EEG practices, EEG in practice

Bálint File

Theoretical Neuroscience and Complex Systems Group, Wigner FK

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Contents

- EEG introduction
- EEG processing
  - Preprocessing
  - Processing
  - Advanced techniques
- EEG in practice
  - Brain machine interfaces
  - Localization of the epileptic focus

Introduction

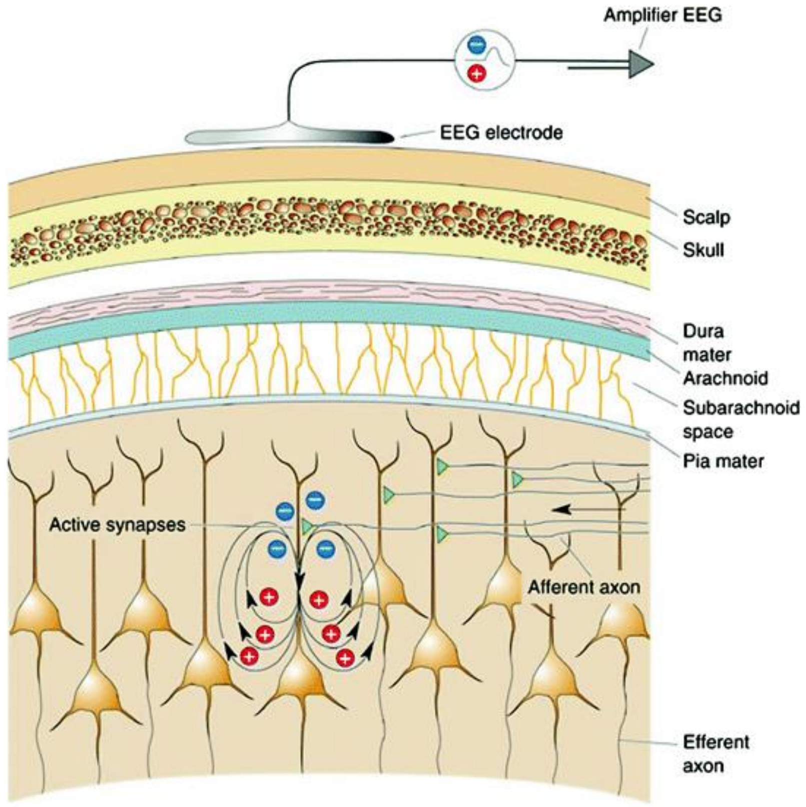
EEG toolboxes, EEG origins, rythms, headsets

Free EEG processing toolboxes

- MATLAB
  - EEGLab: https://sccn.ucsd.edu/eeglab/index.php
  - Brainstorm: https://neuroimage.usc.edu/brainstorm/Introduction
  - Fieldtrip: https://www.fieldtriptoolbox.org/
- Python
  - MNE toolbox: https://mne.tools/stable/index.html

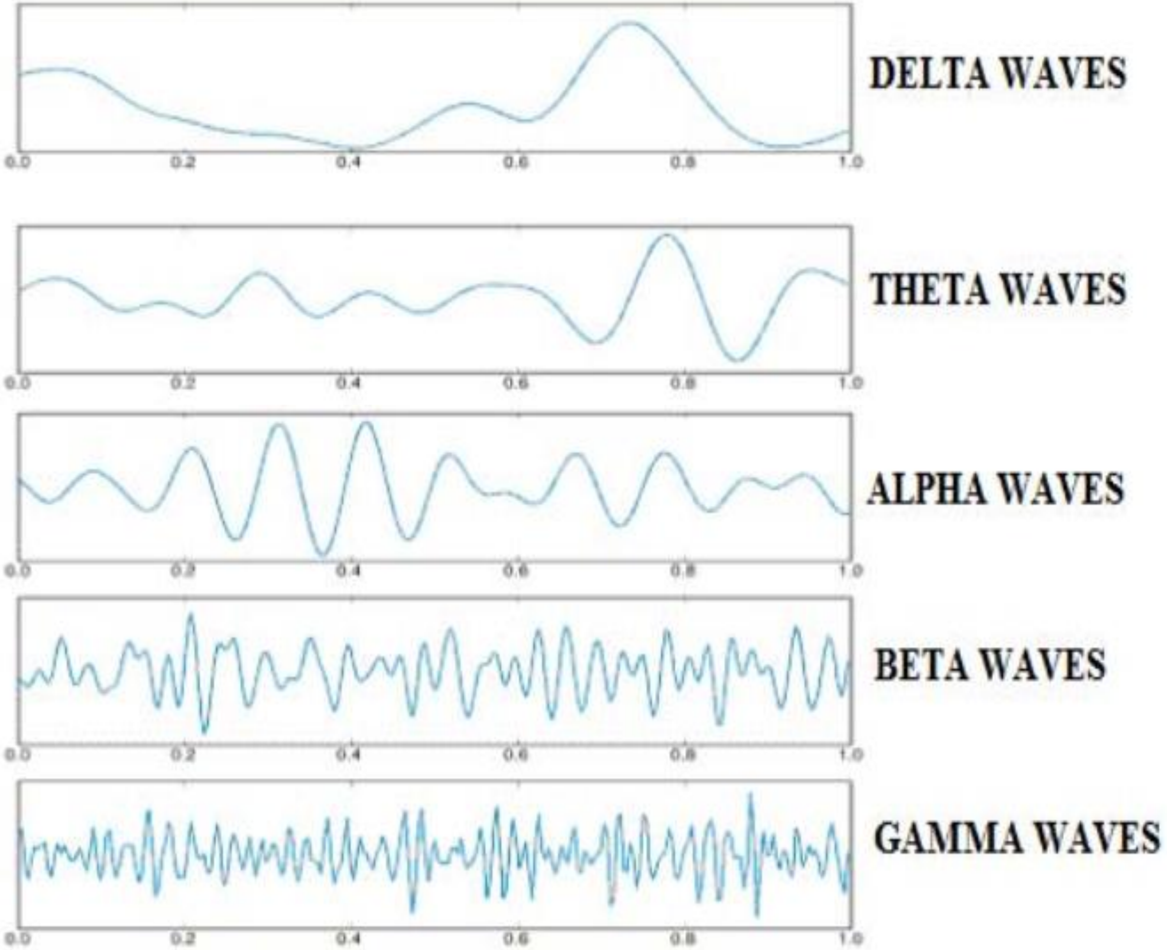
EEG origins

- large cortical pyramidal neurons in deep cortical layers play a major role in the generation of the EEG
- postsynaptic potentials along the apical dendrites (perpendicular to the cortical surface) become electrical dipoles



Siuly, S., Li, Y., & Zhang, Y. (2016). Electroencephalogram (EEG) and Its Background. In *EEG Signal Analysis and Classification* (pp. 3-21). Springer, Cham.

EEG rhythms

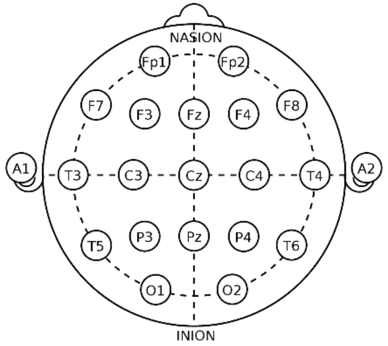


RHYTHYM	FREQUENCY RANGE (Hz)	AMPLITUDE (µv)	STATE OF MIND
DELTA	Up to 4	High amplitude (20-200)	Deep sleep
THETA	4-8	More than 20	Emotional stress, drowsiness and sleep in adults
ALPHA	8-13	30-50	Relaxed awareness
BETA	13-30	5-30	Active thinking, active attention, alert
GAMMA	Above 31	Less than 5	Mechanism of consciousness

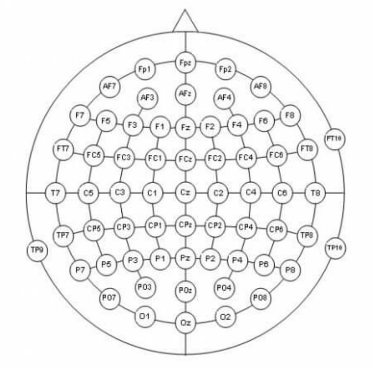
Vaid, et al 2015

EEG headsets

Laboratory setups

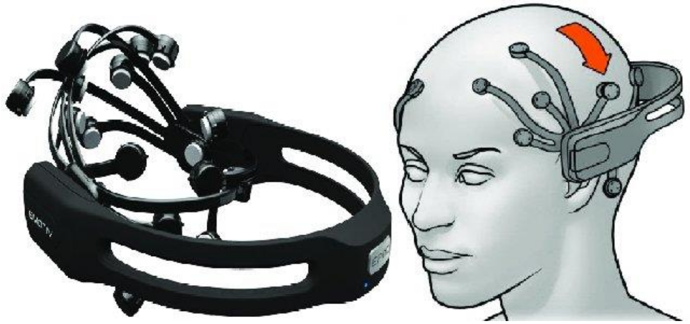


19 channels



64 channels

Portable EEG devices

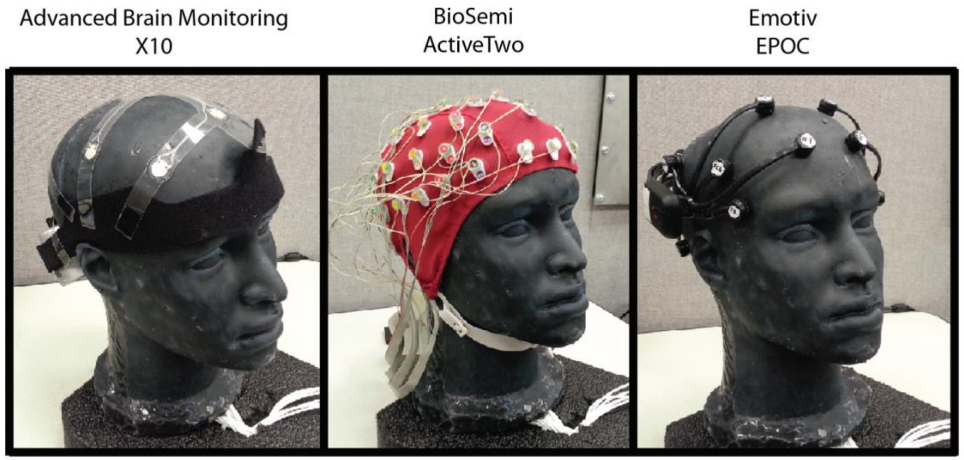


EMOTIV headset with 14 channels

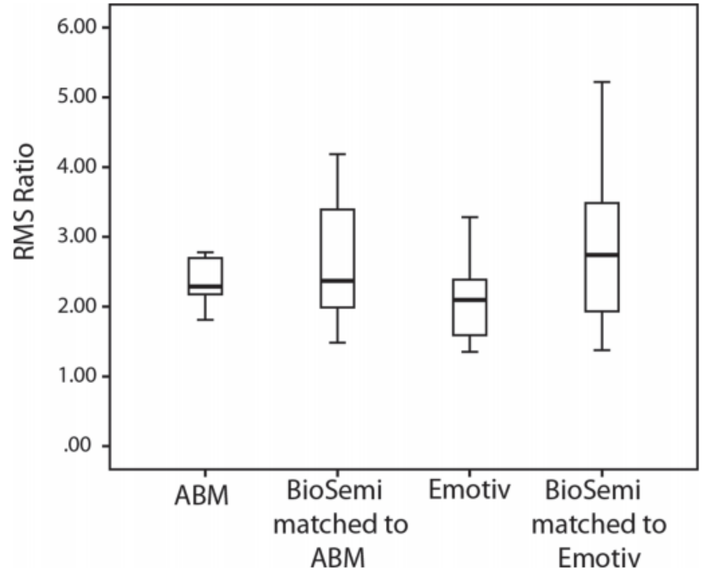
https://www.biopac.com/product/b-alert-wireless-eeg-system-9-ch/

A Comparison of Electroencephalography Signals Acquired from Conventional and Mobile Systems

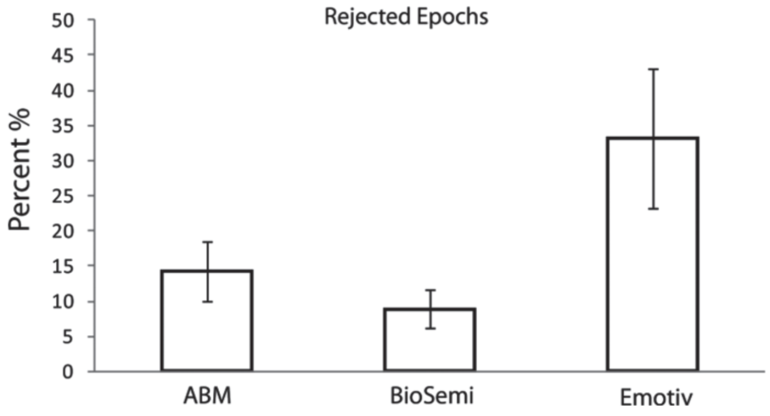
2 portable, 1 laboratory system



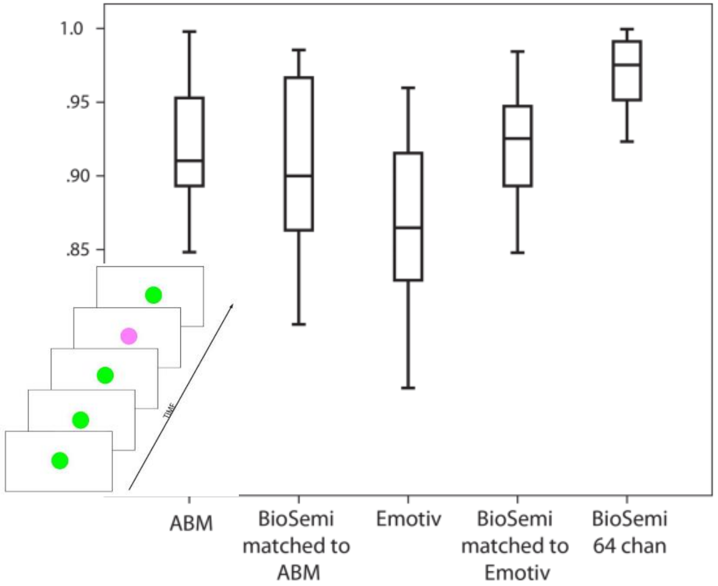
Signal to noise ratio based on pre/poststimulus amplitude



Artefacts



Classification accuracy of single trials in an oddball task



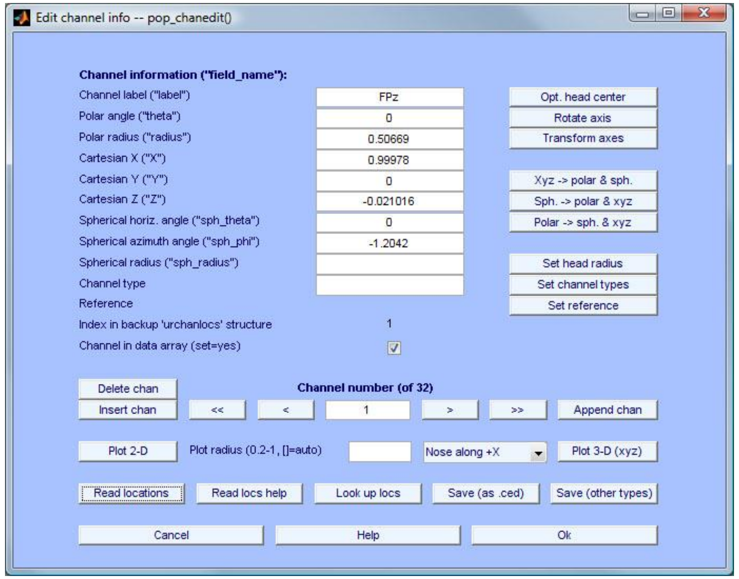
Ries et al, 2014

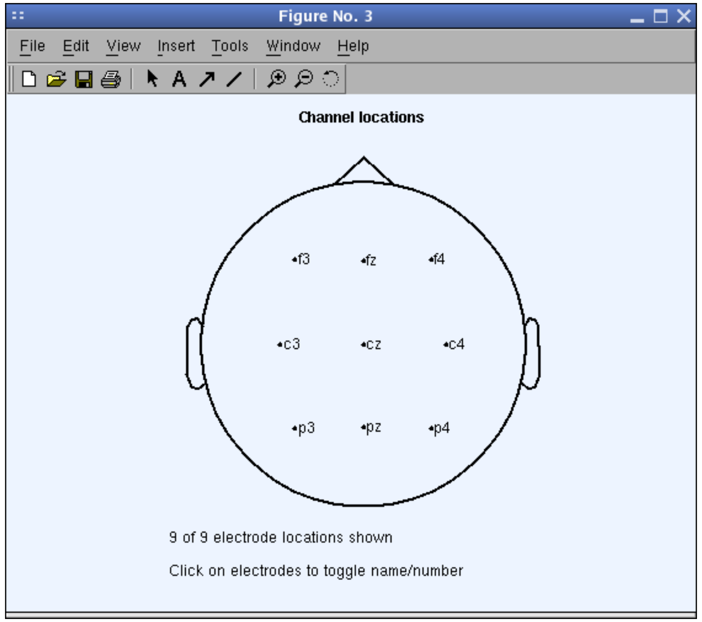
Check the placement of EEG electrodes in EEGLab

- Spherical and MNI coordinates are available
  - MNI for source localization

- In GUI: Edit > Channel locations
- In Command window: >>**pop_chanedit**([]);
- „topoplot.m” function plots the electrode montage on scalp

- Sample data in EEGLab/sample locs
- Cartesian, spherical, polar coordinates were applied





Preprocessing EEG

EEG data structure

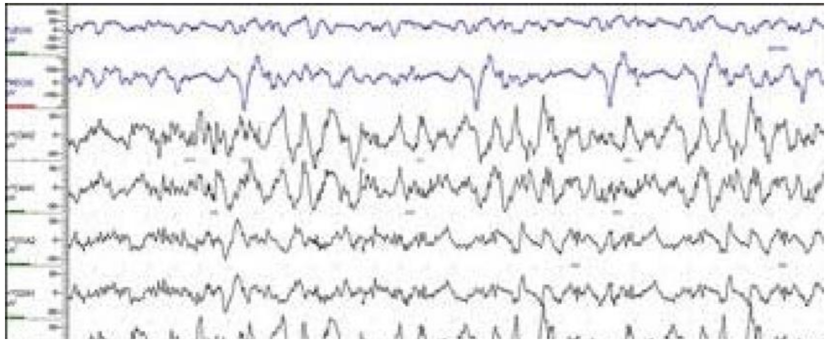
- Basic elements:
  - Amplitude values (2/3D matrix; channels*time points* *epochs*)
  - Channel labels
  - Sampling frequency
  - Reference
- Advanced elements:
  - Filename
  - Channel coordinates
  - Bad channels
  - Bad epochs
  - ICA weights
  - History

EEGLAB struct

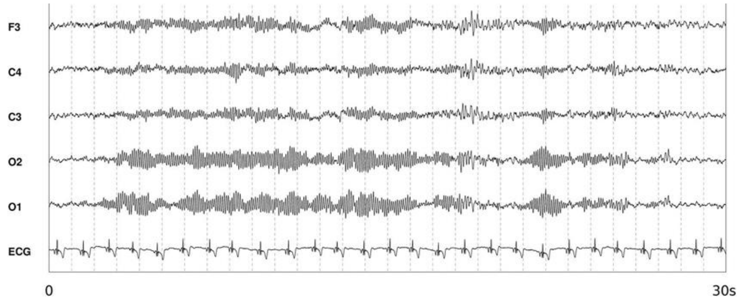
```
EEG =
        setname:           'Epoched from "ee114 continuous"'
        filename:          'ee114squaresepochs.set'
        filepath:          '/home/arno/ee114/'
        pnts:              384
        nbchan:            32
        trials:            80
        srate:             128
        xmin:              -1
        xmax:              1.9922
        data:              [32x384x80 double]
        icawinv:           [32x32 double]
        icasphere:         [32x32 double]
        icaweights:        [32x32 double]
        icaact:            []
        event:             [1x157 struct]
        epoch:             [1x80 struct]
        chanlocs:          [1x32 struct]
        comments:          [8x150 char]
        averef:            'no'
        rt:                []
        eventdescription:  {1x5 cell}
        epochdescription:  {}
        specdata:          []
        specicaact:        []
        reject:            [1x1 struct]
        stats:             [1x1 struct]
        splinefile:        []
        ref:               'common'
        history:           [7x138 char]
        urevent:           [1x154 struct]
        times:             [1x384 double]
```

Continuous recordings versus event-related setup

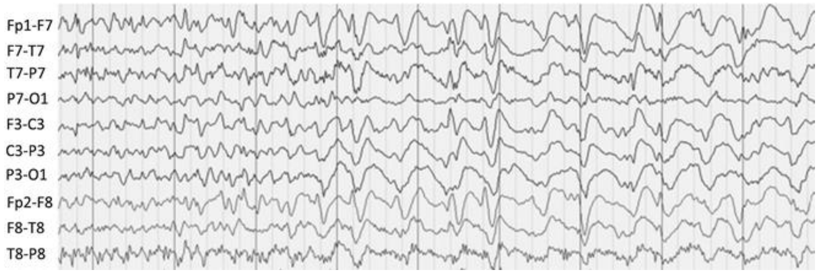
Sleep EEG



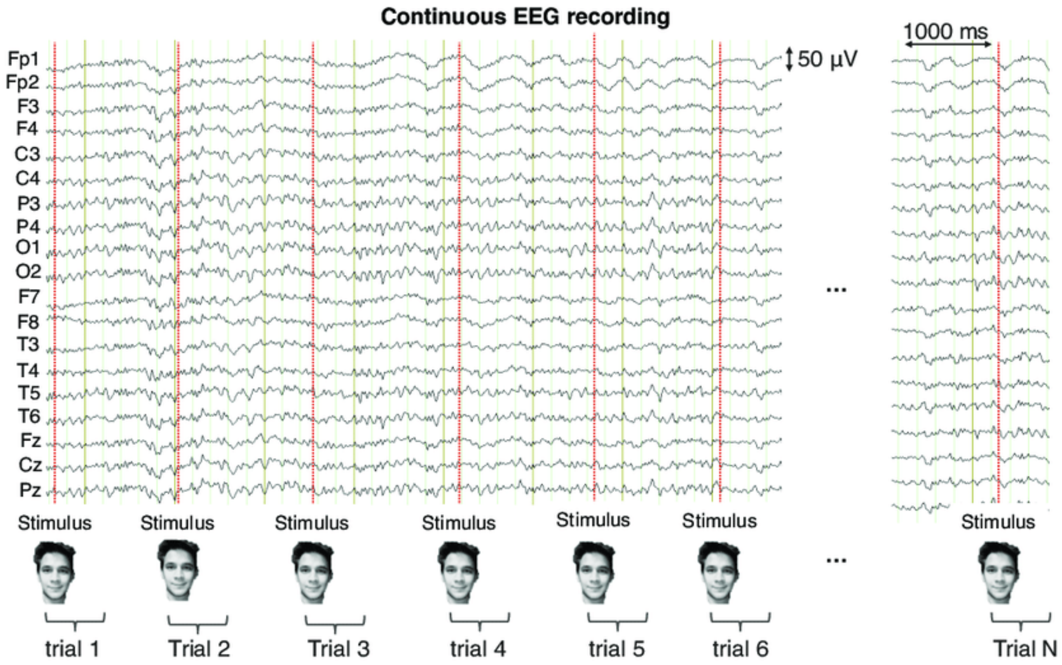
Resting state EEG



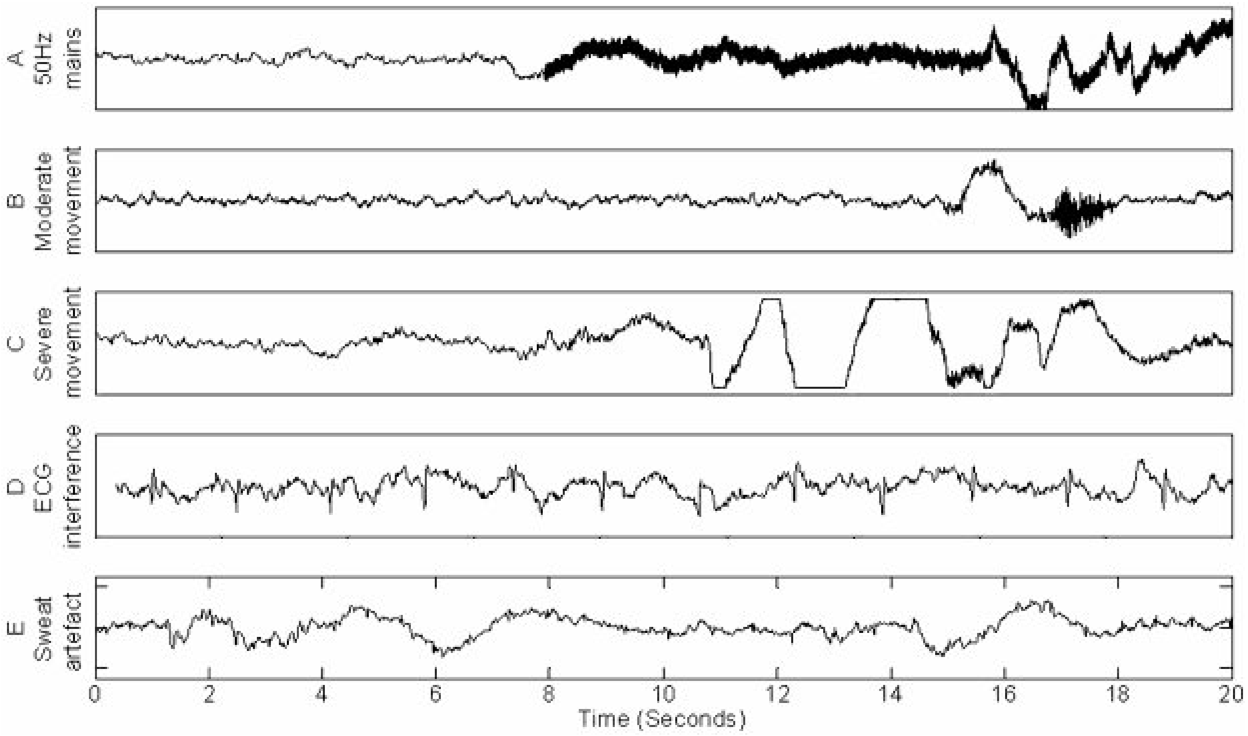
Epileptic interictal EEG



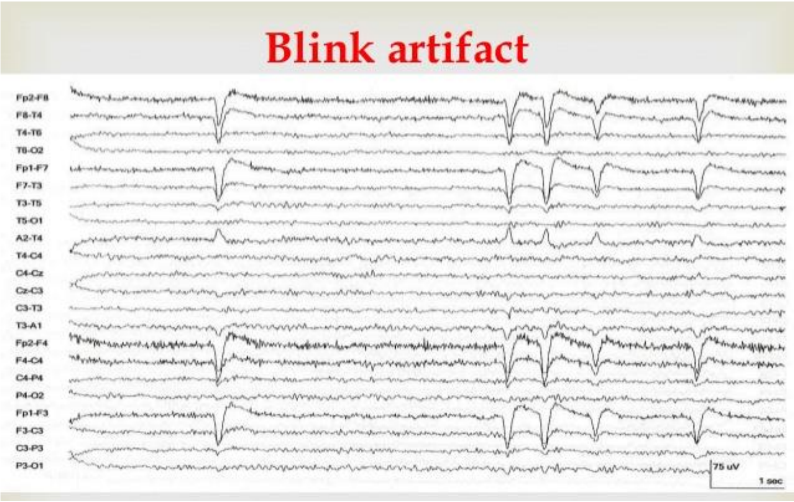
Event-related case: series of stimuli are sent to the subject and we have the corresponding triggers marked in the recordings

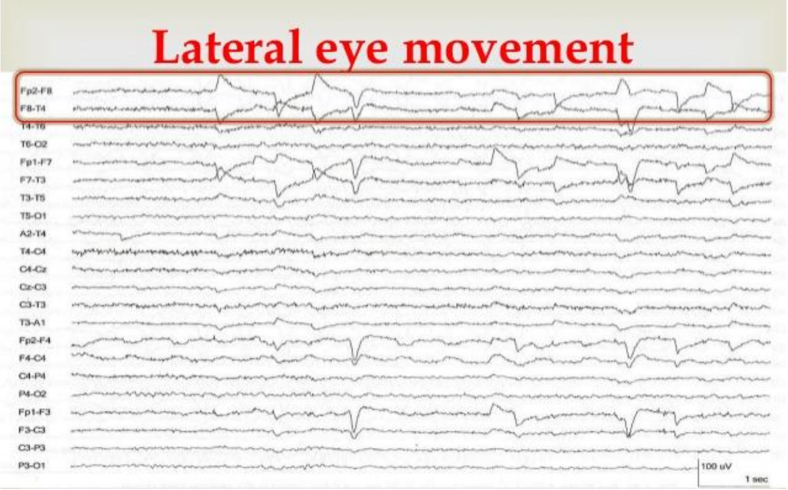


EEG Artefacts



Motamedi-Fakhr, Shayan, et al. "Signal processing techniques applied to human sleep EEG signals—A review." *Biomedical Signal Processing and Control* 10 (2014): 21-33.





Manual and **automatic** artefact filters are avaiable

	Acharjee et al., 2015	Burger et al., 2015	Castellanos et al., 2006	Chen et al., 2014 (1)	Chen et al., 2014 (2)	Cho et al., 2007	Davies et al., 2007	Geetha et al., 2012	Gu et al., 2014	Guerrero-Mosquera et al., 2009	Gwin et al., 2010	Hsu et al., 2012	Hu et al., 2015	Klados et al., 2011	Kong et al., 2013	Krishnaveni et al., 2006 (1)	Krishnaveni et al., 2006 (2)	Kumar et al., 2008	Ma et al., 2011	Mammone et al., 2012	Mijovic et al., 2010	Mognon et al., 2011	Mourad et al., 2007	Mourad et al., 2013
Performed outdoors																								
Portable-wearable-wireless device																								
Real EEG signals	■	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■	■	■		■	■	■	■
Daily-life tasks				■	■				■		■										■			
Simple electrical montage																								
Dry electrodes																								
Complex artifacts				■	■		■				■		■							■	■	■		
Only EEG signals	■	■	■	■	■	■	■		■		■				■	■	■	■	■	■	■	■	■	■
Online		■				■		■	■	■			■			■	■	■					■	
Single active channel				■	■	■	■						■			■	■	■			■			■

	Mowla et al., 2015	Nguyen et al., 2012	Nolan et al., 2010	Peng et al., 2013	Porcaro et al., 2015	Puthusserypady et al., 2006	Raduntz el al., 2015	Romo et al., 2012	Sameni et al., 2014	Schlogl et al., 2007	Shao et al., 2009	Sweeney et al., 2013	Sziboo et al., 2012	Teixeira et al., 2006	Teixeira et al., 2007	Teixeira et al., 2008	Tiganj et al., 2010	Wang et al., 2014	Yong et al., 2009 (1)	Yong et al., 2009 (2)	Zeng et al., 2013	Zhang et al., 2015	Zhao et al., 2014	Zikov et al., 2002*
Performed outdoors																								
Portable-wearable-wireless device				■																			■	
Real EEG signals	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
Daily-life tasks		■			■													■						
Simple electrical montage				■																			■	■
Dry electrodes																								
Complex artifacts	■		■		■		■	■			■	■						■	■	■	■			
Only EEG signals	■	■		■	■		■	■			■	■	■	■	■	■	■	■	■	■	■	■	■	■
Online	■	■		■			■		■	■			■				■						■	■
Single active channel		■		■								■	■	■	■	■	■		■	■	■		■	■

Minguillon et al, 2017

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journal homepage: www.elsevier.com/locate/jneumeth

ELSEVIER

FASTER: Fully Automated Statistical Thresholding for EEG artifact Rejection☆

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Trinity Center for Bioengineering, Trinity College Dublin, Ireland

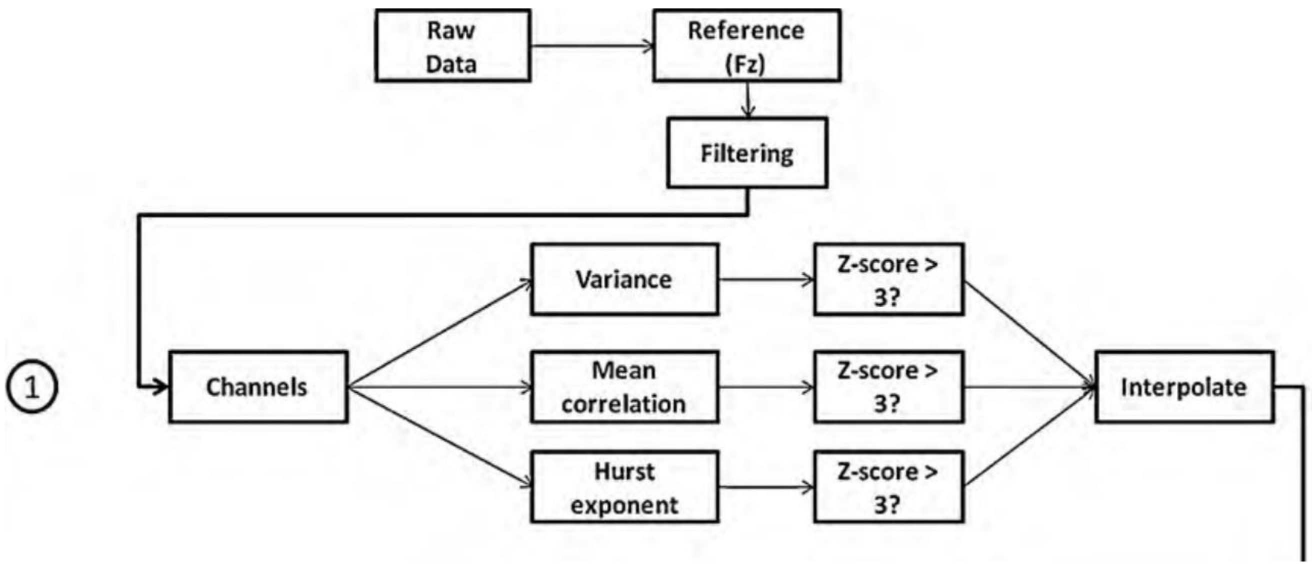
Adding Faster to EEGLab:

Download: https://sourceforge.net/projects/faster/

Unzip Faster to EEGLab>Plugins>Faster folder

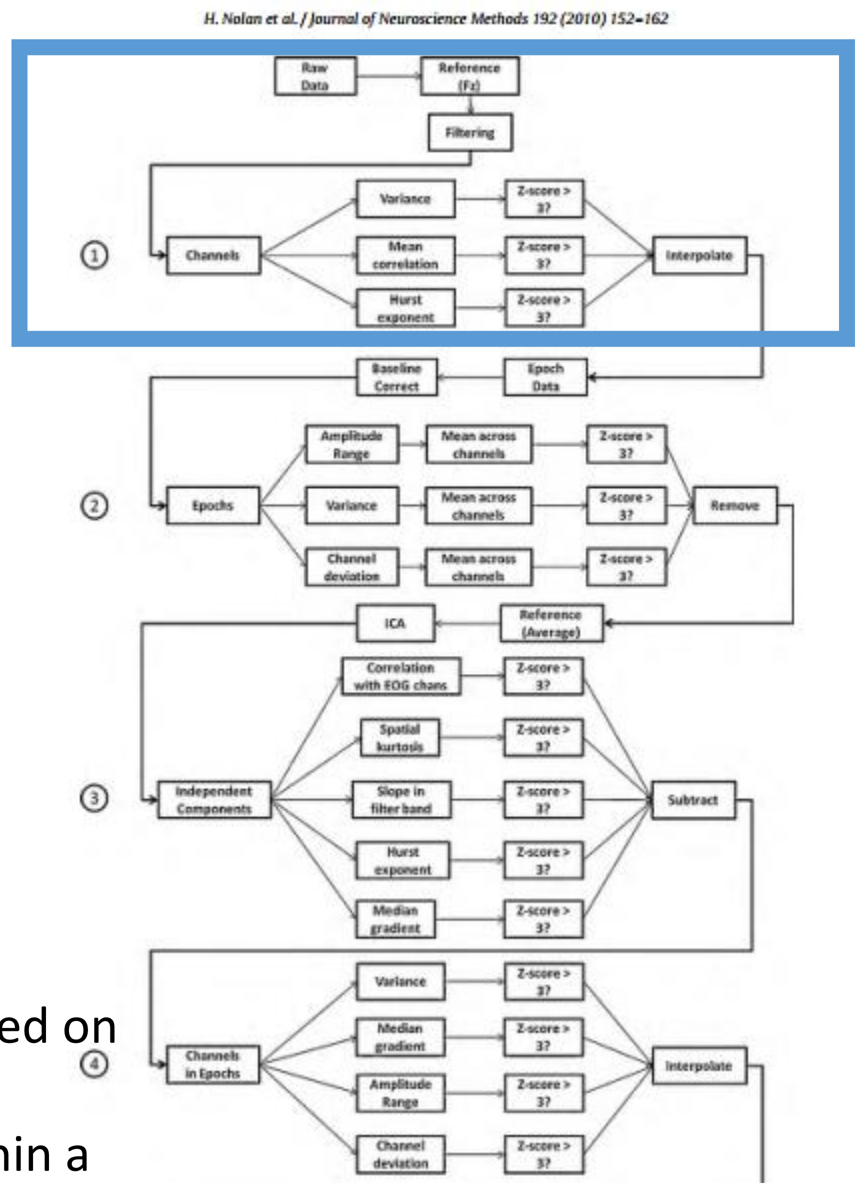
Run EEGLab

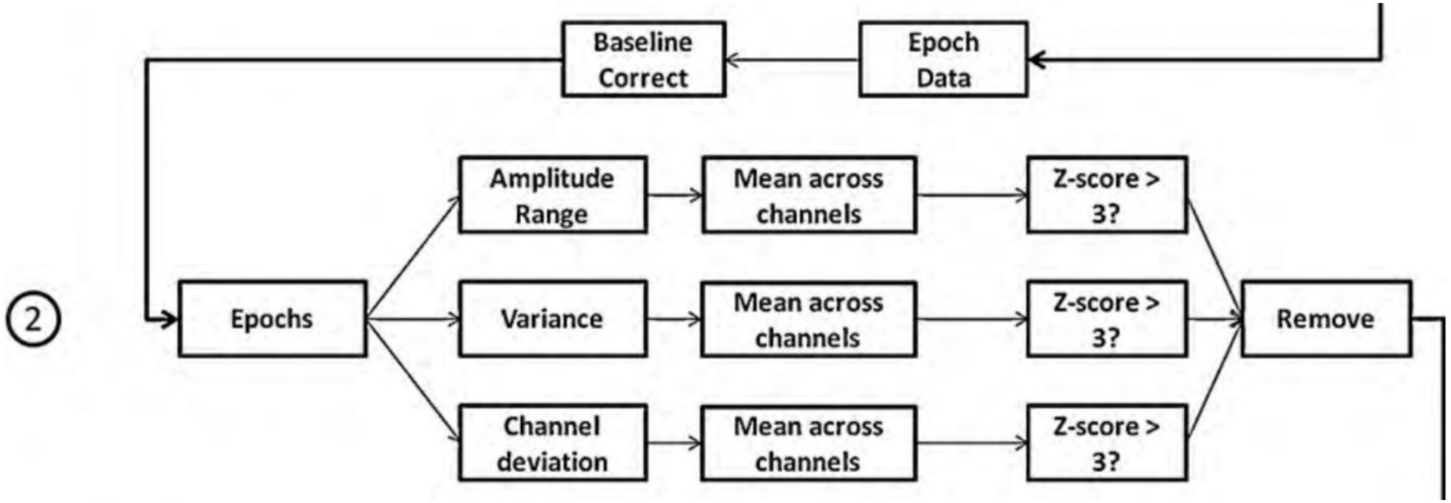
Tools>FASTER

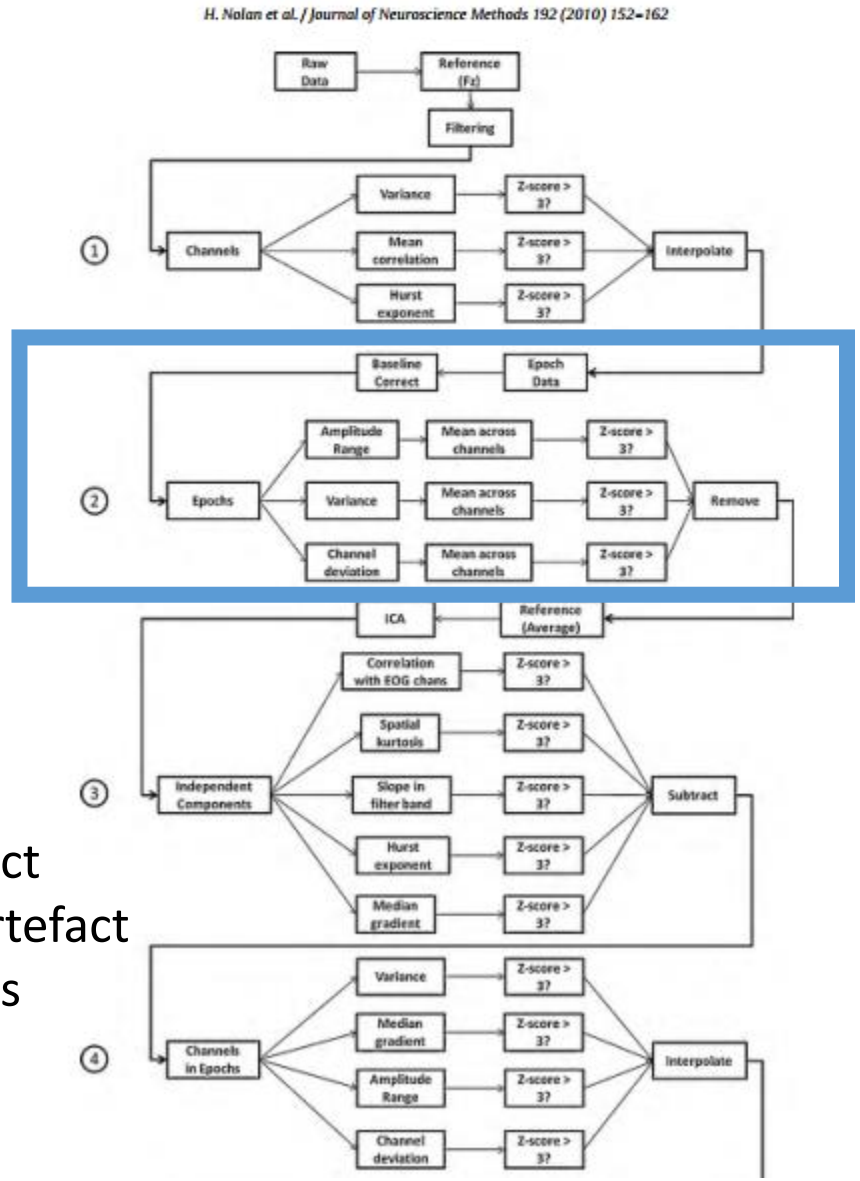


1) Interpolate bad channels globally

- Offline
- Parameters:
  - **Amplitude variance**
  - **Correlation between electrodes:** fit a 2nd order curve based on the distance
  - **Hurst exponent:** measure the long range dependence within a signals (i.e.:trends). Related to autocorrelation

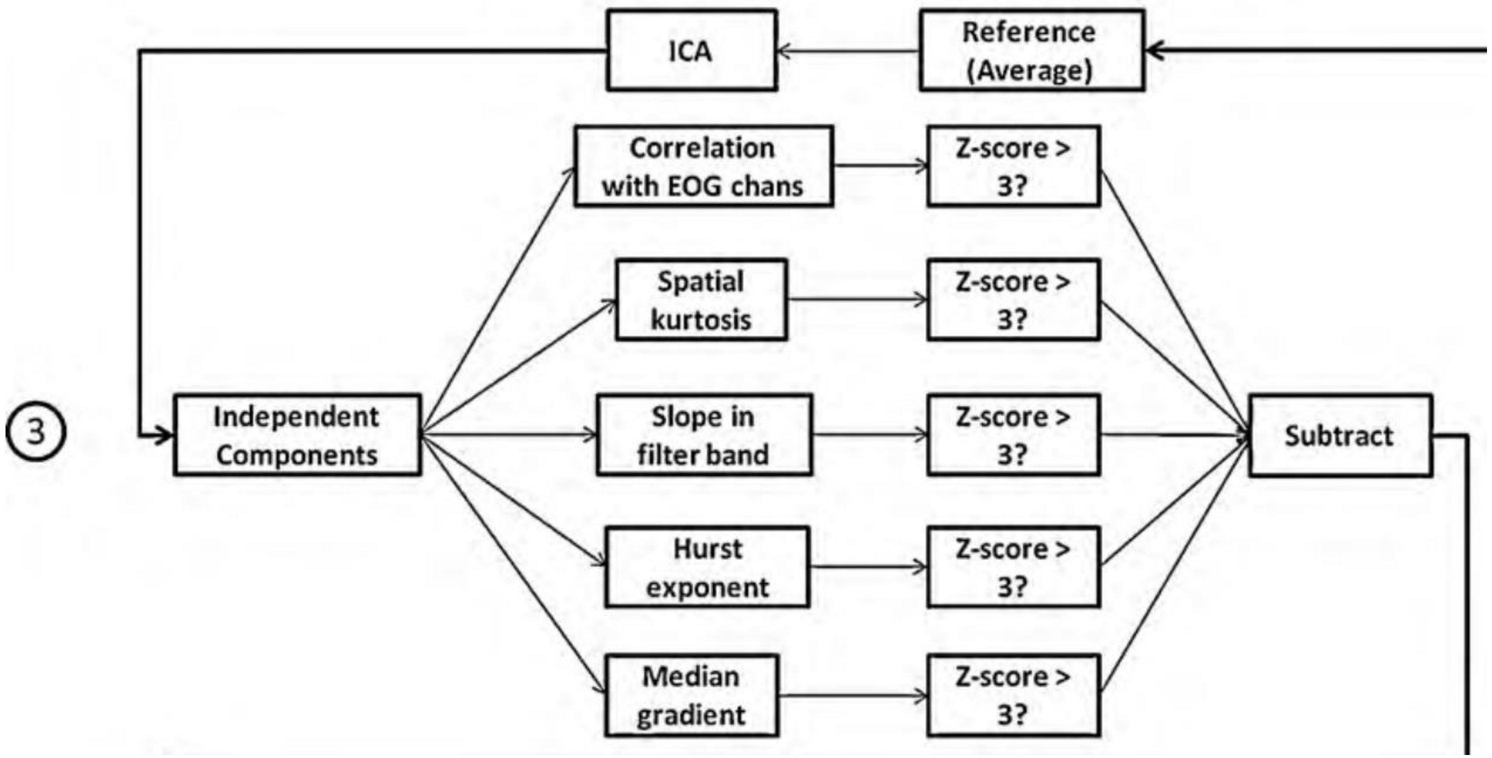






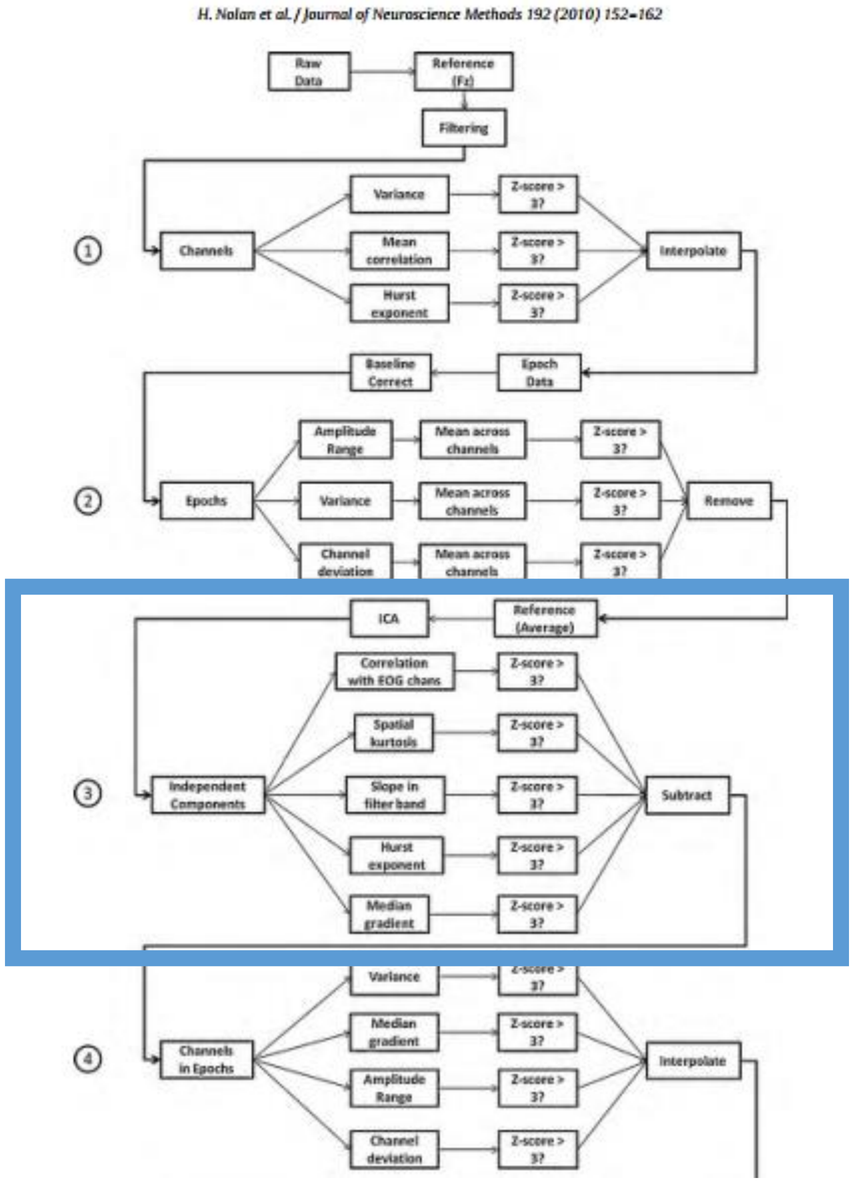
2) Remove bad epochs

- Online
- Parameters:
  - Mean **amplitude range** across channels: for movement artefact
  - Mean **amplitude variance** across channels: : for movement artefact
  - Mean **channel deviation** across channels: for shifting channels



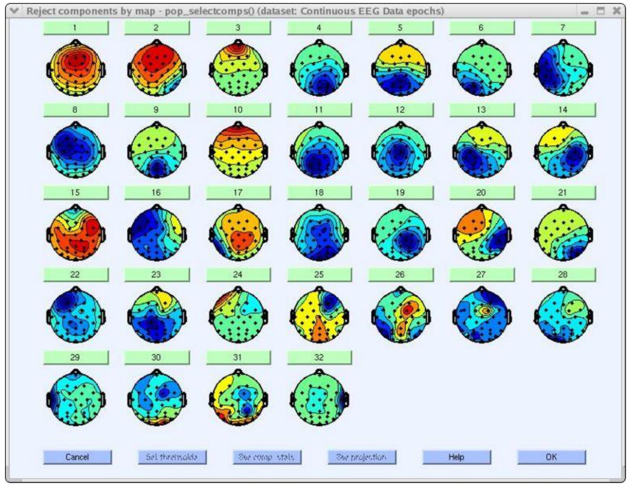
3) Substract independent components (ICs)

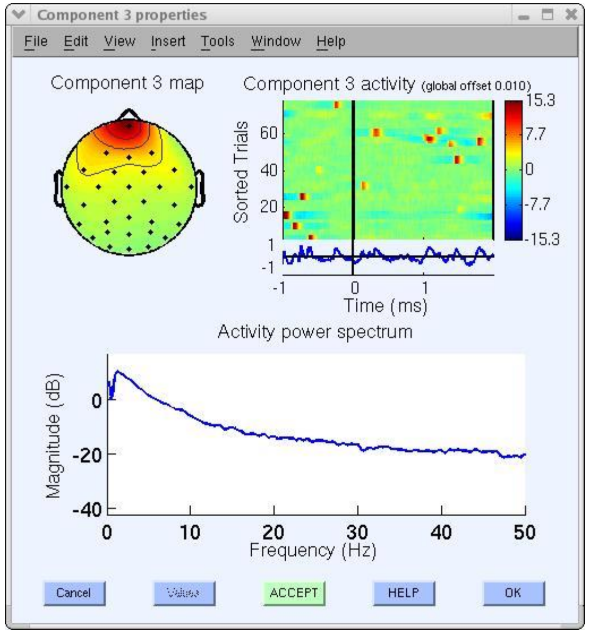
- Online
- IC weights computed offline (~3 min recordings required for 62 channels)
- Eye Channels required! (Fp1, Fp2 applied now)
- Parameters:

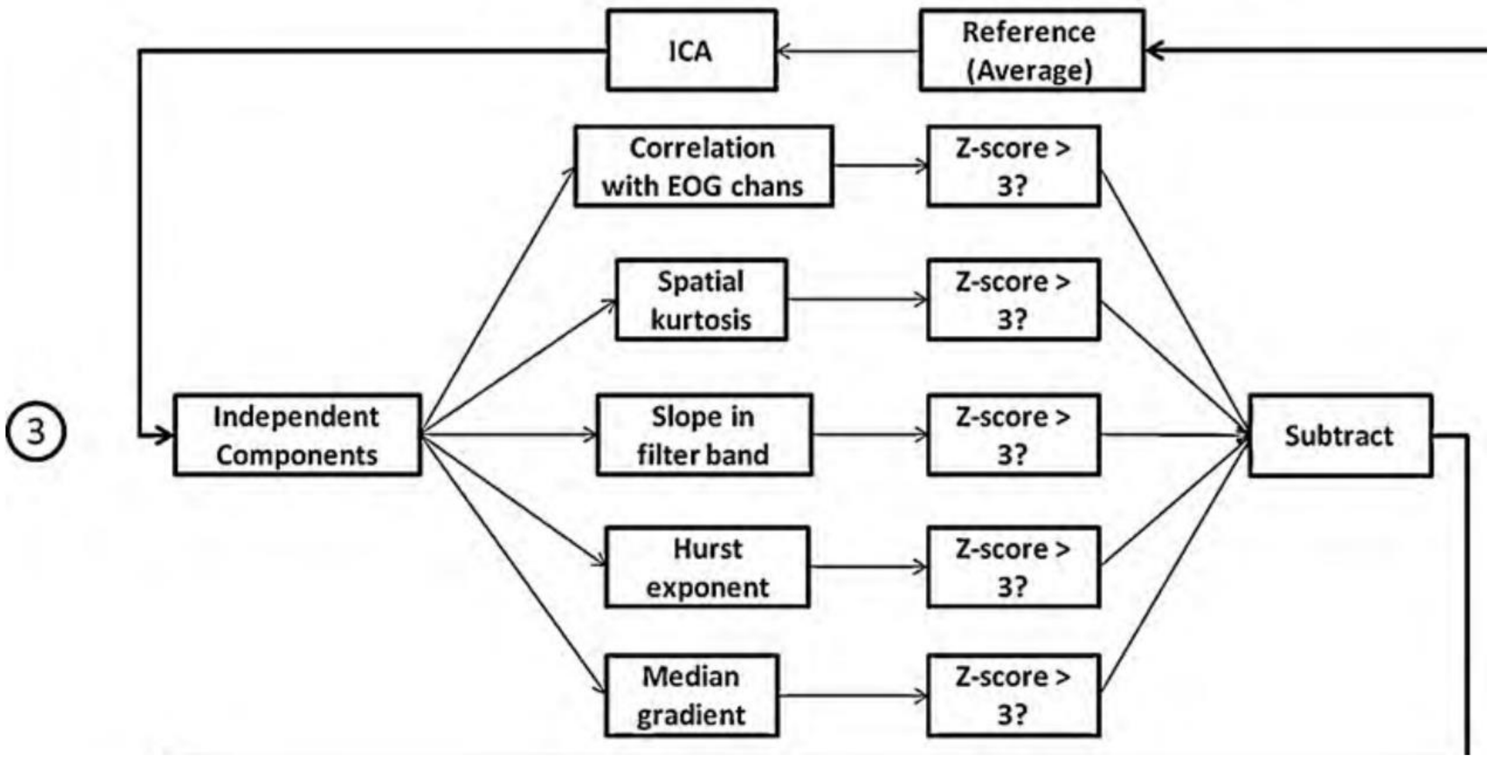


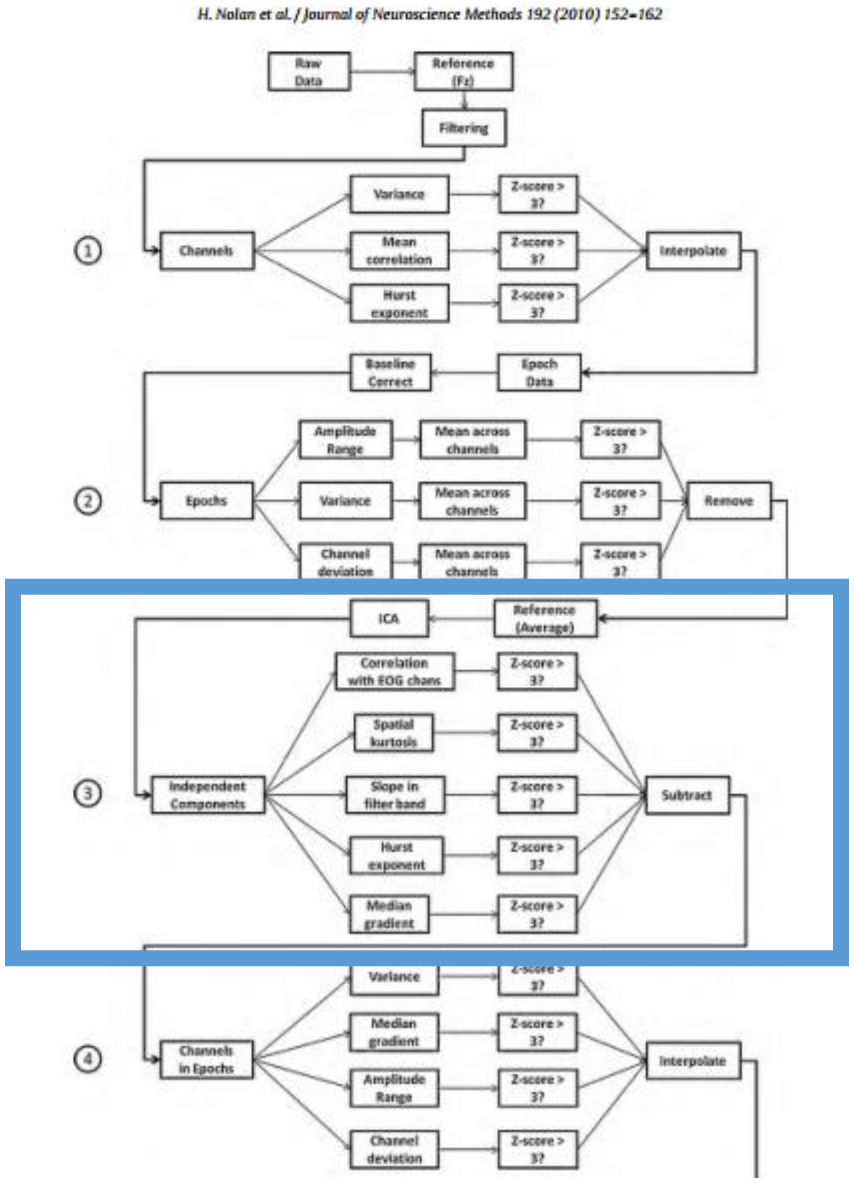
Indipendent component analysis (ICA) in EEGLab

- Indipendent component analysis produces the maximally temporally independent signals available in the channel data. These are, in effect, *information sources* in the data whose mixtures, via volume conduction, have been recorded at the scalp channels.
- In EEGLab:
  - 1) Calculate IC weights:Tools>Decompose data by ICA
  - 2) View&remove components: Tools>Adjust
- Video tutorial: https://www.youtube.com/watch?v=JOvhHSEt-ZU&ab_channel=mathetal



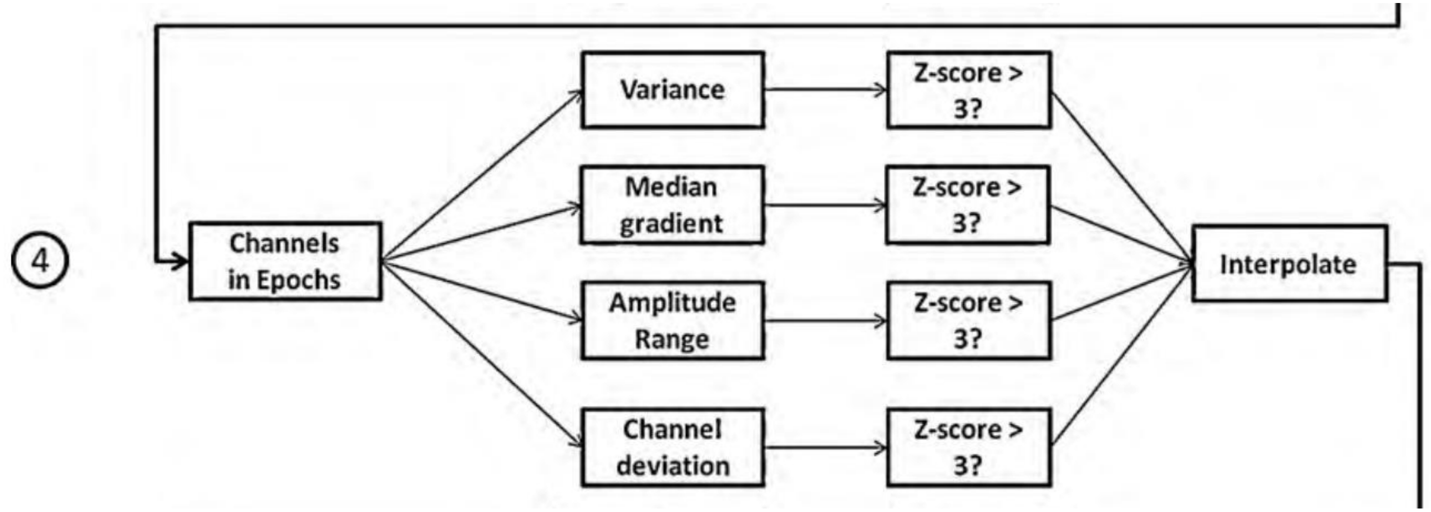






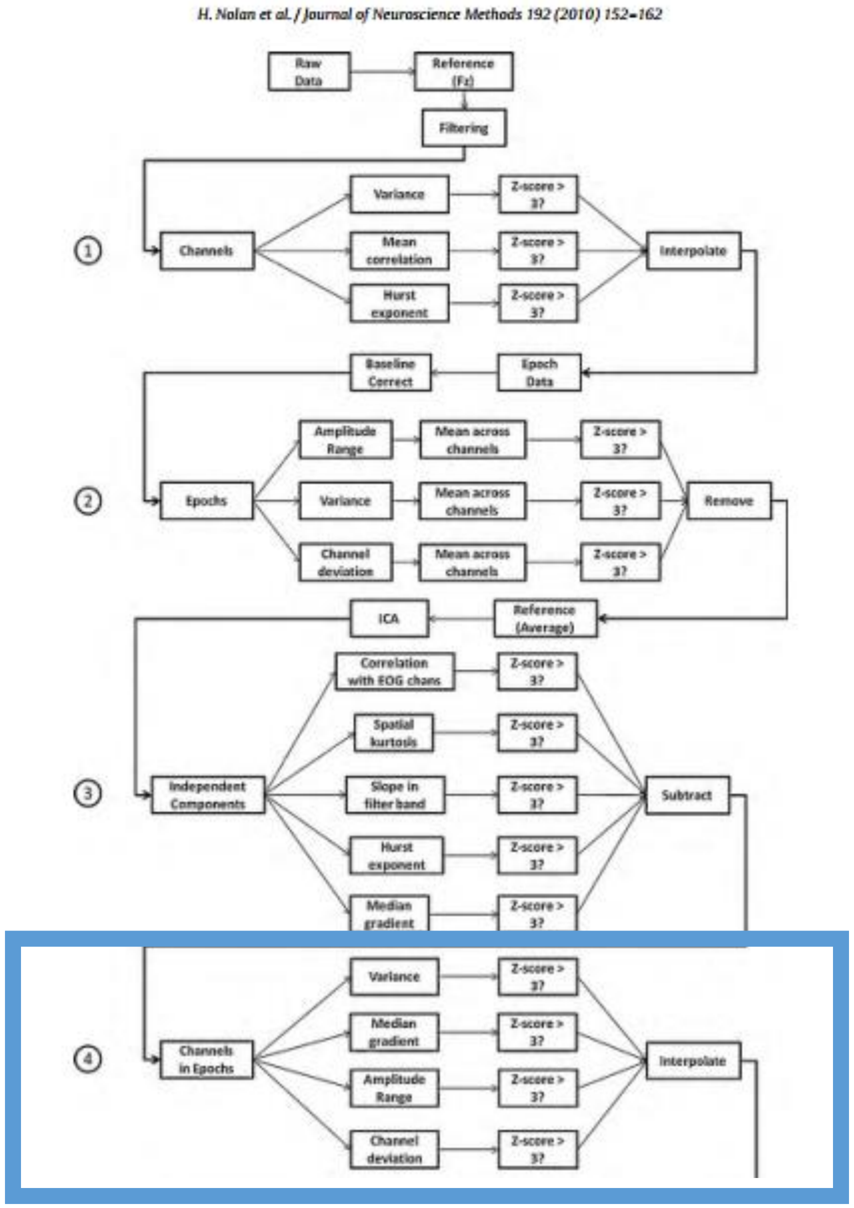
3) Substract independent components (ICs)

- Online
- IC weights computed offline (~3 min recordings required for 62 channels)
- Eye Channels required! (Fp1, Fp2 applied now)
- Parameters:
  - **Correlation with EOG chans**
  - **Spatial kurtosis**: for single channel effects
  - **Slope in filter band**: slope of the spectrum for eliminating white noise
  - **Hurst exponent**
  - **Median gradient:** if the IC have high frequency activity



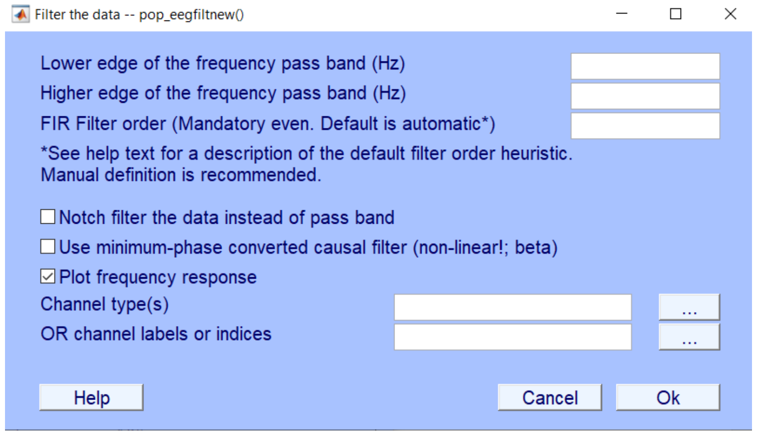
4) Interpolate bad channels within epochs

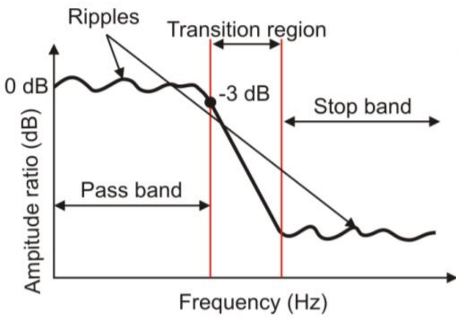
- Online
- Parameters:
  - **Variance**
  - **Mean gradient**
  - **Amplitude range**
  - **Channel deviation**

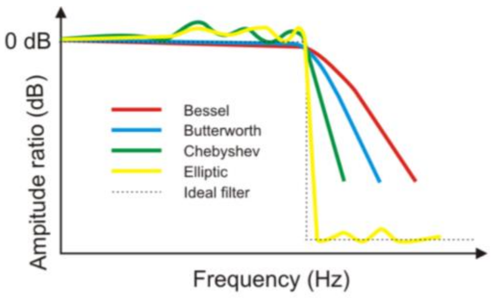


Downsample,filtering, re-referencing

- Downsample (smaller datasets, question of highest frequency of interest)
  - EEGLAB: Tools > Change sampling rate
- Filtering
  - Filtering the continuous data minimizes the introduction of filtering artefacts at epoch boundaries.
  - EEGLAB: Tools > Filter the data > Basic FIR filter (new, default)
  - No phase distortion
- Re-referencing
  - Common/fixed reference: tip of the nose, mastoid, etc
  - Average reference: eliminate the error caused by the noise of the reference
  - Tools > Re-reference the data



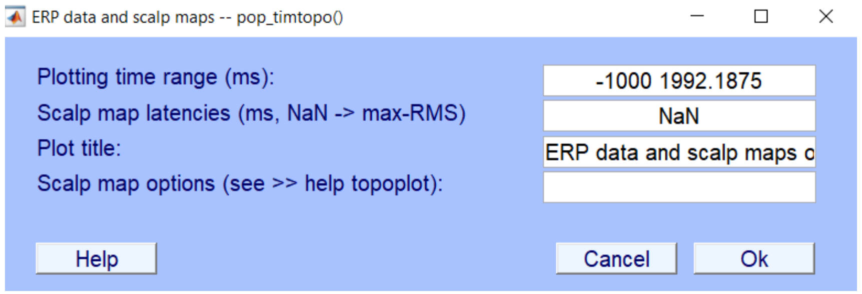


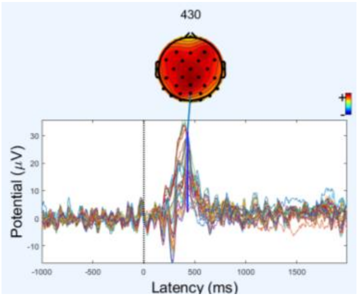


Basic features

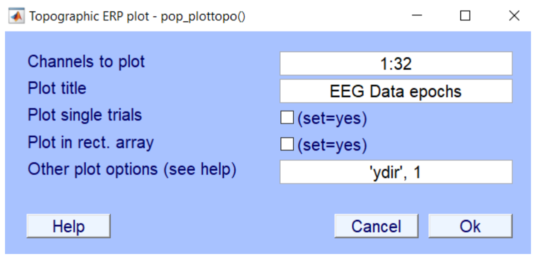
ERP averages and plots

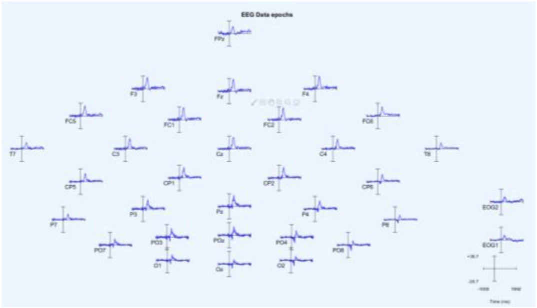
- EEGLab:
  - pop_timtopo(EEG struct, latency);
  - GUI: Plot>Channel ERP> With scalp maps

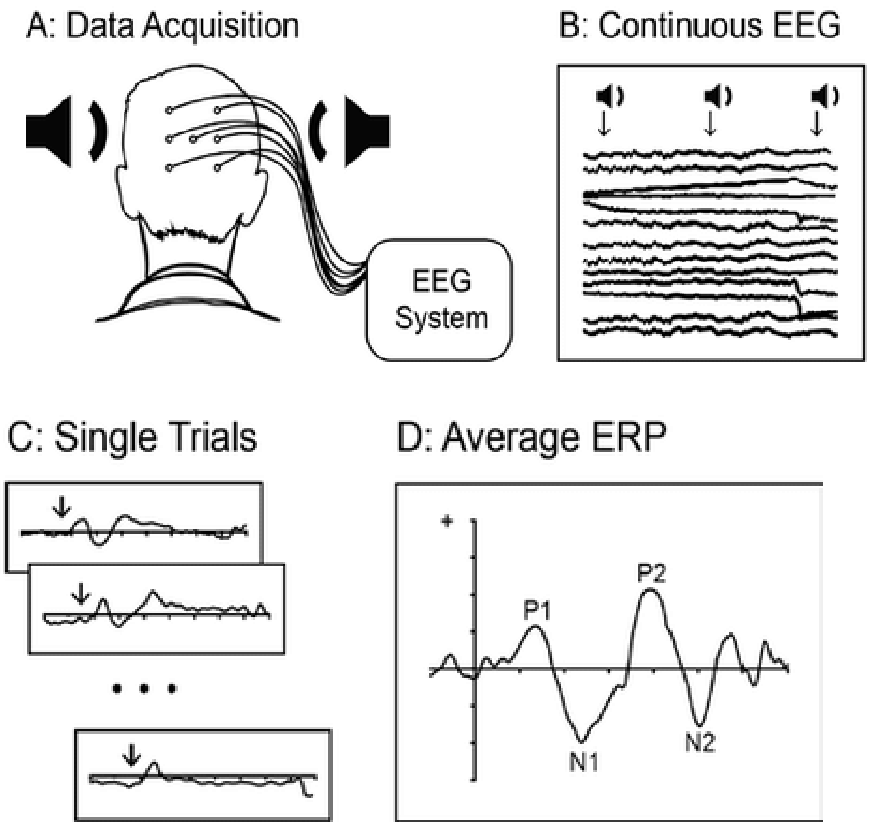




  - GUI: Plot>Channel ERP> In scalp/rect. array





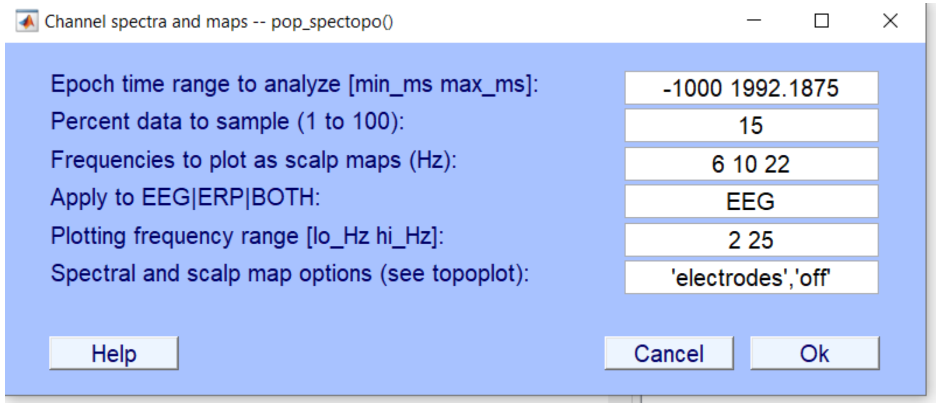


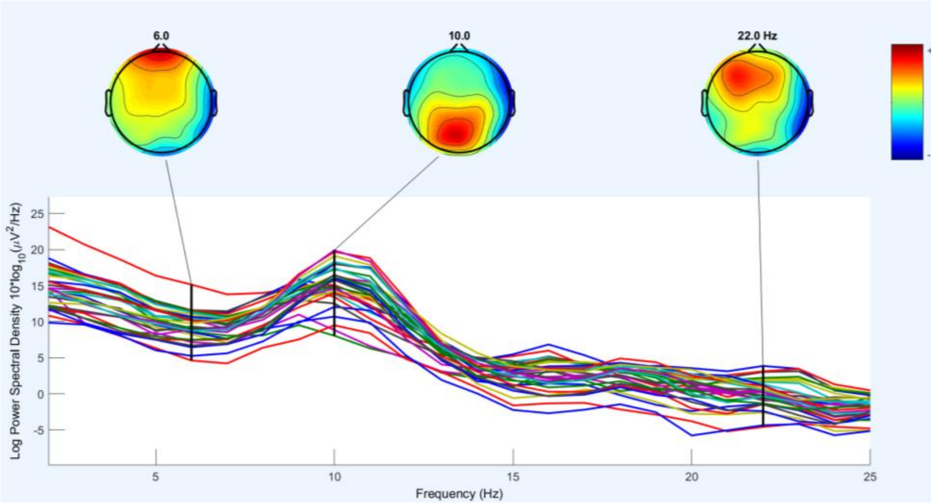
Power spectrum

- Describes the distribution of power into frequency components composing that signal.
- Absolute power:
    - integral of all of the power values within its frequency range
- Relative power:
    - Express the power in a frequency band as a percentage of the total power
    - Correction for absolute differences among the subjects in EEG

In EEGLab:

Plot>Channel spectra maps





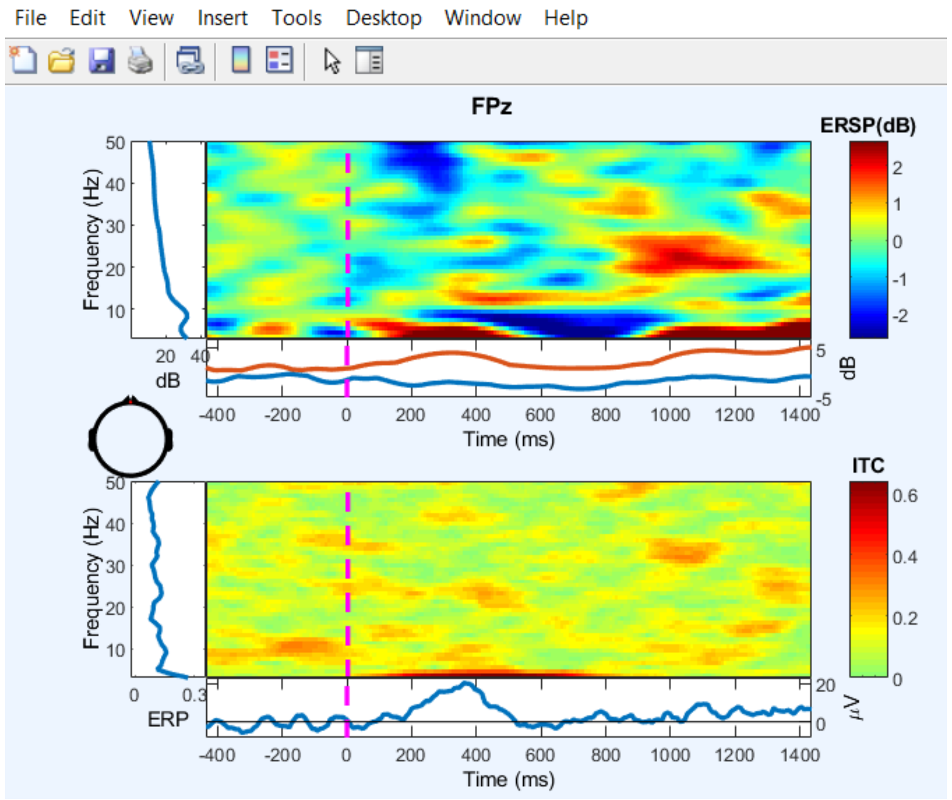
Some advanced features

Time-frequency analysis

- Time/frequency analysis characterizes changes or perturbations in the spectral content of the data considered as a sum of windowed sinusoidal functions (i.e. sinusoidal wavelets).
- Accurate time and frequency resolution
- For trials with triggers:
  - **ERSP** (event-related spectral perturbation): measures average dynamic changes in amplitude of the broad band EEG frequency spectrum as a function of time relative to an experimental event.
  - **ITC** (inter-trial coherence): indicates that the EEG activity at a given time and frequency in single trials becomes phase-locked

EEGLAB:

Plot > Time frequency transforms > Channel time-frequency



Phase amplitude coupling (PAC)

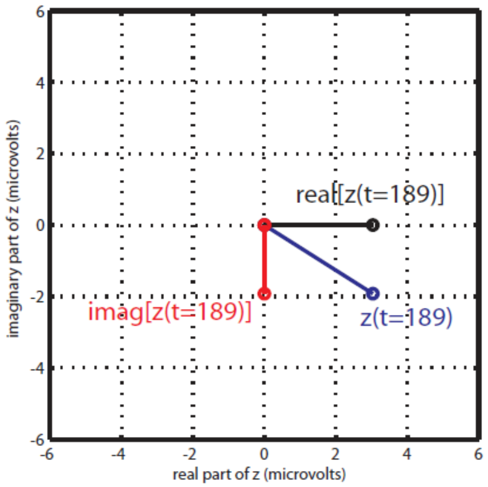
Biological relevance:

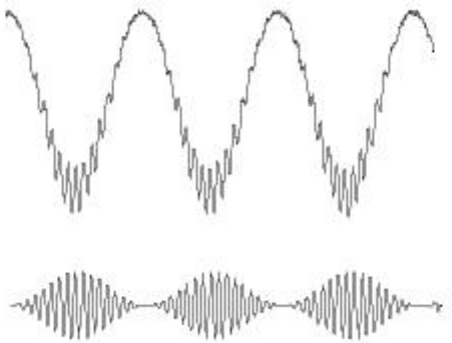
- The current view is that PAC facilitates effective interactions between neurons with similar phase preferences.
- Memory processing
- E.g.: Phase-amplitude coupling of sleep slow oscillatory and spindle activity correlates with overnight memory consolidation

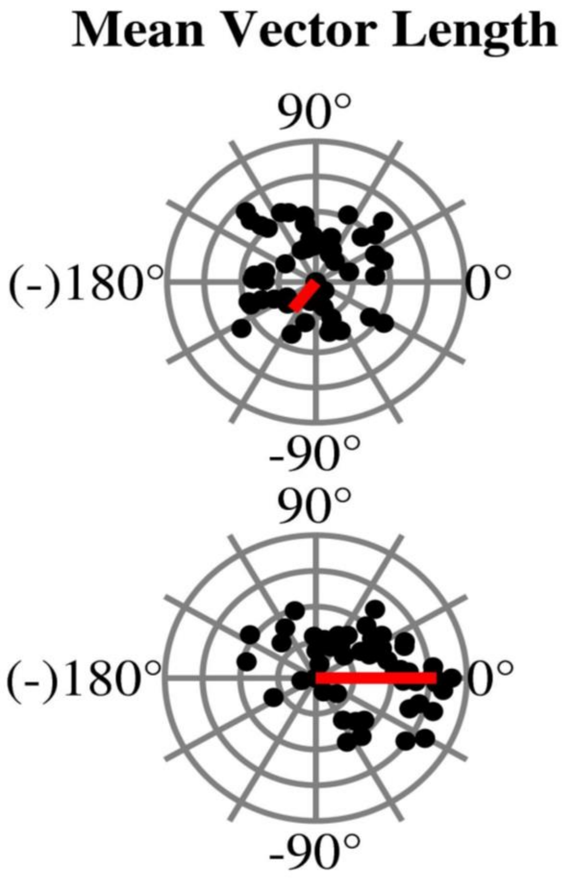
Mean vector length:

- phase of slow; the amplitude of fast rhythm
- length of the complex vector: each instantaneous fast oscillation amplitude component in time
- vector angle: slow oscillation phase of the same time point is represented by the
- PAC= mean vector length

Code:
https://neuroimage.usc.edu/brainstorm/Tutorials/TutPac

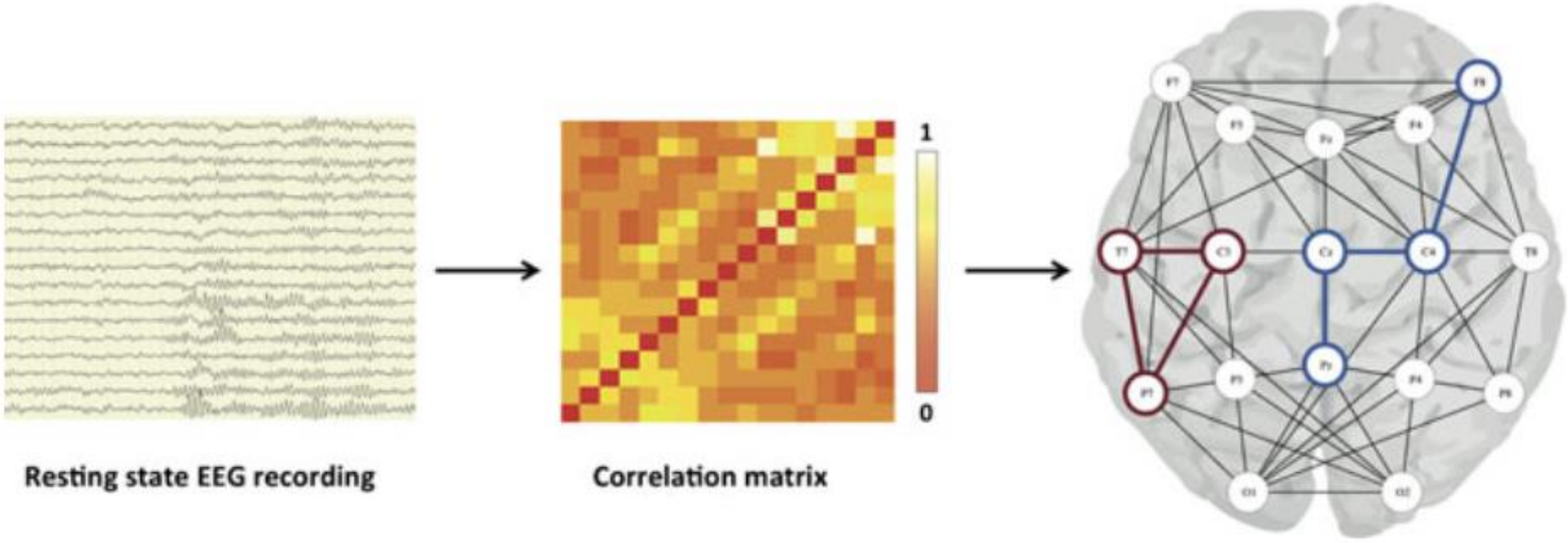






Functional networks in the brain

- Nodes and edges
  - Nodes: recording sites or brain areas (e.g.: source EEG, fMRI)
  - Edges: relation between brain areas (structural or functional)



codes_: https://sites.google.com/site/bctnet/measures/list

Functional connectivity methods

- Functional connectivity (non-directed):
  - Correlation
  - Phase lag index (PLI):
    - asymmetry of the sign of the phase difference
- Effective connectivity (directed):
  - Linear (Granger-causality):
    - based on autoregression,
    - if a signal X_1 "Granger-causes" (or "G-causes") a signal X_2, then past values of X_1 should contain information that helps predict X_2 above and beyond the information contained in past values of X_2 alone.
  - Nonlinear (e.g.: Transfer entropy):
    - measures the increased predictability of Y signal caused by an additional X signal as the difference between the Shannon Entropy of Y conditioned on its own past values and the Shannon Entropy of Y conditioned its own and X signal's past

$$PLI = |\langle \text{sign}[\Delta\phi(t_k)] \rangle|$$

$$X_1(t) = \sum_{j=1}^{p} A_{11,j} X_1(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + E_1(t)$$

$$X_2(t) = \sum_{j=1}^{p} A_{21,j} X_1(t-j) + \sum_{j=1}^{p} A_{22,j} X_2(t-j) + E_2(t)$$

$$T_{X \to Y} = H\left(Y_t \mid Y_{t-1:t-L}\right) - H\left(Y_t \mid Y_{t-1:t-L}, X_{t-1:t-L}\right),$$

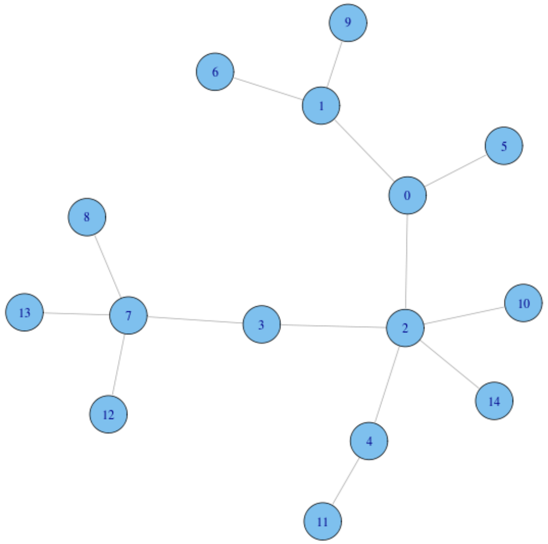
Codes/help:https://neuroimage.usc.edu/brainstorm/Tutorials/Connectivity

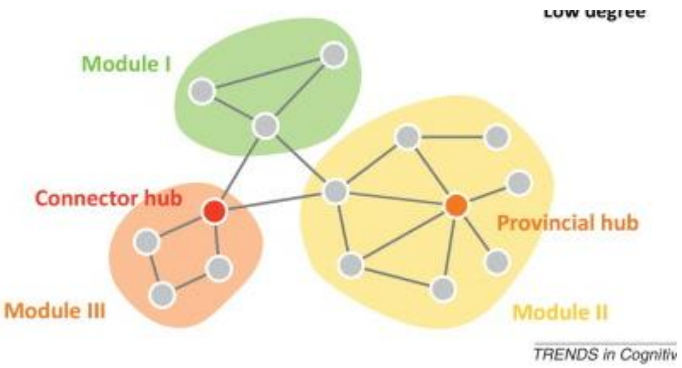
Local network parameters

- Express the role of the individual node
- Comparisons can be made between nodes, or states/conditions/groups

Examples (centrality measures):

- Node strength: sum of weights of links connected to the node
- Betweeness centrality: the fraction of all shortest paths in the network that contain a given node
- Local connectedness: sum of weights of links in the neighbouring nodes
- Modular hubs: strong connections within a module



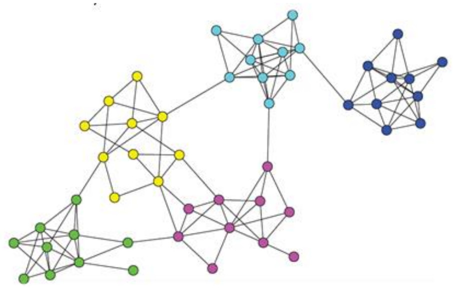


Global network organizations

Community structure

nonoverlapping (Overlapping)

Densely connected subnetworks

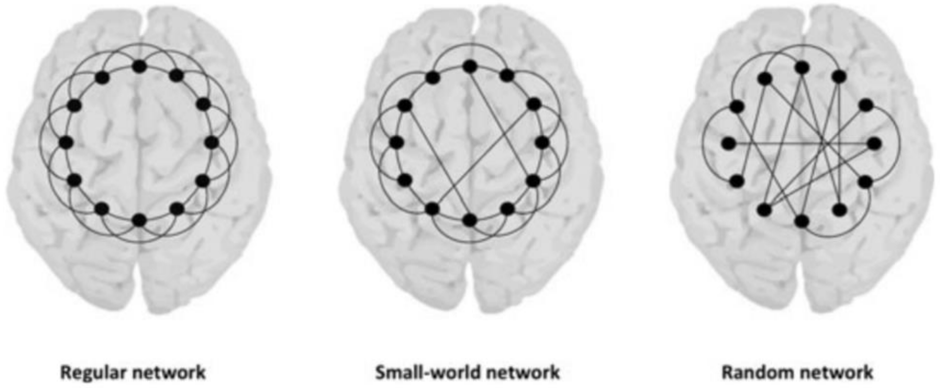


-Express the state of the whole brain network

-Comparisons can be made between states/conditions/groups

Clustering coefficient: $\gamma = \frac{Cl}{\langle Cl_{\text{rand}} \rangle}$, >1

Average path length: $\lambda = \frac{L}{\langle L_{\text{rand}} \rangle}$, ~1

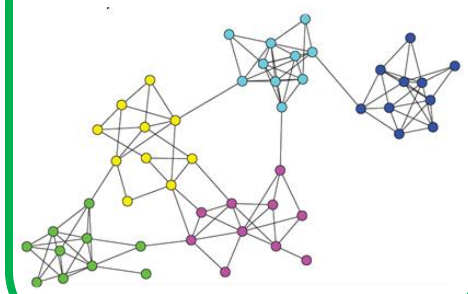


Global network organizations

Community structure

nonoverlapping (Overlapping)

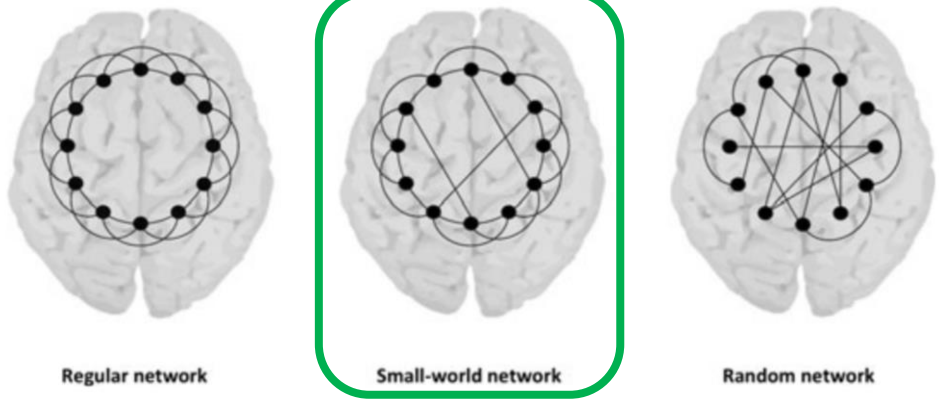
Densely connected subnetworks



HEALTHY BRAIN

Clustering coefficient: $\gamma = \frac{Cl}{\langle Cl_{\text{rand}} \rangle}$, >1

Average path length: $\lambda = \frac{L}{\langle L_{\text{rand}} \rangle}$, ~1



EEG in practice

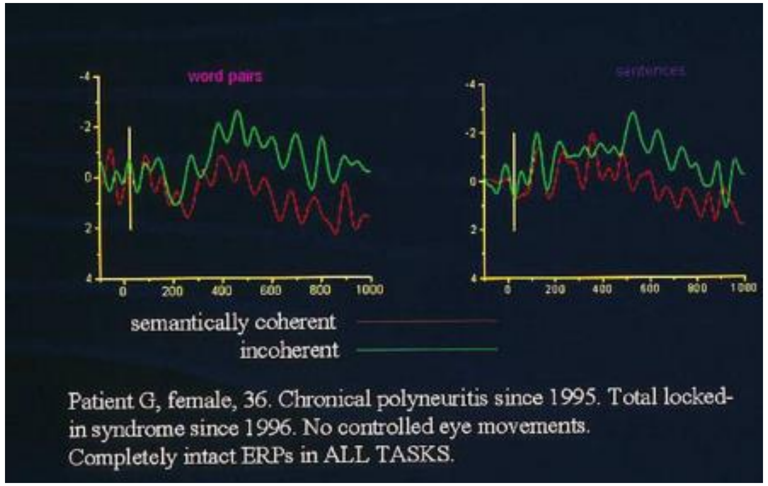
EEG in practice

- Medical application:
  - **Epilepsy (**diagnosis, seizure prediction, **focus localization,…)**
  - Brain tumor
  - Brain damage from head injury
  - Brain dysfunction that can have a variety of causes (encephalopathy)
  - Inflammation of the brain (encephalitis)
  - Stroke
  - Sleep disorders
- **Brain computer interface (non-invasive[EEG],** invasive [ECoG] **)**

Applications of BCI

- replace functions
  - „Locked-in syndrome" (e.g.: Amyotrophic lateral sclerosis, Brainstem (pons) stroke)
- restore functions:
  - stroke rehabilitation
- improve functions:
  - Memory improvement using wearable EEG headset by identifing poorly or well-memorized words from parito-occipital power

Image from Prof. Niels Birbaumer



Prof György Karmos

EEG-BCI

DRAWBACKS:

- poor spatial resolution
- low signal-to-noise ratio (any evoked response which gets embedded within on-going background activity)

ADVANTAGES:

- excellent temporal resolution of less than a millisecond
- portable devices available
- Low cost

Artefacts rejection, filtering, etc

Temporal, spectral, spatial features

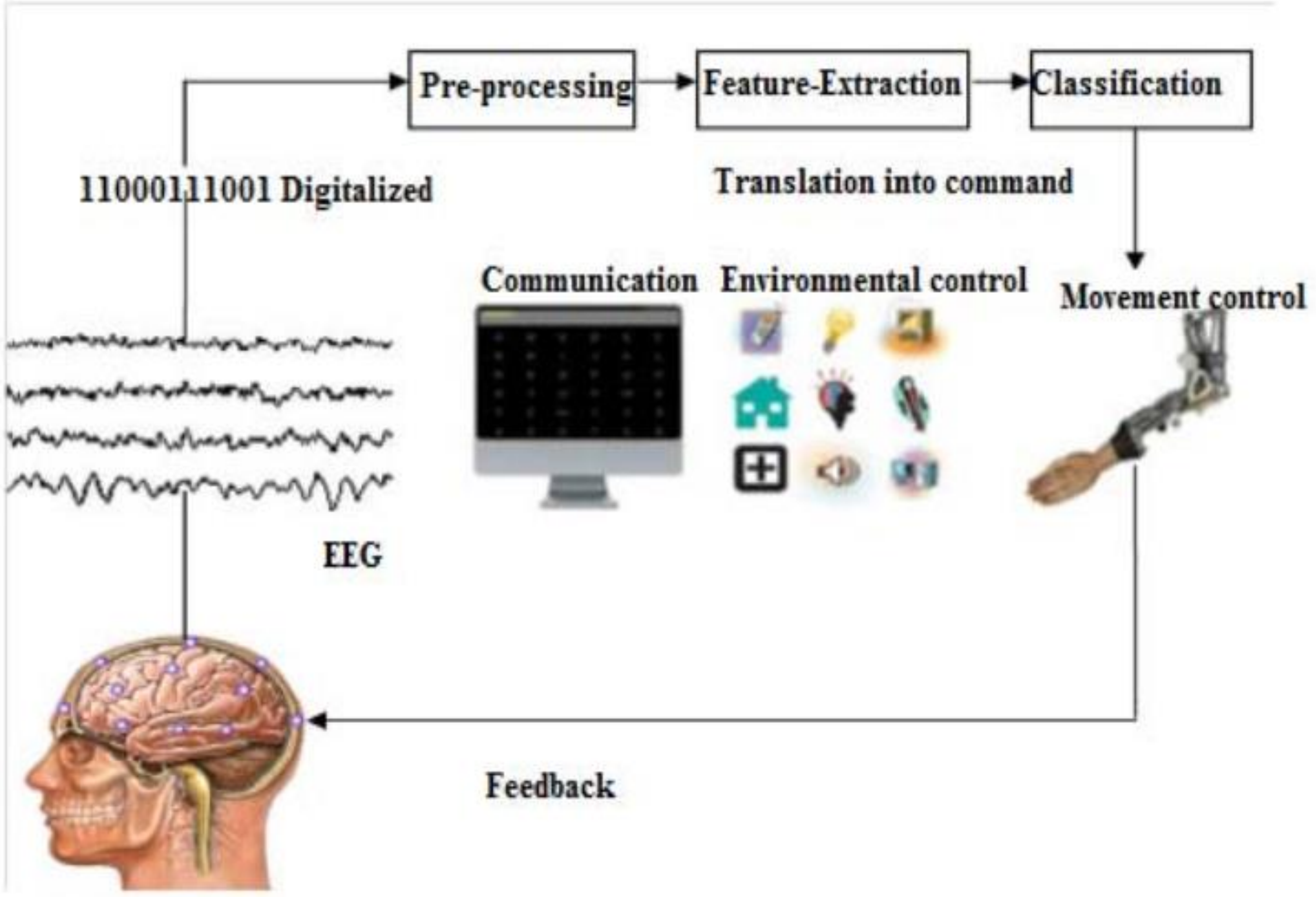
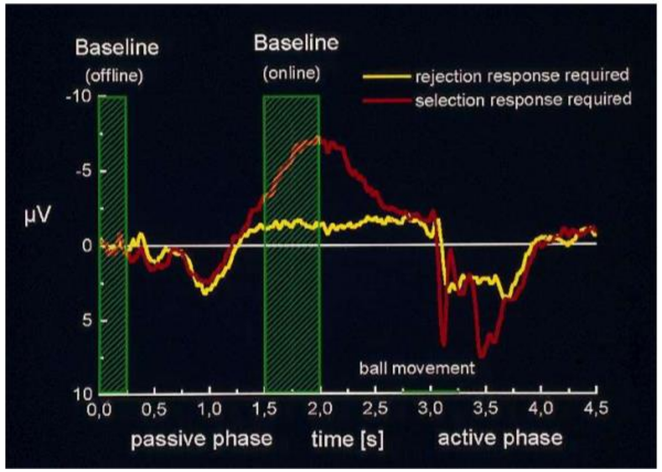


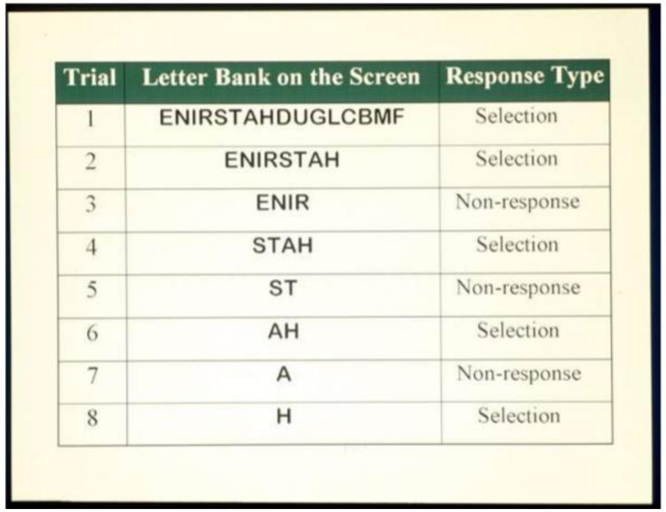
Figure 2: Model of a BCI System

Vaid et al 2015

1) Slow cortical potentials (SCP)

- low frequency potentials (e.g., less than 1 Hz) recorded from the scalp
- Patients are **train**ed to modify SCPs based on feedback and use this paradigm for BCI-based communication (Prof. Niels Birbaumer, Thought Translation Device).





Trial	Letter Bank on the Screen	Response Type
1	ENIRSTAHDUGLCBMF	Selection
2	ENIRSTAH	Selection
3	ENIR	Non-response
4	STAH	Selection
5	ST	Non-response
6	AH	Selection
7	A	Non-response
8	H	Selection

Prof György Karmos

2) Sensorimotor rhythms (SMR) paradigms

Overview

- Defined as the imagination of movements of large body parts
- causes event-related desynchronization (ERD) in mu (8–12 Hz) and beta rhythms (18–26 Hz) in the contralateral central electrodes (motor cortex)
- Require training (weeks, months)

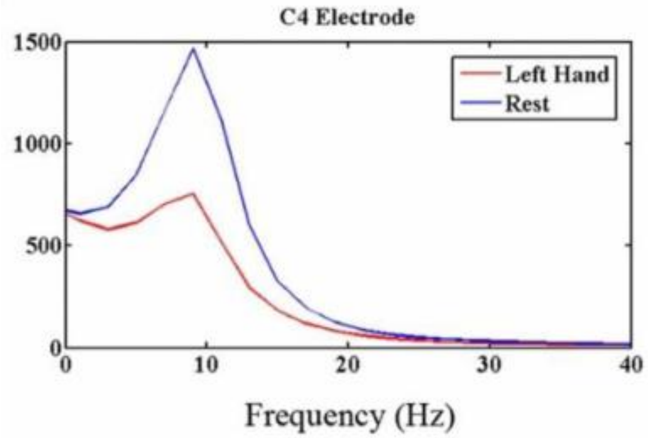
Analysis and classification methods

- SVM outperforms the other classifiers in SMR features classification
- time-frequency features could better depict the non-stationary nature of EEG SMR

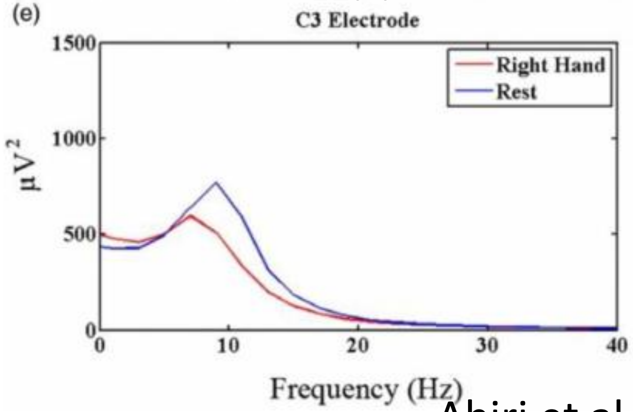
Applications

- one-dimensional computer cursor movement
- Open and close a prosthetic hand with imagined right or left-hand movement.
- restore hand grasp in a patient with tetraplegia
- control objects such as quadcopters

RIGHT

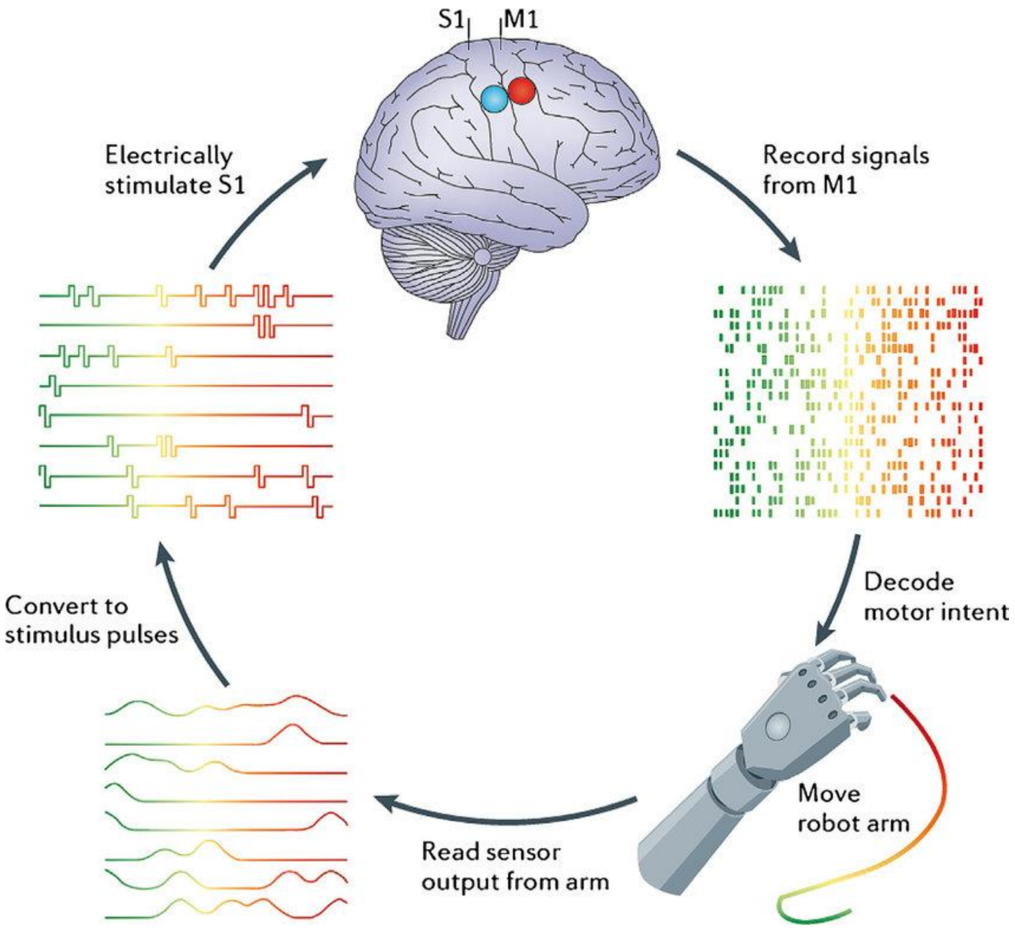


LEFT



Abiri et al 2019

BCI – based on the activity of motor cortex (invasive)



Prof György Karmos

3) Imagined body kinematics paradigms

Overview

- low-frequency components of EEG signals (<2 Hz) located over motor cortex carry kinematic information
- subject is asked to imagine the continuous movement of only one body part in multi-dimensional space

Analysis and classification methods

- wrist rotation and extension at fast and slow speeds.
    - EEG signals were low-pass filtered at 2 Hz and the negative slope 2 s before the movement onset known as Bereitschaftspotential (BP).
    - BP has two parts, the NS1 (Negative Slope of early BP) and the NS2 (steeper Negative Slope of late BP). The NS1, NS2, and the mu (8–12 Hz) and beta rhythms (18–26 Hz) constituted the feature space in their study
- By comparing the decoding performance with and without EOG contaminated brain signals, they found that eye movement plays a significant role in IBK tasks

Applications

- poor decoding of EEG signals
- can be operated with zero-training

Abiri et al 2019

4) Visual P300 paradigms

Overview

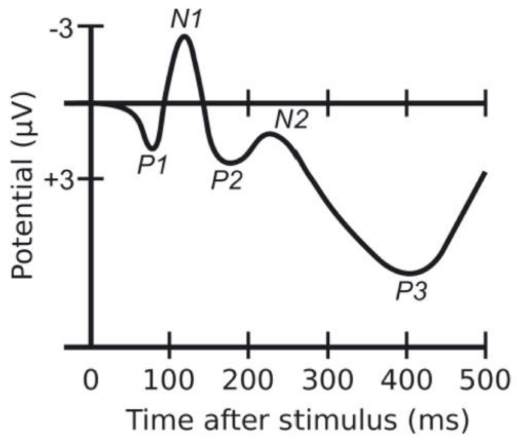
- P300 component is elicited in response to infrequently presented events using what is known as an ‘oddball paradigm’
- Advantege:
    - subjects can use it with very high accuracy and it can be calibrated in minutes
- Disadvanteges:
    - fatigue from the high level of attention and visual focus
    - inability for people with visual impairments to use the system

Analysis and classification methods

- Farwell and Donchin P300 speller
- speed/accuracy trade-off: presenting multiple trials and averaging the EEG response is required to increase the signal-to-noise ratio
- extract an analog control signal with a single-trial approach using a genetic algorithm
- adding occipital electrode locations to the p300 speller (central midline) significantly improved the discriminability of data samples
- language model to enhance typing speed was utilized

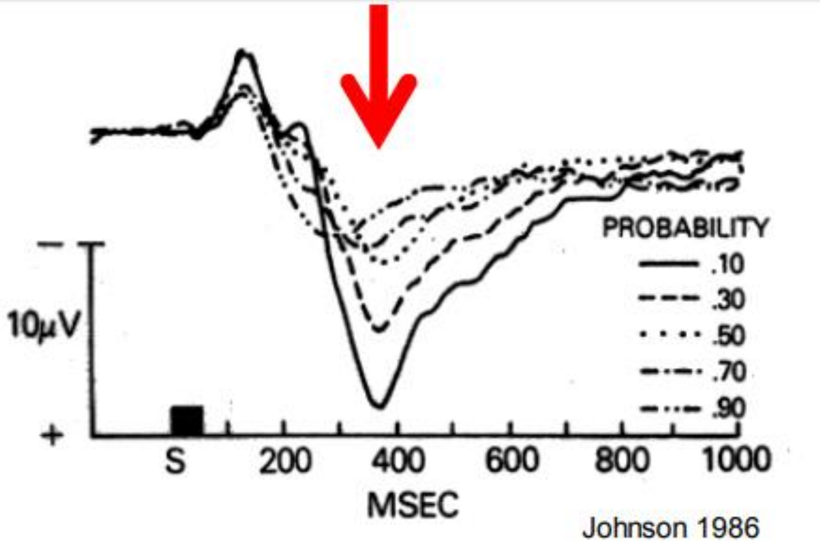
Applications

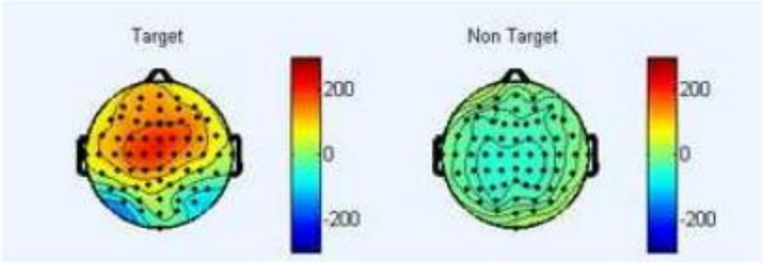
- keyboards to provide a pathway of communication for disabled patients
- navigate a wheelchair
- his paradigm was also employed to control a computer cursor in 2D space by paralyzed patients.

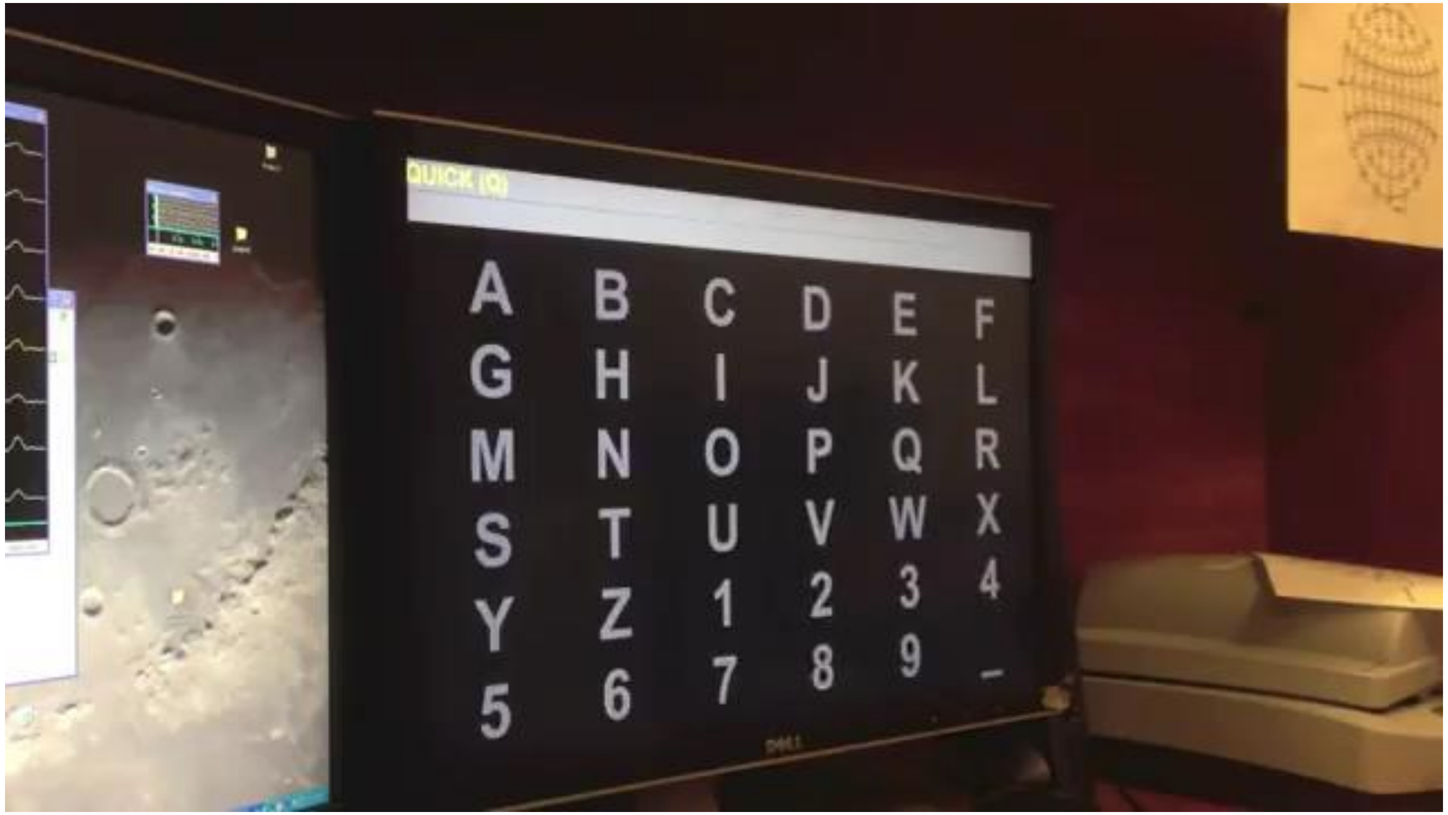


Abiri et al 2019

P300 BCI







Prof Karmos György

5) Steady state visual evoked potential paradigms

Overview

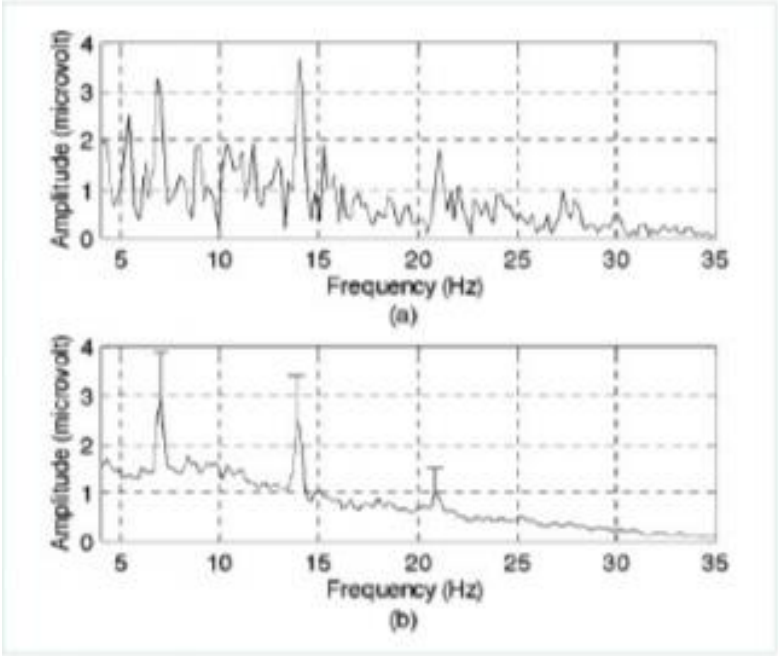
- shift gaze and as well as their attention to flickering stimuli, which requires highly accurate eye control
- strong correlation between flicker frequency and the observed frequency of the EEG in visual areas
- no-training paradigm that can be used by many subjects
- flickering stimuli could lead to fatigue for the subject, mainly when using low flickering frequency (high-frequency flicker (60–100 Hz) is preferred)

Analysis and classification methods

- SSVEP is less vulnerable to artifacts -> mobile applications can be developed
- Fast information transfer rate: P300 or SMR paradigms reach 4–60 bits min−1 information transfer, SSVEP-based BCIs yield 100 bits min−1
- determination of user-specific optimal stimulation duration and phase interval

Application

- control a humanoid robot
- exoskeleton could be accurately controlled
- used to allow a cockroach to navigate the desired path
- navigate in a two-dimensional BCI game



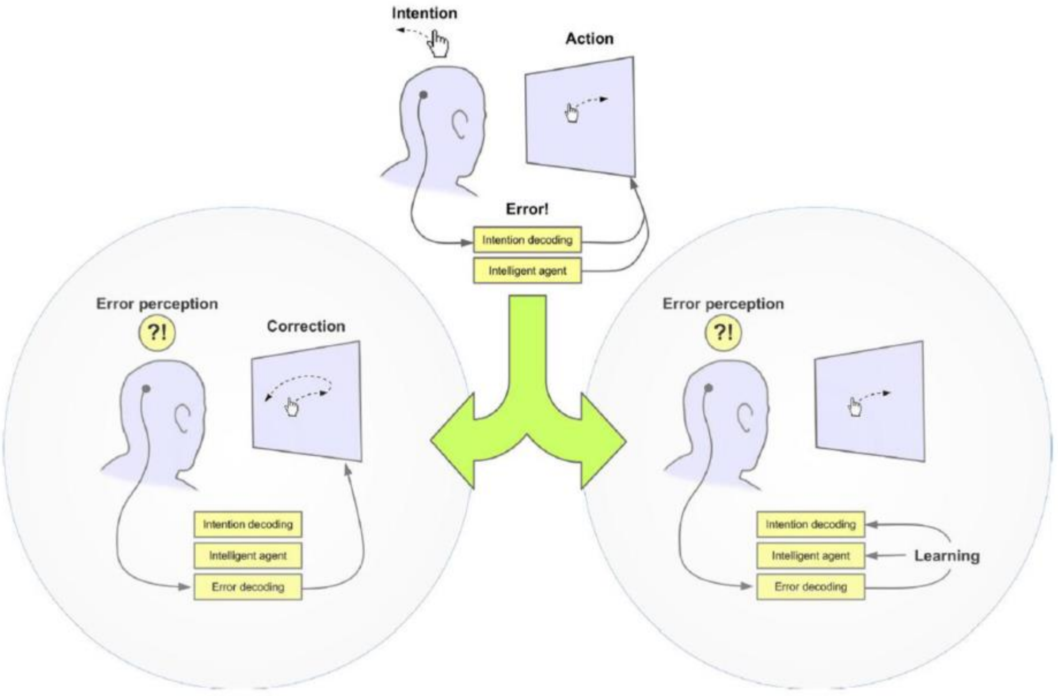
Amplitude spectrum of SSVEP to 7 Hz stimulation .
a: single trial spectrum
b: average of 40 trials, vertical lines give SD

Abiri et al 2019

Prof György Karmos

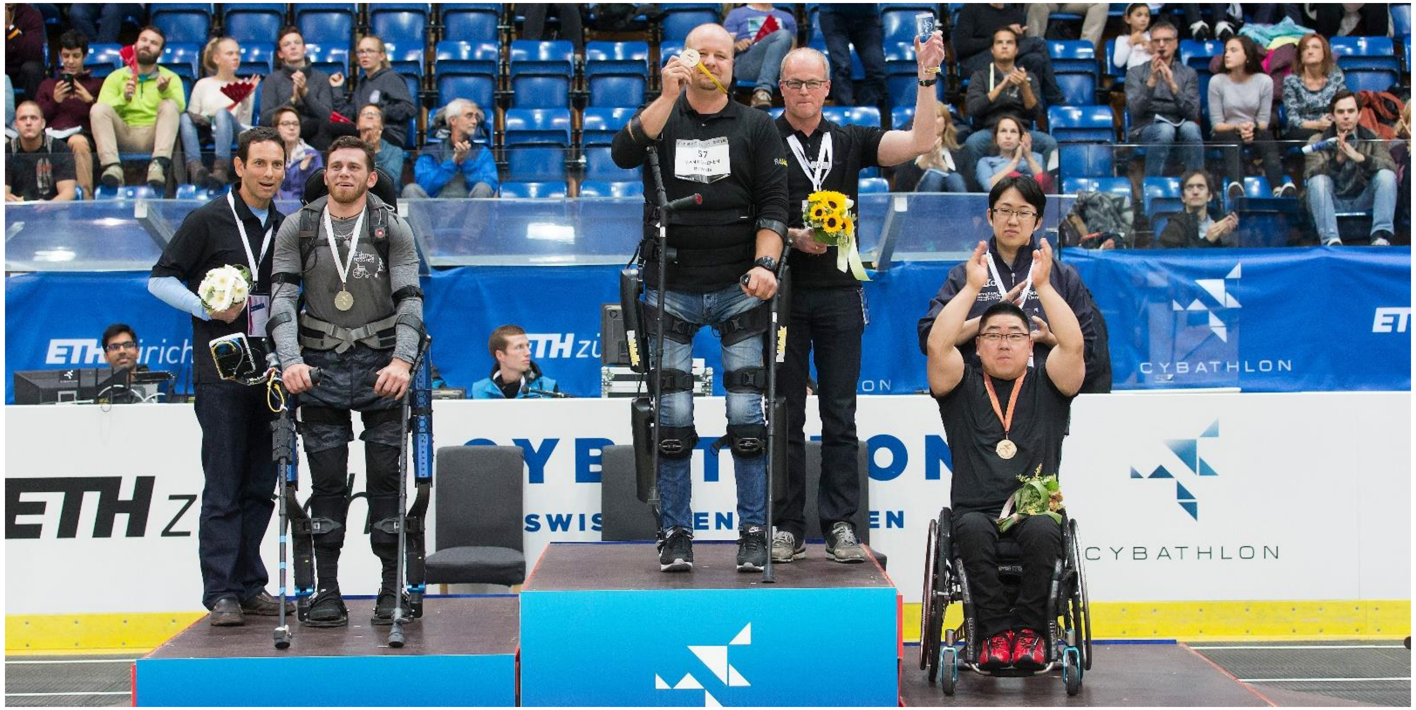
6) Error-related potential (ErrP)

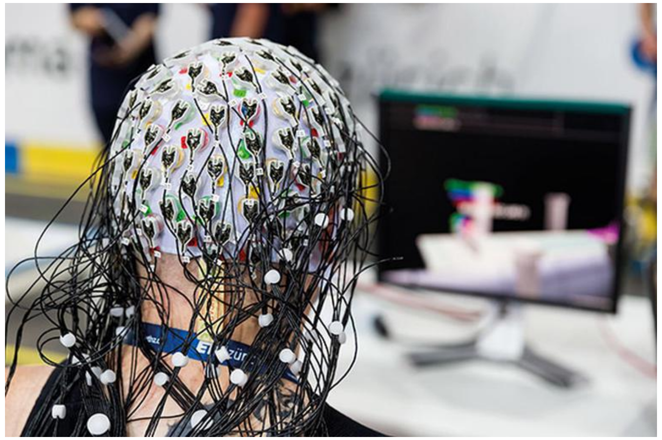
- ErrP occurs when there is a mismatch between a subject's intention to perform a given task and the response provided by the BCI.
- frontal and central lobes and has a latency of 200–700ms
- The ErrP can be used to adjust the input control signals to the device
- Problems:
  - In contrast to a traditional control system, in which error signal can be sensed in milliseconds, the brain does not produce an ErrP until 200 ms–700ms after the subject receives feedback: makes real-time implementation difficult.
  - ErrP does not contain any information about direction or magnitude



Abiri et al 2019

Cybathlon – Bionic Olimpics





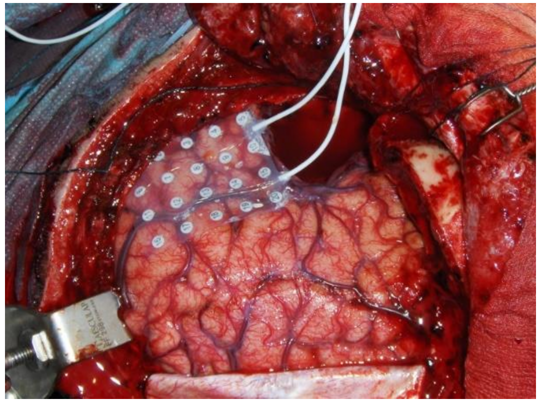
Application	Time to market
Control of devices	5-10 yrs
User state monitoring	3-5 yrs
Evaluation	1-3 yrs
Training and education	3-5 yrs
Gaming and entertainment	Now
Cognitive improvement	3-5 yrs
Safety and security	5-10 yrs

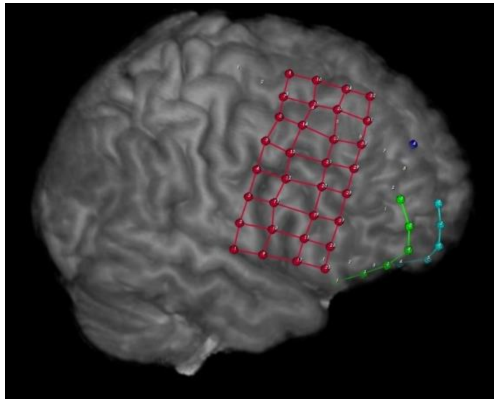
Table 1. BCI market overview

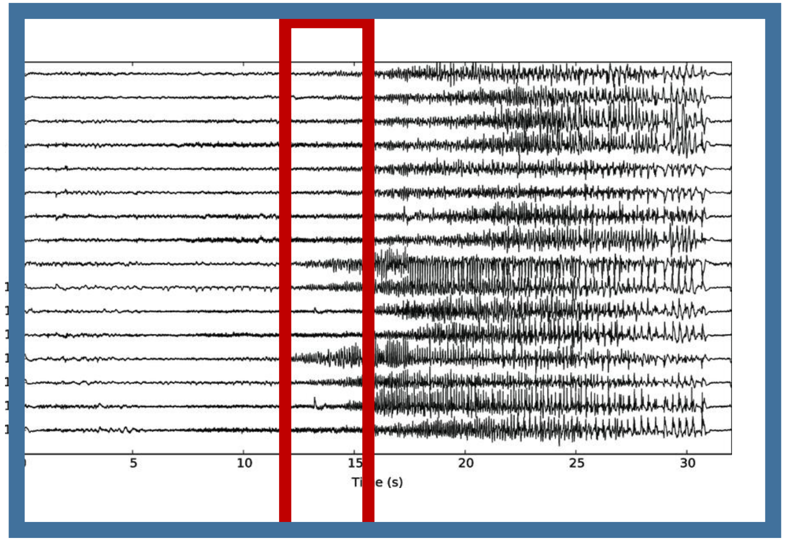
Bularka et al, 2016

Traditional localization of the seizure onset zone

- occurrence of unprovoked seizures and affects ~1% of the world’s population
- approximately one-third of people with epilepsy continue to have seizures despite taking medications
- in such cases, one treatment option is surgical resection of the brain tissue responsible for seizures
- depends critically on accurate localization of the pathological brain tissue, which is referred to as the seizure onset zone (SOZ)
- SOZ localization requires implanting of electrodes for intracranial EEG (iEEG) that is recorded over several days to allow suffcient time for spontaneous seizures to occur
- Problem with seizure initialization:
  - Long (several days) monitoring
  - Low number of seizures
  - Heterogenous seizure initialization







Seizure onset seizure

Interictal electrophysiological biomarkers of epilepsy

Univariate biomarkers (on single channels)

- HFOs (high-frequency oscillations)
- interictal epileptiform discharges (IEDs)
- PAC (Phase-amplitude coupling)
- CFC (Cross-frequency coupling)

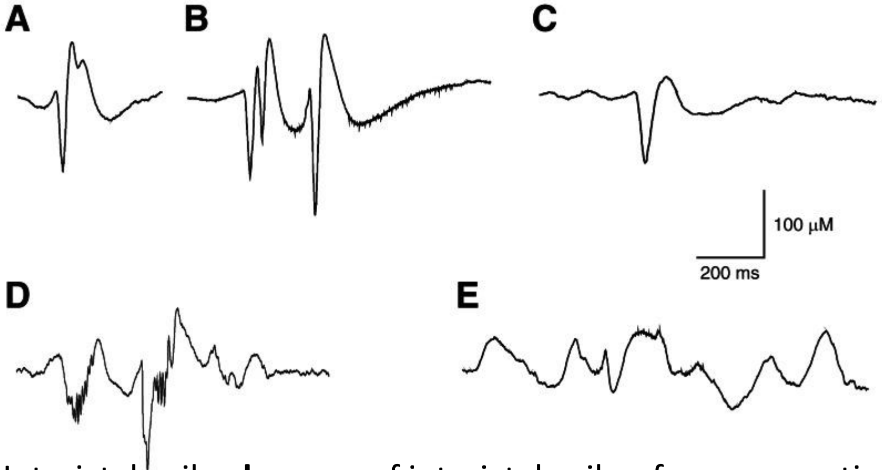
Bivariate biomarkers (on multiple channels)

- Functional/effective connectivity
- Network parameters

1) Integrating artificial intelligence with real-time intracranial EEG monitoring to automate interictal identification of seizure onset zones in focal epilepsy

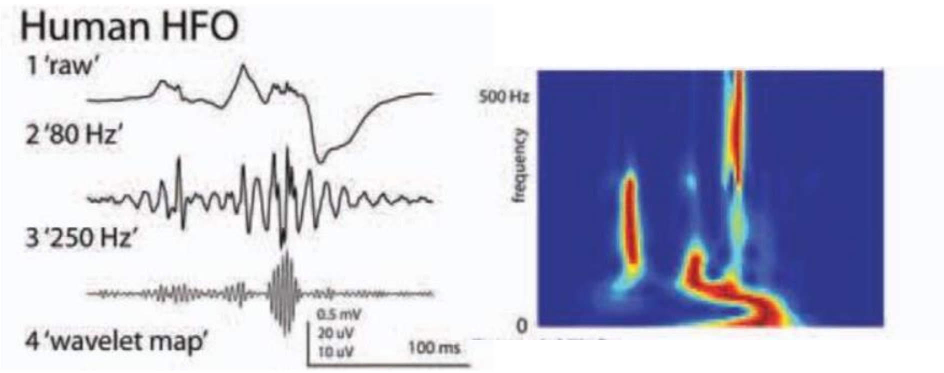
Univariate biomarkers (on single channels)

- HFOs (high-frequency oscillations)
  - neurons firing asynchronously
  - >80Hz, EEG needs to be sampled at least at 2kHz
- interictal epileptiform discharges (IEDs)
  - diverse ligand-gated mechanisms activate IEDs and lead to network hyperexcitability
- PAC (Phase-amplitude coupling)



Curtis et al, 2012

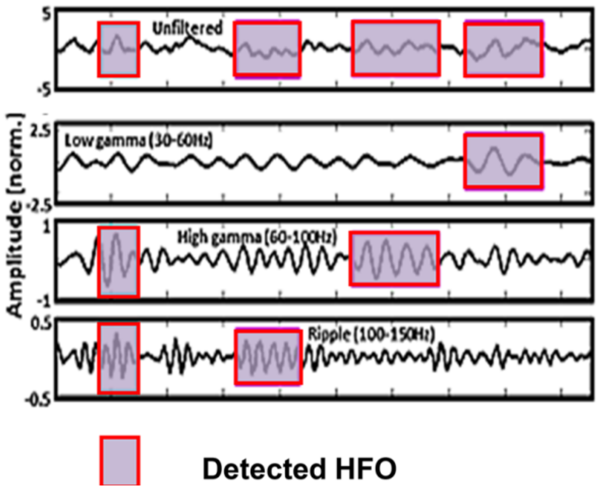
a Interictal spike; **b** group of interictal spikes from neocortical dysplasia, **c** sharp wave from a lesional partial epilepsy; **d** fast activity (brushes) riding on a spike recorded from a Taylor type II focal cortical dysplasia; **e** paroxysmal slow activity superimposed to slow spikes recorded in a lesional partial epilepsy.

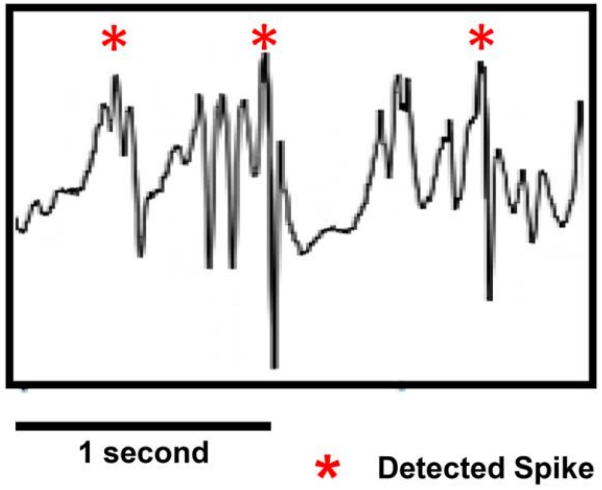


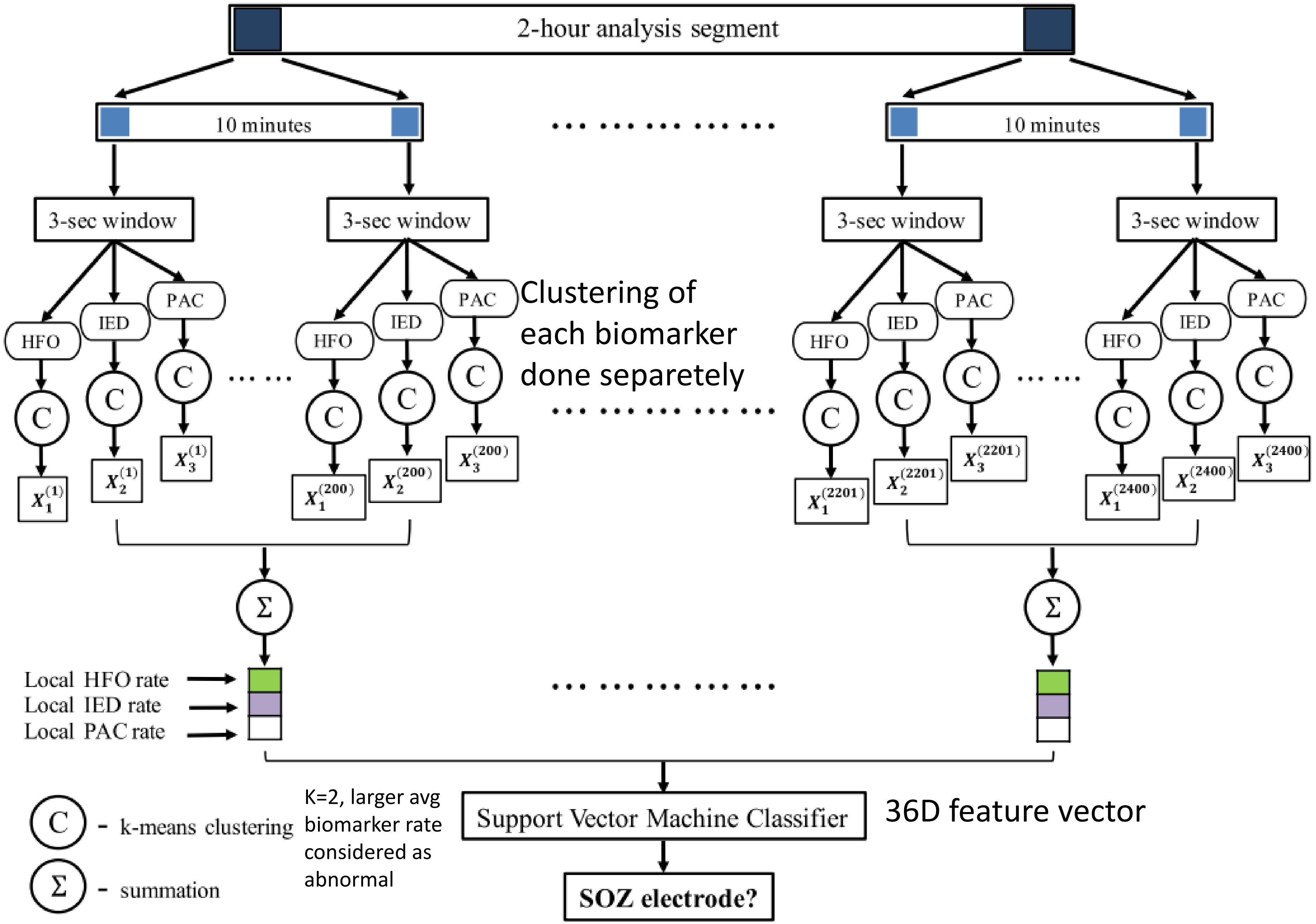
Yogatheesan Varatharajah *et al* 2018
Zijlmans et al, 2012

Detection of HFOs, PAC, IEDs

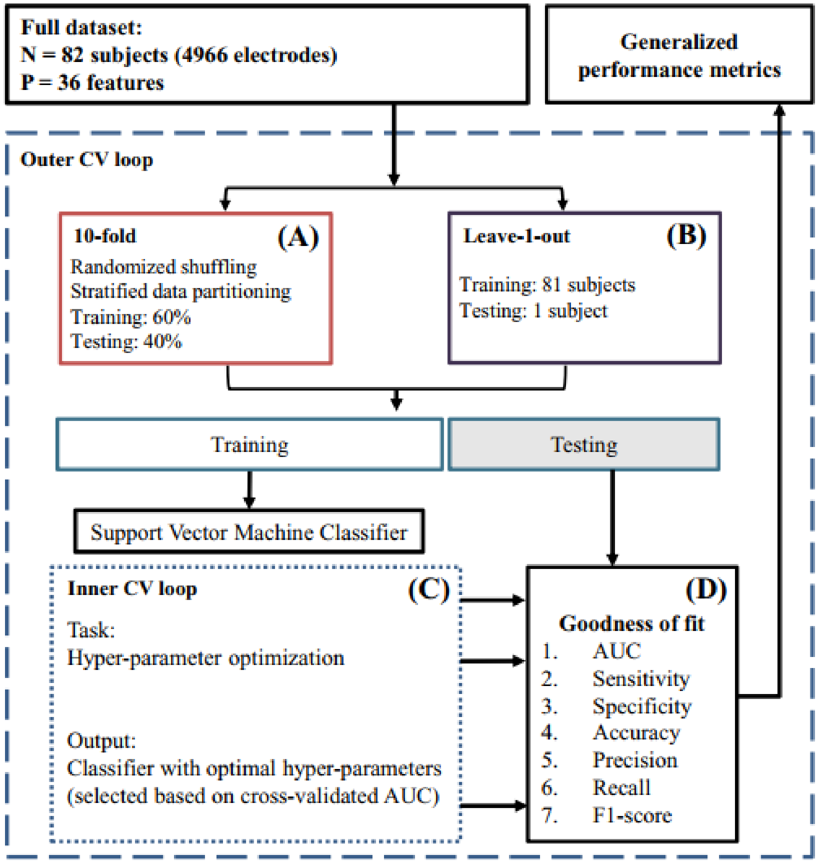
- HFO (Cimbalnik et al 2016):
  - Oscillations that have an amplitude of three standard deviations above the mean and lasting for more than one complete cycle in low-gamma (30–60 Hz), high-gamma (60–100 Hz), and ripple (100–150 Hz) bands are detected.
- PAC (Canolty, et al, 2006):
  - correlating instantaneous phase of the low-frequency signal with the corresponding amplitude of a high frequency signal
  - 0.1–30 Hz was chosen as the low-frequency (modulating)
  - 65–115 Hz was chosen as the high-frequency (modulated)
  - The specific phase of Low Frequency Oscillation modulates and promotes the amplitude of HFOs in tune surge ,and strengthen the synchronization of HFOs.
- IED (Barkmeier *et al* 2012):
  - Spike detection algorithm
  - 4.times SD of the baseline






2-hour analysis segment
10 minutes
10 minutes
3-sec window
3-sec window
3-sec window
3-sec window
HFO
IED
PAC
C
$X_1^{(1)}$
$X_2^{(1)}$
$X_3^{(1)}$
$X_1^{(200)}$
$X_2^{(200)}$
$X_3^{(200)}$
$X_1^{(2201)}$
$X_2^{(2201)}$
$X_3^{(2201)}$
$X_1^{(2400)}$
$X_2^{(2400)}$
$X_3^{(2400)}$
Clustering of each biomarker done separetely
Σ
Local HFO rate
Local IED rate
Local PAC rate
C - k-means clustering
Σ - summation
K=2, larger avg biomarker rate considered as abnormal
Support Vector Machine Classifier
36D feature vector
SOZ electrode?

J. Neural Eng. 15 (2018) 046035



Bio-marker	Method	AUC	Sensitivity (%)	Specificity (%)	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
10-fold CV								
All	SVM-LIN	0.56(0.03)	32.20(4.17)	75.09(0.02)	67.23(0.78)	22.42(2.31)	32.2(4.17)	26.43(3.01)
All	SVM-RBF	0.79(0.01)	70.36(1.78)	75.09(0.00)	74.22(0.33)	38.79(0.60)	70.36(1.78)	50.01(0.95)
HFO	SVM-RBF	0.68(0.01)	53.71(1.70)	75.16(0.09)	71.23(0.29)	32.66(0.66)	53.71(1.70)	40.62(1.00)
IED	SVM-RBF	0.68(0.01)	55.11(2.53)	75.07(0.03)	71.41(0.45)	33.14(1.01)	55.11(2.53)	41.39(1.50)
PAC	SVM-RBF	0.73(0.01)	60.63(2.74)	75.09(0.02)	72.44(0.51)	35.31(1.03)	60.63(2.74)	44.63(1.57)
ALL	RATE	0.58(0.01)	35.91(2.03)	75.09(0.02)	67.91(0.37)	24.43(1.03)	35.91(2.03)	29.07(1.40)
HFO	RATE	0.56(0.01)	32.39(2.20)	76.31(0.62)	68.26(0.77)	23.48(1.46)	32.39(2.20)	27.22(1.74)
IED	RATE	0.58(0.01)	35.19(1.42)	75.18(0.09)	67.85(0.27)	24.14(0.74)	35.19(1.42)	28.63(0.99)
PAC	RATE	0.62(0.01)	43.76(2.25)	75.27(0.12)	69.49(0.42)	28.41(1.03)	43.76(2.25)	34.45(1.46)
Leave one (subject) out CV								
ALL	SVM-RBF	0.73(0.02)	57.45(2.82)	79.49(0.57)	73.3(0.90)	38.71(2.45)	57.45(2.82)	43.49(1.99)
HFO	SVM-RBF	0.63(0.01)	35.53(2.89)	84.16(0.86)	73.10(1.00)	34.63(2.72)	35.53(2.89)	35.09(2.11)
IED	SVM-RBF	0.60(0.01)	33.50(2.22)	80.77(0.66)	69.47(0.89)	30.55(2.42)	33.50(2.22)	29.16(1.55)
PAC	SVM-RBF	0.69(0.01)	47.70(2.81)	81.03(0.63)	72.63(0.93)	36.23(2.39)	47.70(2.81)	39.06(1.94)

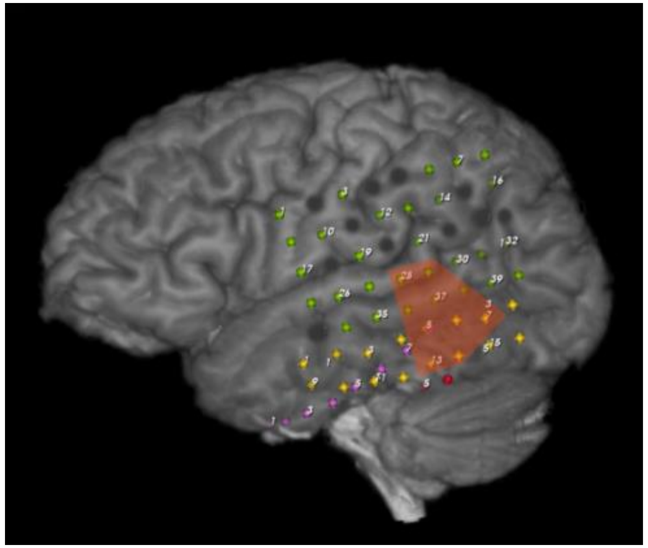
-accuracy of approximately 70% on 82 patients, using interictal iEEG

-recordings durations less than 2 h is enough for localization

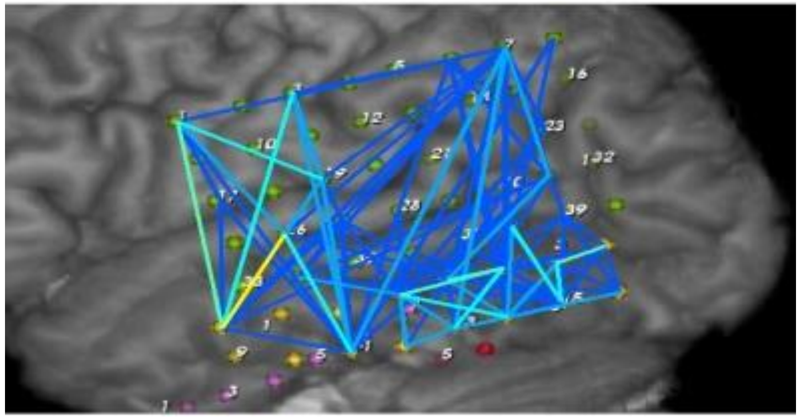
-combination of multiple parameters results in a better performance

2) Interictal localization in iEEG recordings applying functional connectivity parameters

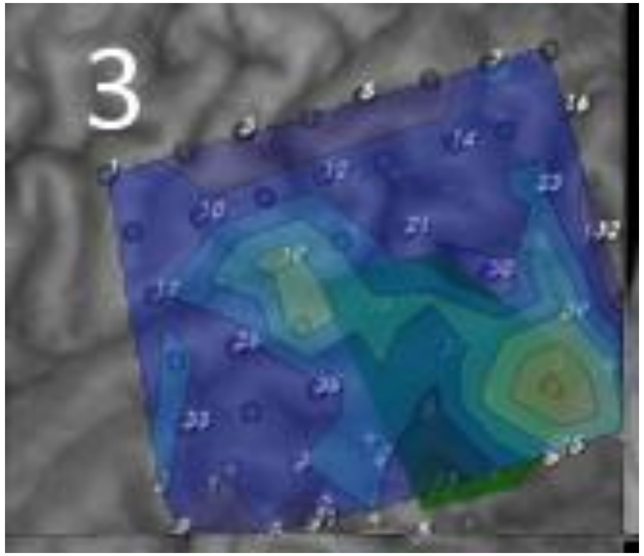
ECoG



Functional network



Graph parameters on functional network



Effective graph parameters for localizing EZ in interictal iEEG recordings

Consequences:

1.) Hub measurements

- nodal strength
- BC

2.) Local connections

- local synchronization

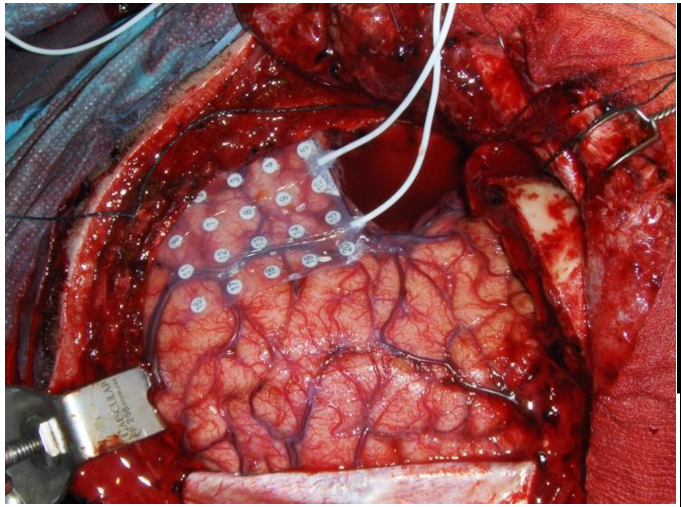
3.) Directionality of the connectivity

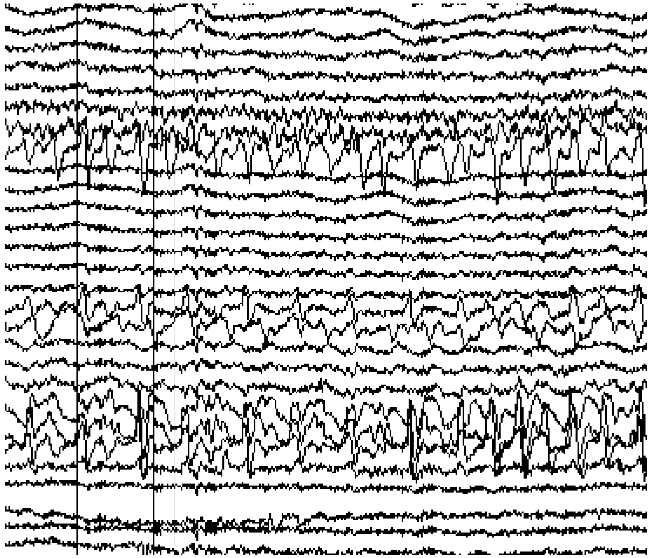
-outflow

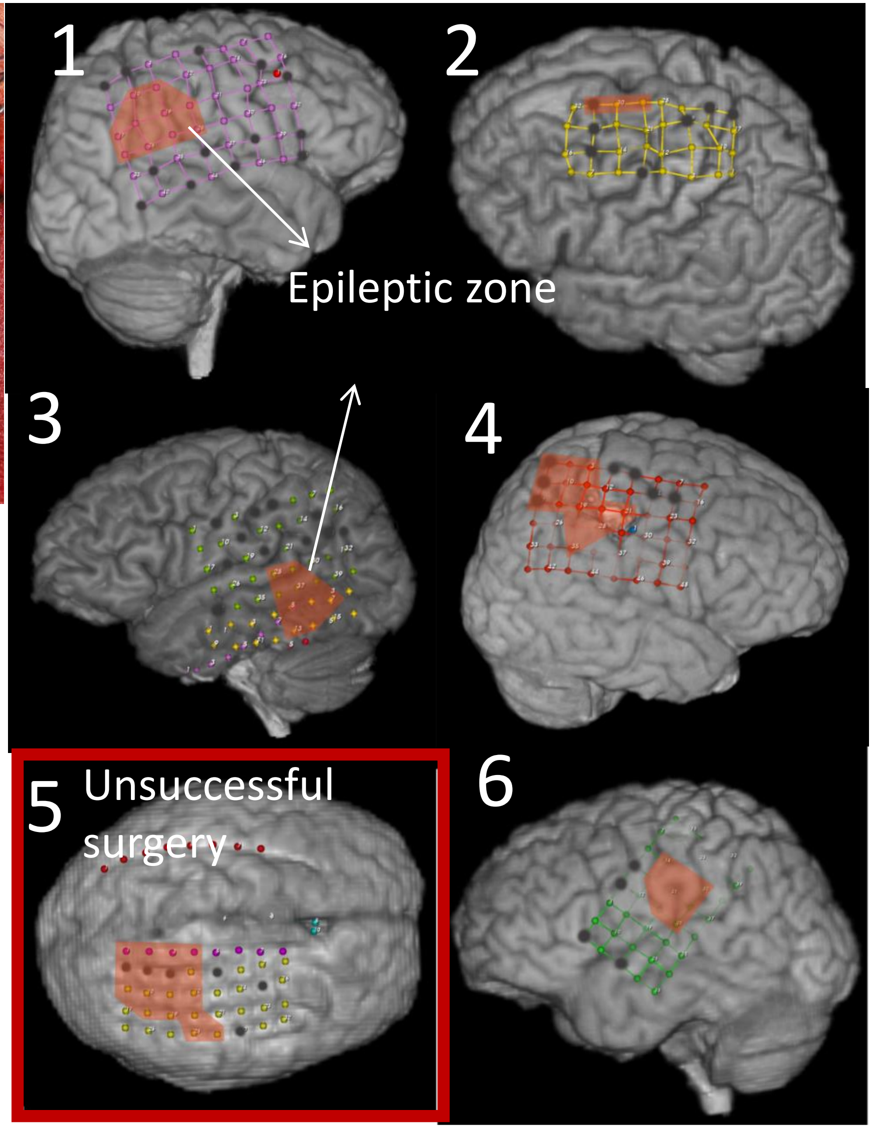
First author /year of publication	Number of patients	Applied functional connectivity method	Graph parameters connected to the EZ	Journal published
Schevon, 2007	8	Phase coherency	**Local synchronization**	NeuroImage
Ortega, 2008	5	correlation	**BC (MST)**	Neurosci. Lett.,
Wilke, 2010	11	DTF	**Strength**	Epilepsia
Wilke, 2011	25	DTF	**BC**	Epilepsia
Yung, 2011	16	DTF	**Outflow strength**	Seizure
Varotto, 2012	10	PDC	**Outflow strength, BC**	NeuroImage
Palmigiano, 2012	20	correlation	**Stability of the local synchronization**	PLoS ONE
Mierlo, 2012	8	swADTF	**Outflow strength**	Epilepsia
Kim, 2014	4	PLV	**BC**	Brain Dev.

Ictal/Intracranial EEG for epileptic patients

- 6 presurgery patients
  - 1 unsuccessful surgery
- Available recordings:
  - Interictal
- FOIs:
  - gamma (30-45 Hz)
- Epoching:
  - 2 s epochs







Phase lag index

Analitic signal

$$z(t) = x(t) + i\tilde{x}(t)$$

Instantaneous phase of the signals

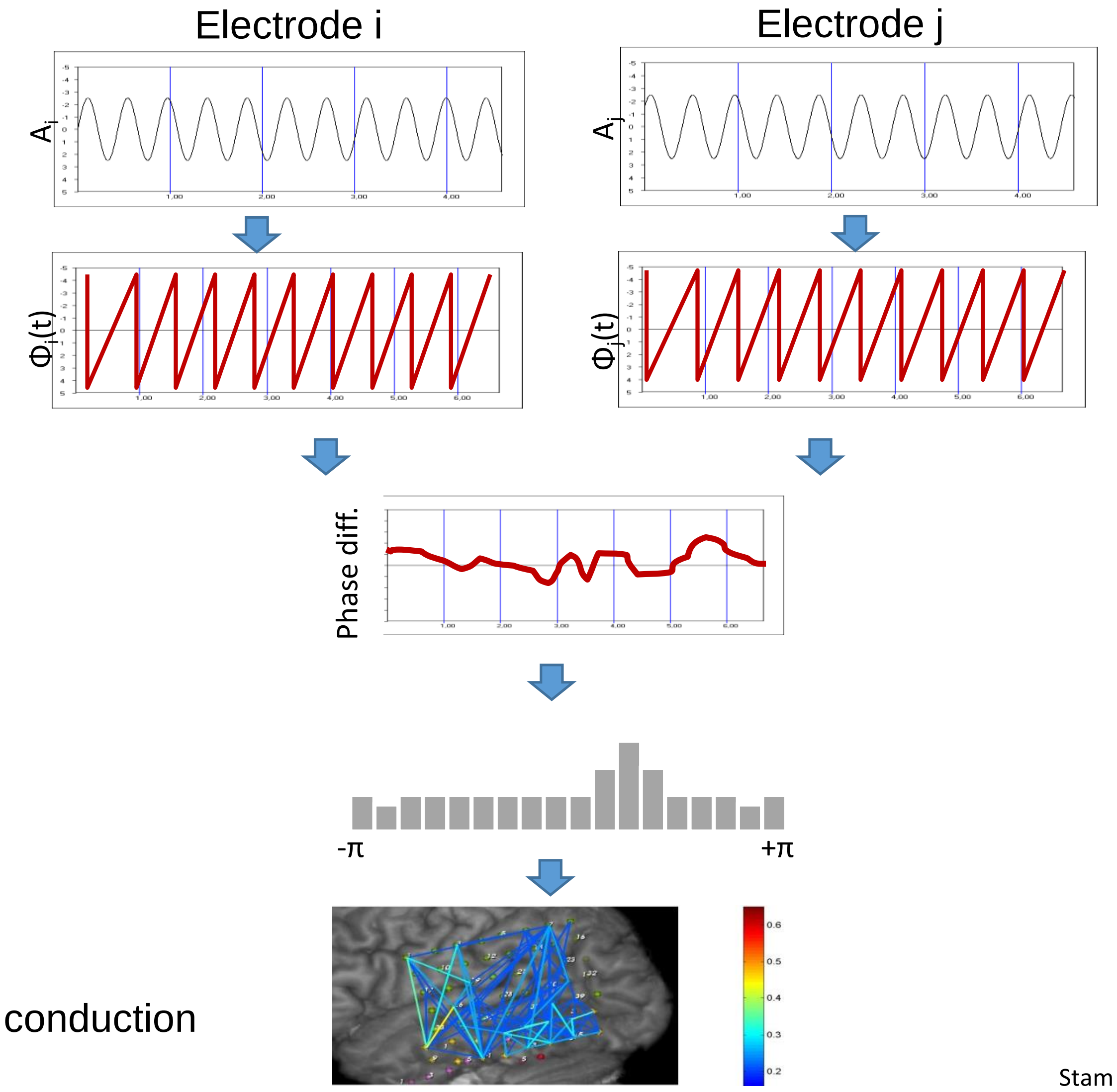
$$\phi(t) = \arctan \frac{\tilde{x}(t)}{x(t)}$$

Phase difference between the 2 signals: ($\Delta\Phi(t)$)

Histogram of the phase difference

PLI=|<sign[$\Delta\Phi(t_k)$]>|

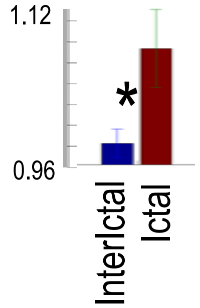
Goal: Elimination of volume conduction



Stam CJ1, Nolte G, Daffertshofer A. (2007):

Epileptic changes in the small-world configuration in higher frequency bands

Clustering coefficient



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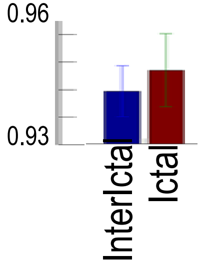
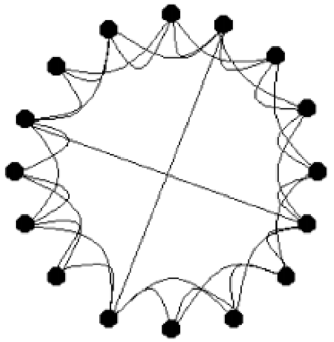
Avg. Path length



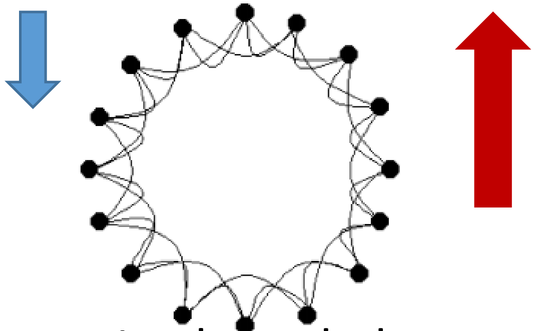
Global network changes

Interictal – small world



Loss of long-range connections

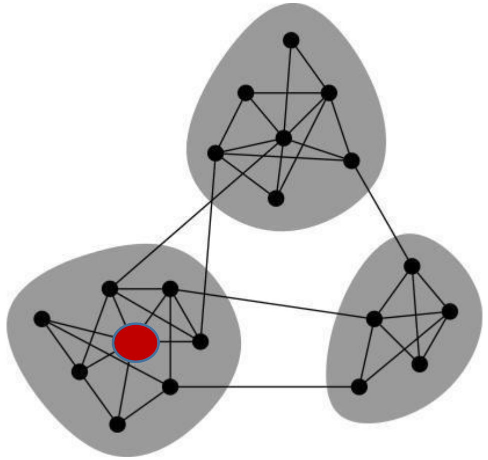
Strengthen the local connections



Ictal – orded

?

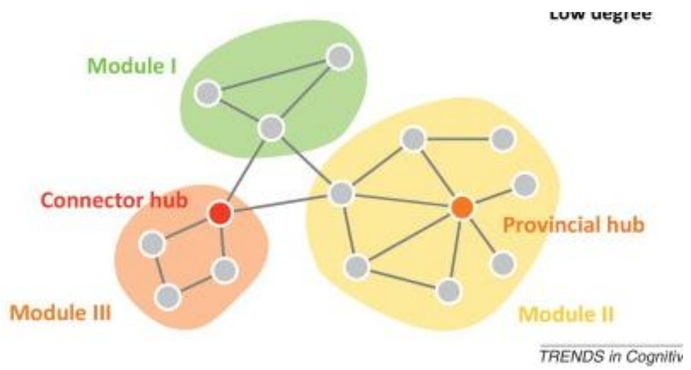
Local network changes



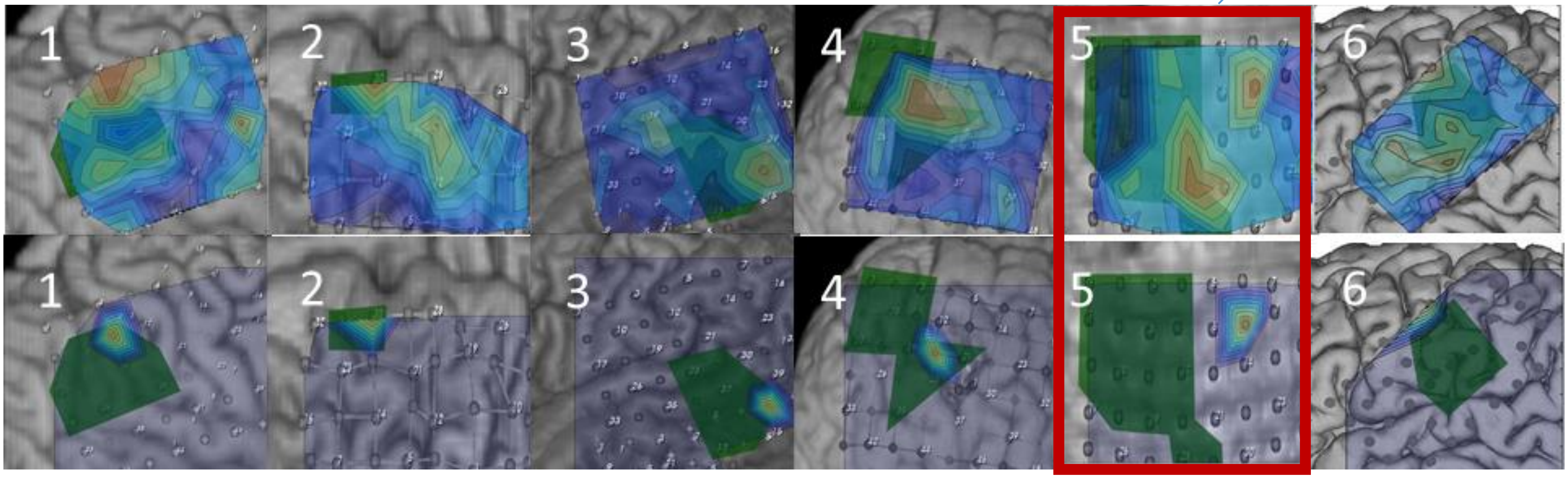
- The epileptic network may has high local modular hubs in the epileptic zone:
  - High within module degree
  - Low between modul connectivity

Intreictal/Ictal iEEG: Ponten, 2007

Local modular hubs (interictal, gamma band)

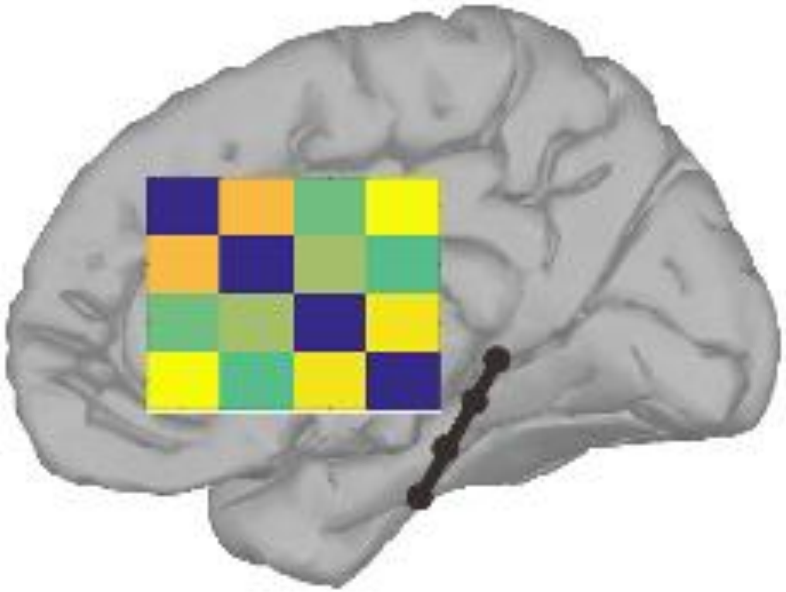


Unsuccessful surgery

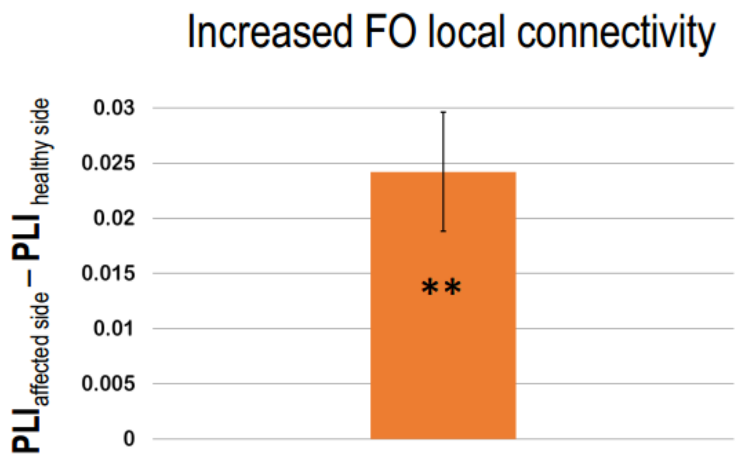


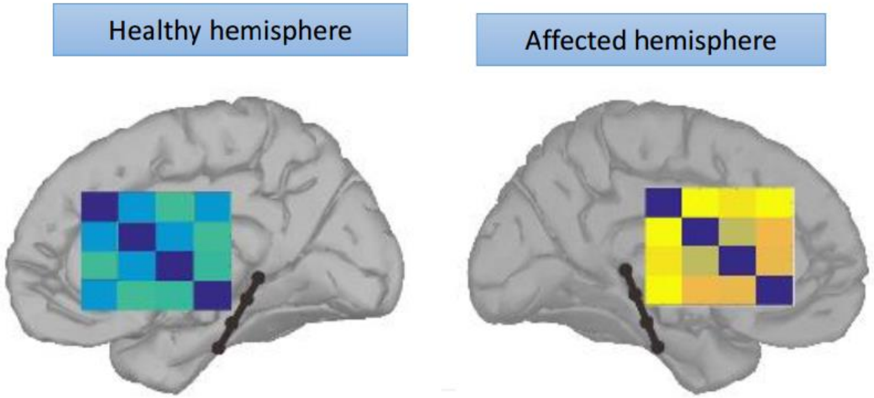
3) Interictal localization in foramen ovale recordings applying functional connectivity parameters

- 12 patients with unilateral (7 left, 5 right) mesial temporal lobe epilepsy
- 5 separate, 60 seconds long, interictal EEG and FO recordings
  for each patient during sleep
- Filtered to gamma band (30-45 Hz), segmented to 0.5 sec epochs
- Phase lag index was calculated between electrode contacts on the same side
- PLI(affected side)-PLI(healthy side) predicts the epileptic focus

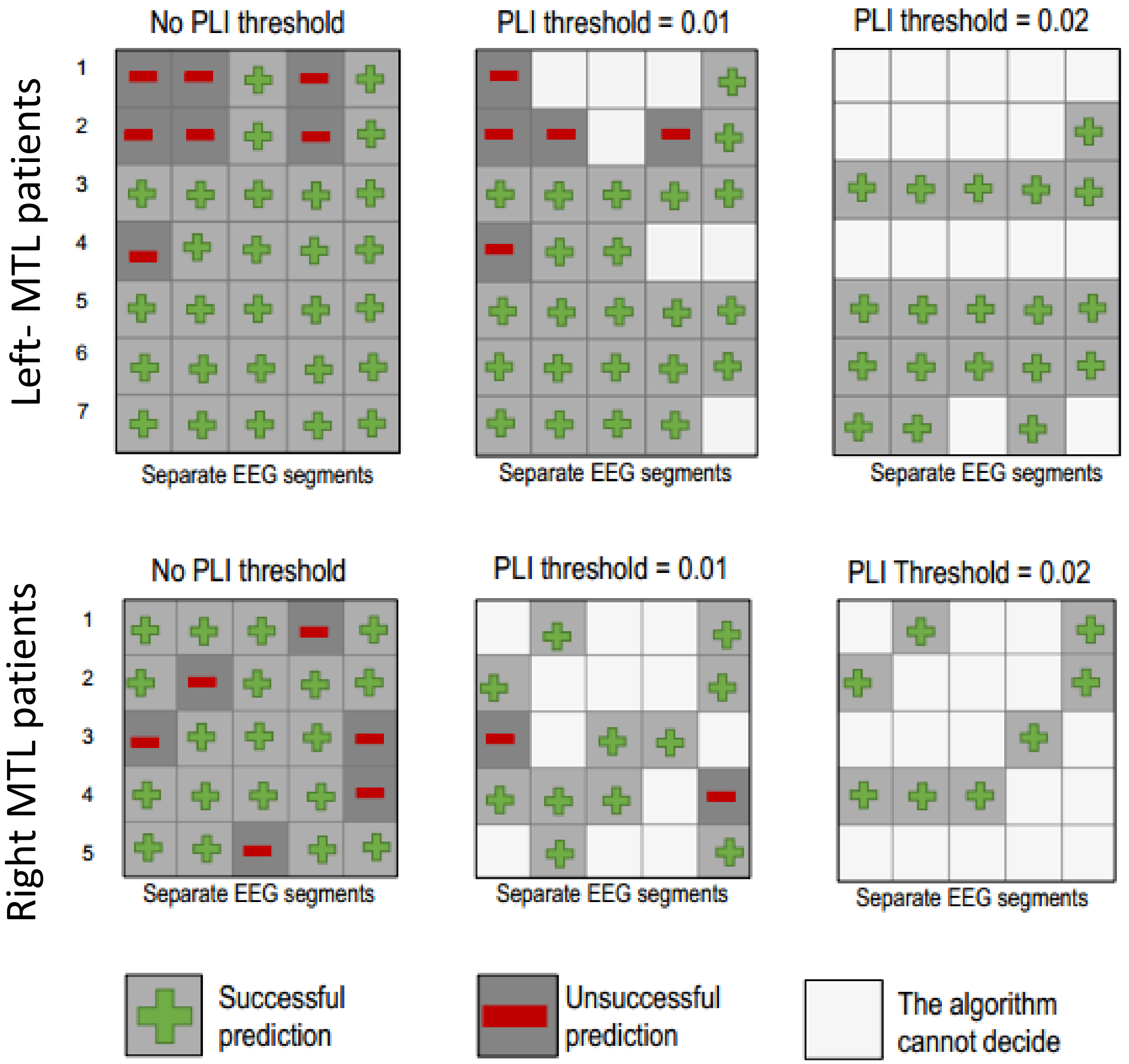


GROUP LEVEL RESULTS





Interictal FO phase synchronization predicts the lateralization of MTL epilepsy



References

- Siuly, S., Li, Y., & Zhang, Y. (2016). Electroencephalogram (eeg) and its background. In *EEG Signal Analysis and Classification* (pp. 3-21). Springer, Cham.
- Vaid, S., Singh, P., & Kaur, C. (2015, February). EEG signal analysis for BCI interface: A review. In *2015 fifth international conference on advanced computing & communication technologies* (pp. 143-147). IEEE.
- Ries, A. J., Touryan, J., Vettel, J., McDowell, K., & Hairston, W. D. (2014). A comparison of electroencephalography signals acquired from conventional and mobile systems. *Journal of Neuroscience and Neuroengineering*, *3*(1), 10-20.
- Minguillon, J., Lopez-Gordo, M. A., & Pelayo, F. (2017). Trends in EEG-BCI for daily-life: Requirements for artifact removal. *Biomedical Signal Processing and Control*, *31*, 407-418.
- Nolan, H., Whelan, R., & Reilly, R. B. (2010). FASTER: fully automated statistical thresholding for EEG artifact rejection. *Journal of neuroscience methods*, *192*(1), 152-162.
- Abiri, R., Borhani, S., Sellers, E. W., Jiang, Y., & Zhao, X. (2019). A comprehensive review of EEG-based brain–computer interface paradigms. *Journal of neural engineering*, *16*(1), 011001.
- Bulárka, S., & Gontean, A. (2016, October). Brain-computer interface review. In *2016 12th IEEE International Symposium on Electronics and Telecommunications (ISETC)* (pp. 219-222). IEEE.
- Varatharajah, Y., Berry, B., Cimbalnik, J., Kremen, V., Van Gompel, J., Stead, M., ... & Worrell, G. (2018). Integrating artificial intelligence with real-time intracranial EEG monitoring to automate interictal identification of seizure onset zones in focal epilepsy. *Journal of neural engineering*, *15*(4), 046035.
- de Curtis, M., Jefferys, J. G., & Avoli, M. (2012). Interictal epileptiform discharges in partial epilepsy. *Jasper's Basic Mechanisms of the Epilepsies [Internet]. 4th edition*.
- Cimbalnik, J., Kucewicz, M. T., & Worrell, G. (2016). Interictal high-frequency oscillations in focal human epilepsy. *Current opinion in neurology*, *29*(2), 175.
- Canolty, R. T., Edwards, E., Dalal, S. S., Soltani, M., Nagarajan, S. S., Kirsch, H. E., ... & Knight, R. T. (2006). High gamma power is phase-locked to theta oscillations in human neocortex. *science*, *313*(5793), 1626-1628.
- Barkmeier, D. T., Shah, A. K., Flanagan, D., Atkinson, M. D., Agarwal, R., Fuerst, D. R., ... & Loeb, J. A. (2012). High inter-reviewer variability of spike detection on intracranial EEG addressed by an automated multi-channel algorithm. *Clinical Neurophysiology*, *123*(6), 1088-1095.
- Stam, C. J., Nolte, G., & Daffertshofer, A. (2007). Phase lag index: assessment of functional connectivity from multi channel EEG and MEG with diminished bias from common sources. *Human brain mapping*, *28*(11), 1178-1193.
- Ponten, S. C., Bartolomei, F., & Stam, C. J. (2007). Small-world networks and epilepsy: graph theoretical analysis of intracerebrally recorded mesial temporal lobe seizures. *Clinical neurophysiology*, *118*(4), 918-927.

From an office door of TTK