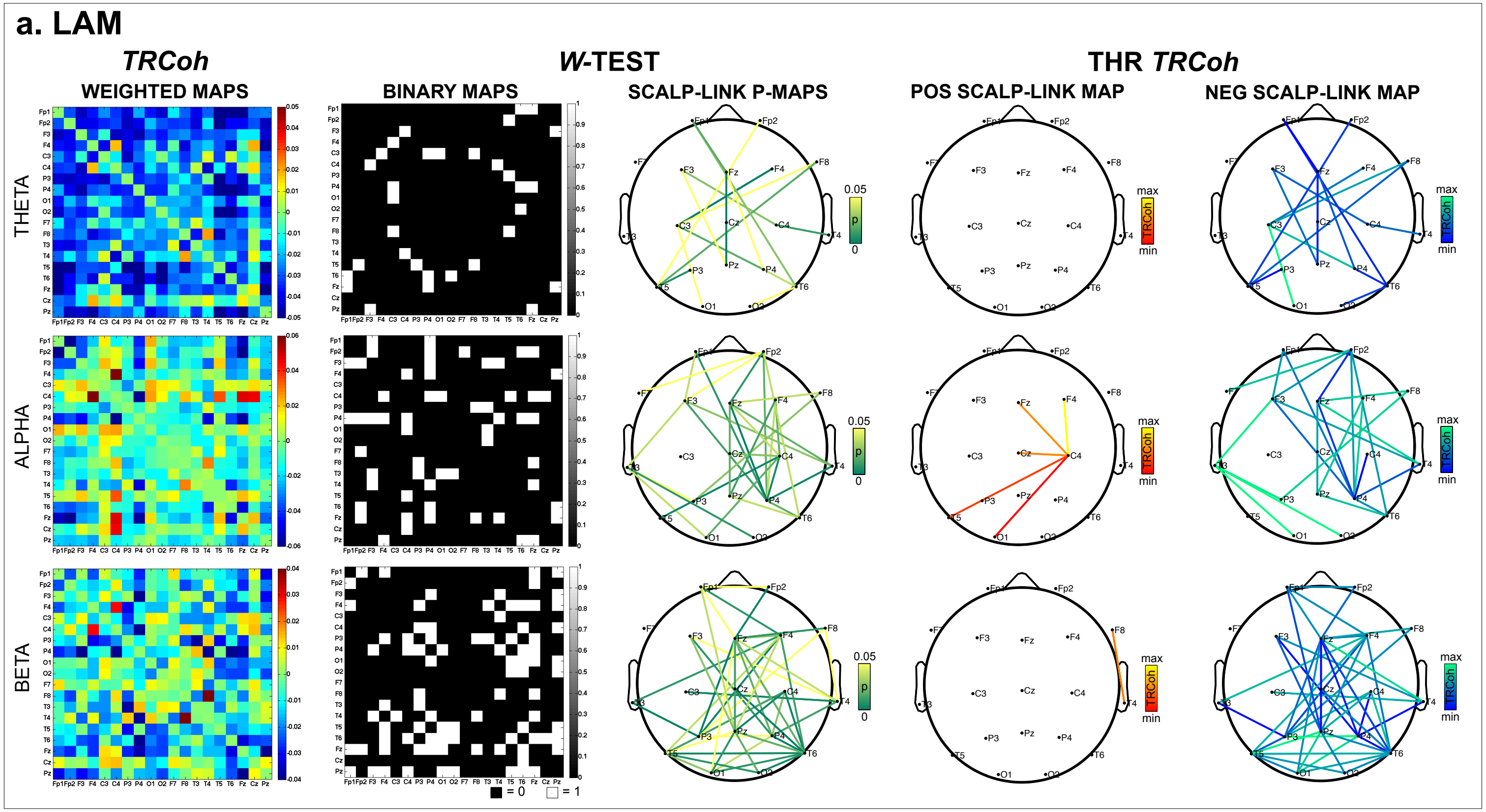
right arm movement (RAM)



Application (EEG)
Coherence

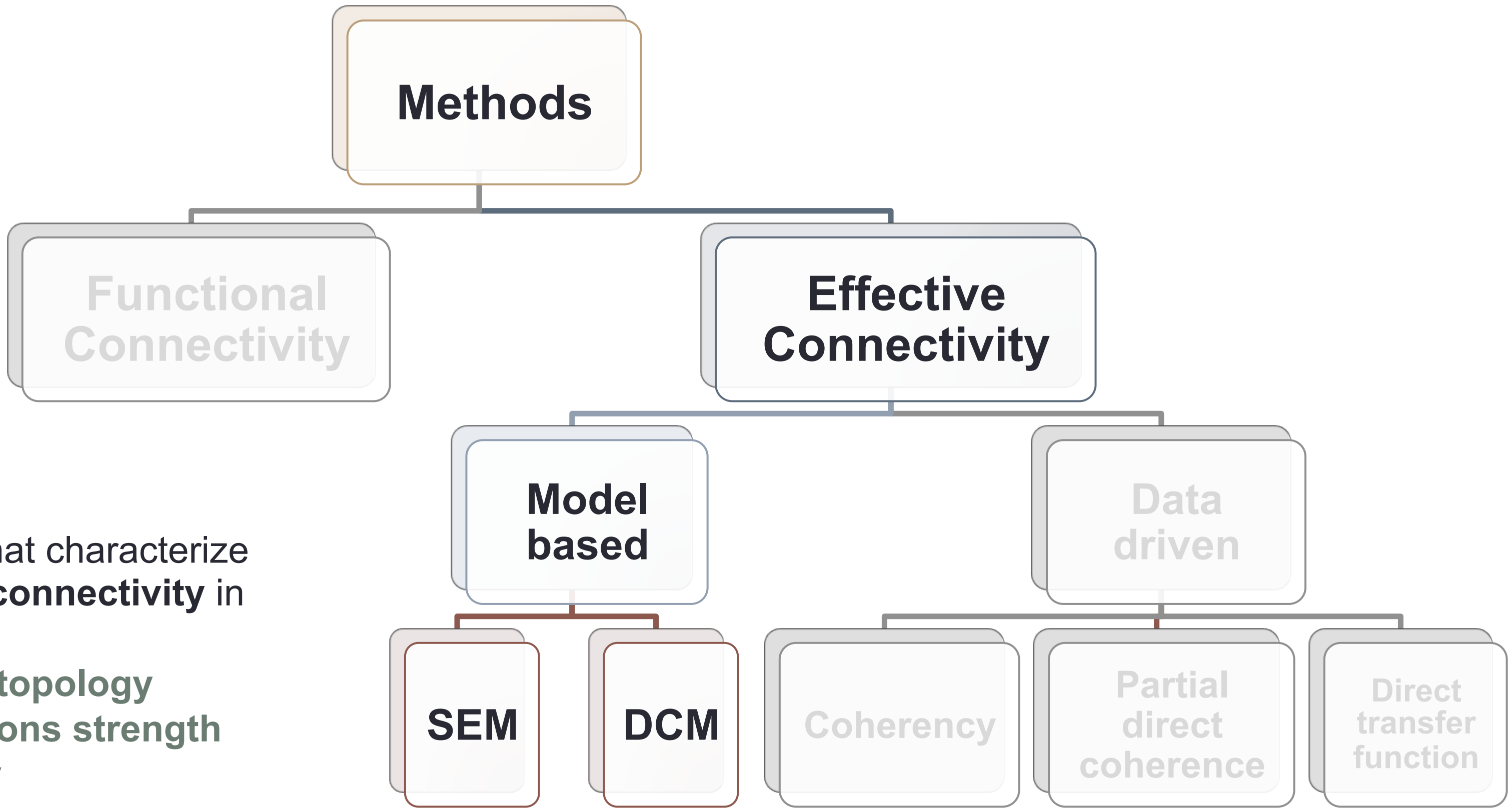
Functional connectivity based on EEG

Left arm movement task-related coherence-based connectivity matrices and links



Storti ClinEEGNeurosci 2015

Methods to estimate Effective Connectivity



Methods that characterize **the brain connectivity** in terms of:

- **network topology**
- **connections strength**
- **causality**

model topology is postulated from a priori knowledge and only the connections strength is estimated from the data

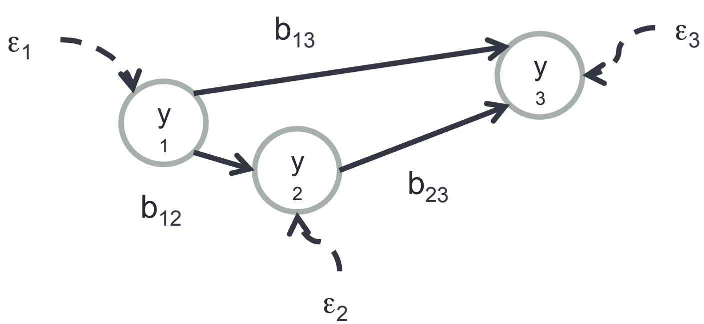
Structural Equation Modeling (SEM) or Path Analysis

SEM is a multivariate technique used to test hypothesis regarding the influences among interacting variables. These structural equations represent causal relationships among the variables in the model.

GENERAL MODEL for a network of n regions:

$$Y = \beta Y + \varepsilon$$

Y : measured time series
βs are the path coefficients that represent the strength of each connection $y_i \rightarrow y_j$
ε is the residuals vector
Hypothesis about causal relations are based on prior **anatomical knowledge**.



$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ b_{12} & 0 & 0 \\ b_{13} & b_{23} & 0 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix}$$

McIntosh et al. 1991, 1994
Büchel & Friston 1997
Bullmore et al. 2000

Wright, 1921. Journal of Agricultural Research.
Herbert, 1953. New York: Wiley.
Judea, 2000. Cambridge University Press.

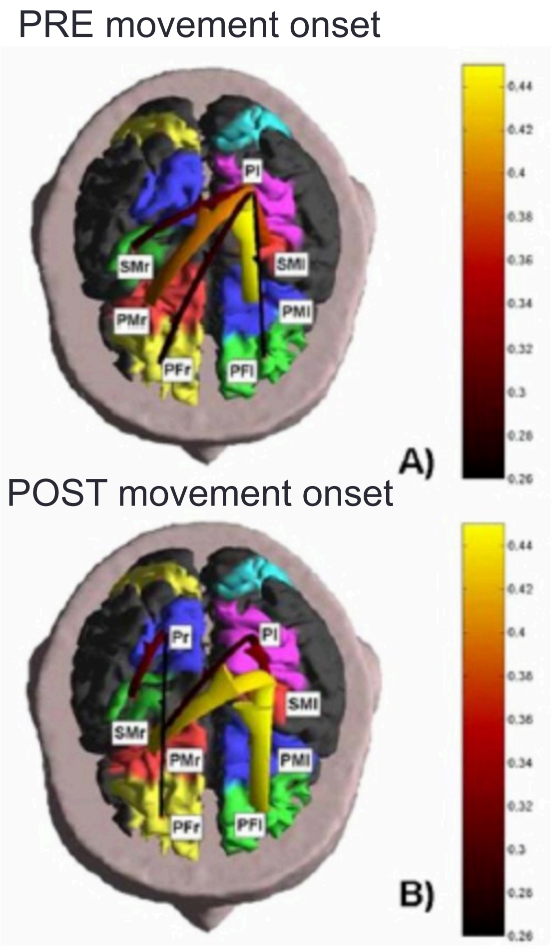
Application (high-resolution EEG)

Cortical connectivity pattern obtained with the SEM method

Alpha (8-12 Hz)
The connectivity pattern is represented with arrows moving from one cortical area toward another one.
The colors and sizes of arrows code the level of strengths of the functional connectivity observed between ROIs.

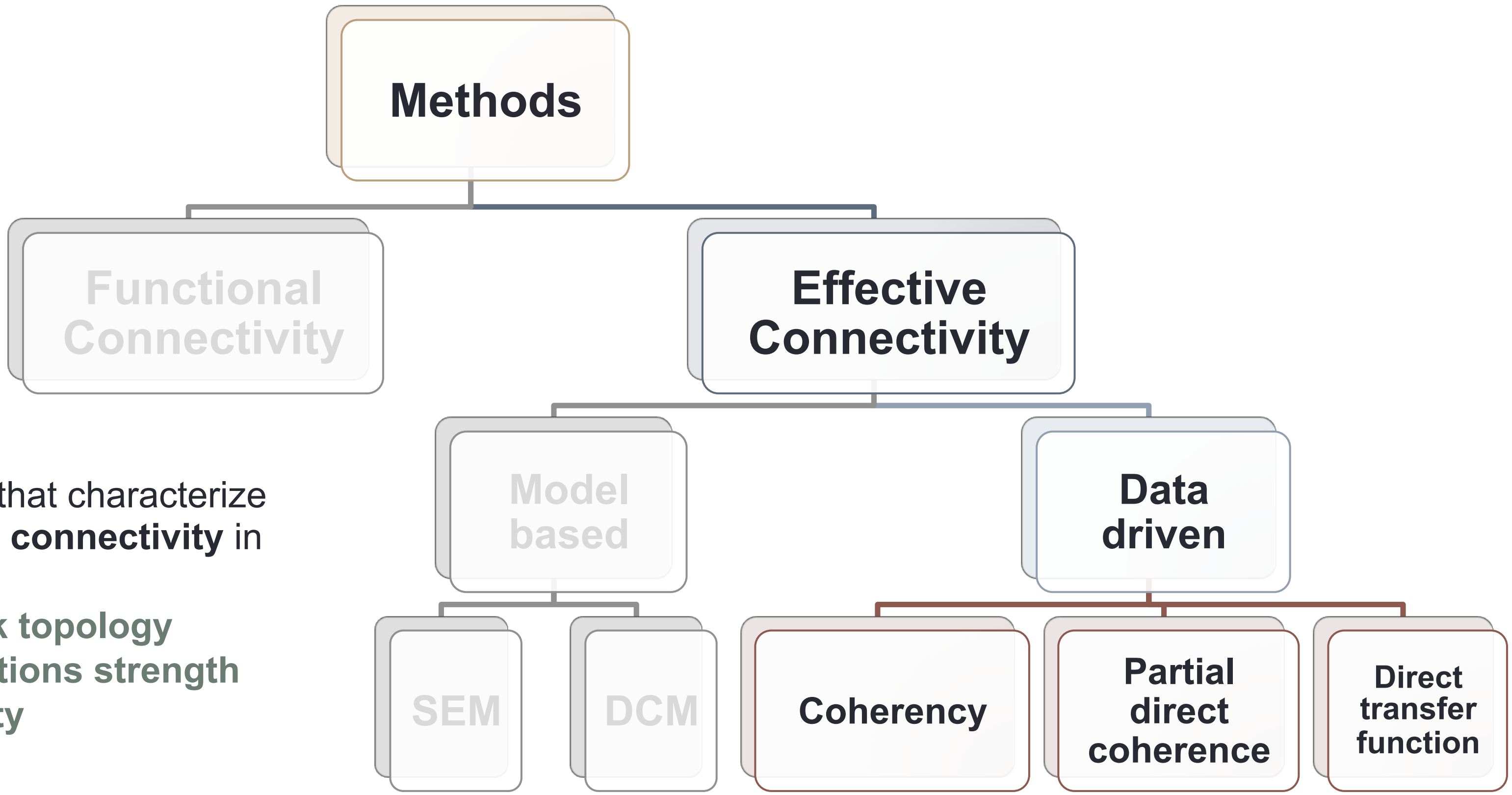
A) Connectivity pattern obtained from ERP data before the onset of the right finger movement (electromyographic onset; EMG).

B) Connectivity patterns obtained after the EMG onset.



Astolfi et al., 2005 IEEE Transactions On Biomedical Engineering

Methods to estimate Effective Connectivity

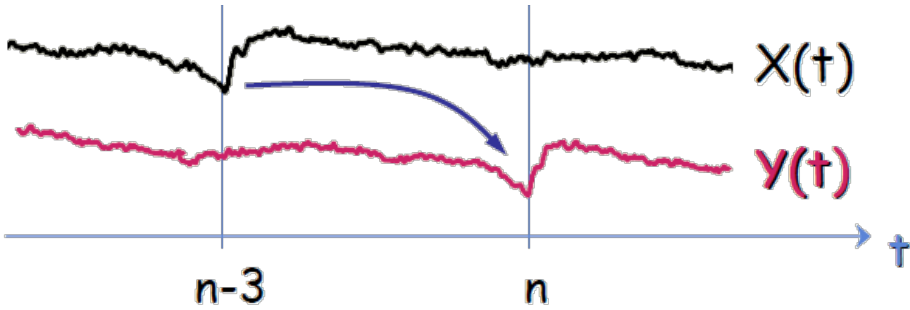


Methods that characterize **the brain connectivity** in terms of:

- network topology
- connections strength
- causality

Topology, causality and strength are all inferred from data

Granger Causality



Granger causality between two time series reads:
"an observed time series X(t) granger-causes another series Y(t), if the knowledge of past of X(t) significantly improves the prediction of Y(t)."

According to the definition, an appropriate framework for studying neural connectivity is the auto-regressive (AR) model.

Class of parametric techniques based on Granger Causality

- Granger Causality index (GC)
- The Partial Directed Coherence (PDC)
- The Directed Transfer Function (DTF)

Wiener, 1956; Granger, 1969

MultiVariate Autoregressive (MVAR) model

The MVAR model with N variables is expressed as:

$$x(n) = \sum_{k=1}^{p} A(k)x(n-k) + e(n)$$

where $y(n) = [y_1(n), y_2(n) \ldots y_N(n)]^T$ is the data vector of dimension N containing the n-samples of the N time series, p is the model order, $A(k)$, k =1...p, are the N x N matrices containing model coefficients, $e(n) = [e_1(n), e_2(n) \ldots e_N(n)]^T$ is the vector containing the n-samples of the prediction errors, i.e. it is a multivariate white noise process with diagonal covariance matrix $\sum_e diag[\sigma_1^2, \sigma_2^2, \ldots, \sigma_N^2]$

MVAR can be treated as a black-box model with the noises at the input and the signal as the output.

Transforming the model to **frequency domain** we obtain: $A(f)X(f) = E(f)$

which can be presented as: $X(f) = A^{-1}(f)E(f) = H(f)E(f)$

Partial Directed Coherence (PDC)

Direct Transfer Function (DTF)

PDC and DTF has been introduced to detect **casual relationship** between processes in multivariate dynamic systems.

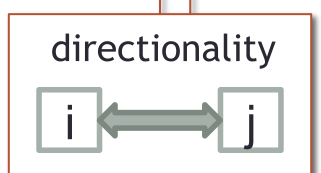
The PDC is based on the Fourier transform of the MVAR coefficients Aij (f)

$$|PDC_{ij}(f)|^2 = \frac{|A_{ij}(f)|^2}{\sum_{k=1}^{m} |A_{kj}(f)|^2}$$

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

asimmetry

PDC is able to detect not only direct but also indirect pathways



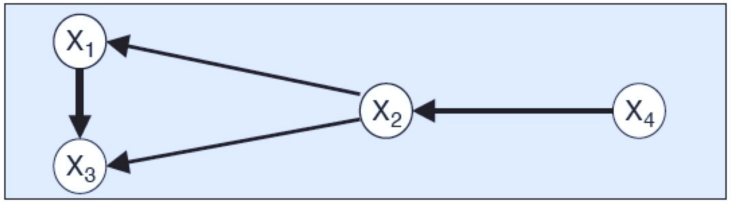
The DTF is constructed from transfer matrix of the MVAR model H(f).

$$|DTF_{ij}(f)|^2 = \frac{|H_{ij}(f)|^2}{\sum_{j=1}^{m} |H_{ij}(f)|^2}$$

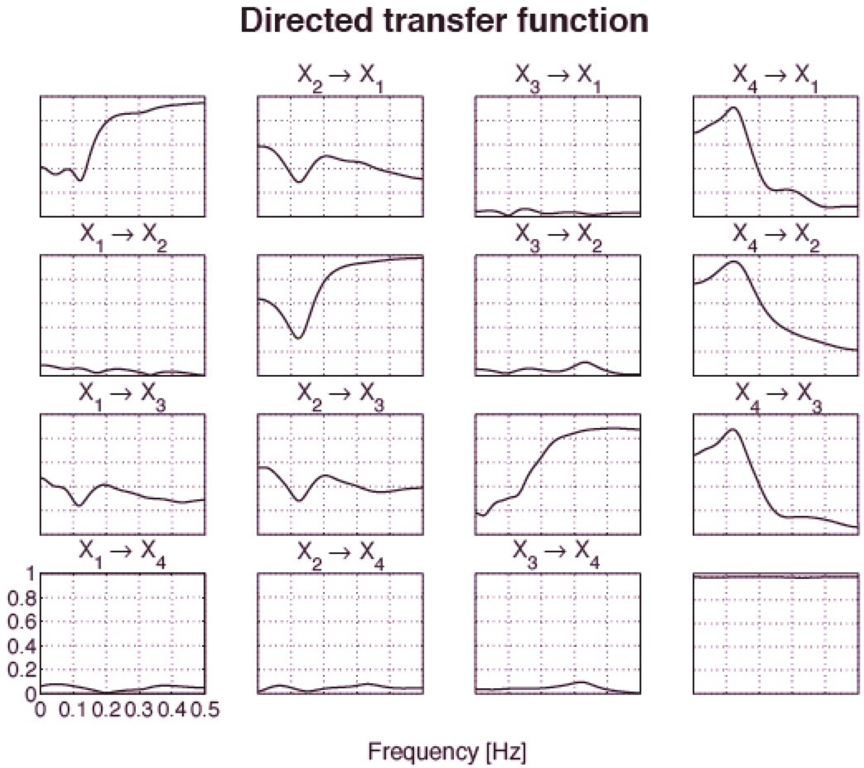
$H_{ij}(f) = A_{ij}^{-1}(f)$

Sameshima and Baccalá, 1999

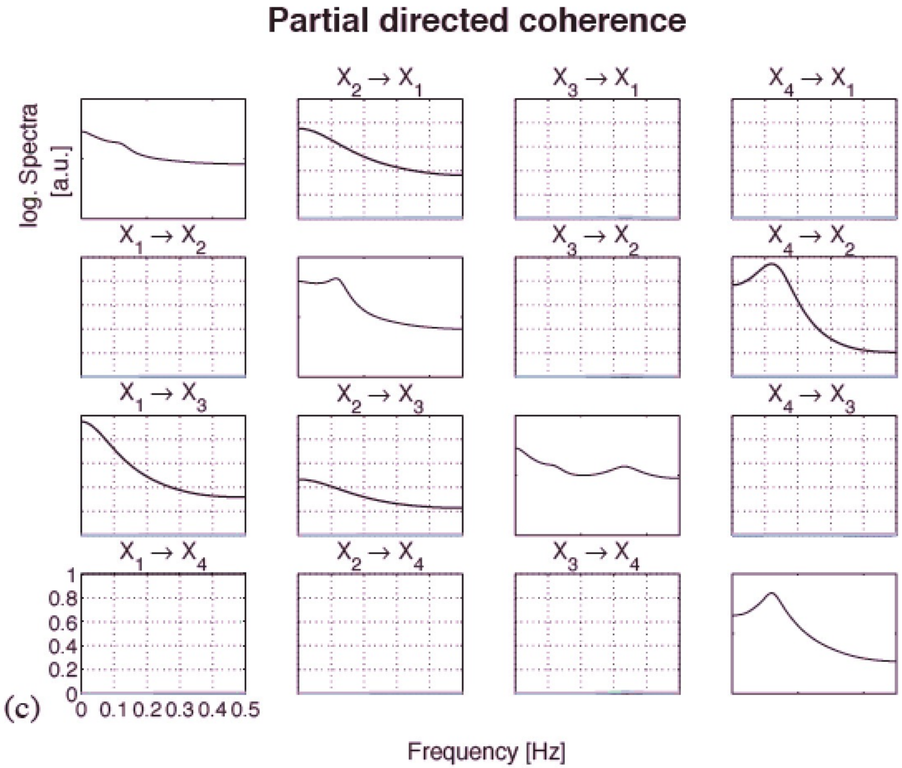
Kaminiski and Blinowska, 1991



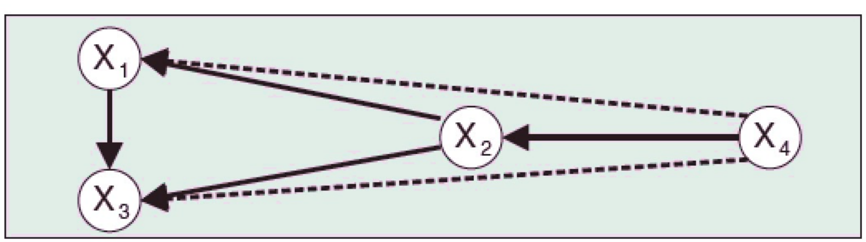
$$x_1(t) = 0.8x_1(t-1) + 0.65x_2(t-4) + \eta_1(t)$$
$$x_2(t) = 0.6x_2(t-1) + 0.6x_4(t-5) + \eta_2(t)$$
$$x_3(t) = 0.5x_3(t-3) - 0.6x_1(t-1) + 0.4x_2(t-4) + \eta_3(t)$$
$$x_4(t) = 1.2x_4(t-1) - 0.7x_4(t-2) + \eta_4(t)$$



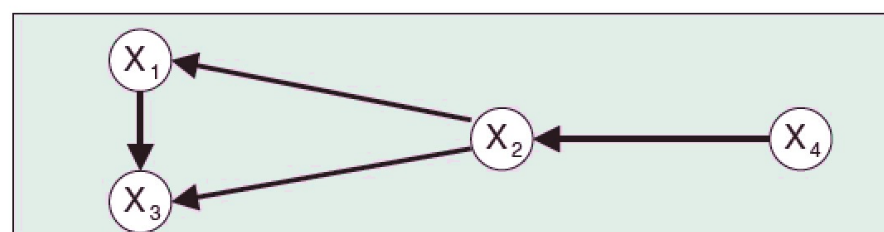
(a)



(c)



(b)

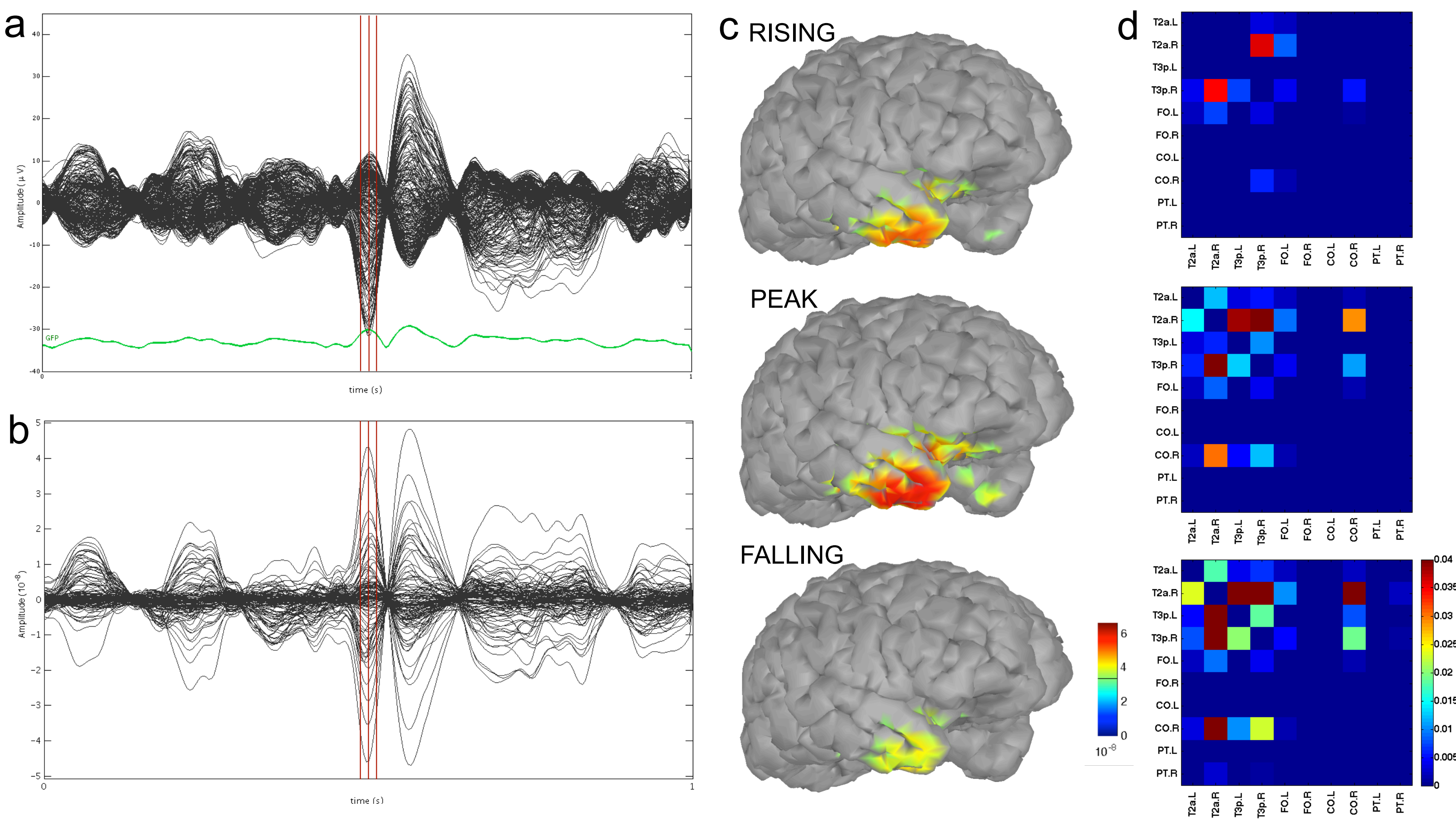


(d)

Winterhalder et al., Signal Processing 2005

Application (EEG)

Adaptive DTF



Dynamic patterns of epileptic networks in focal epilepsy by using the high-density EEG recordings