Ulster University

Investigating time series neural data: Experimental design & processing

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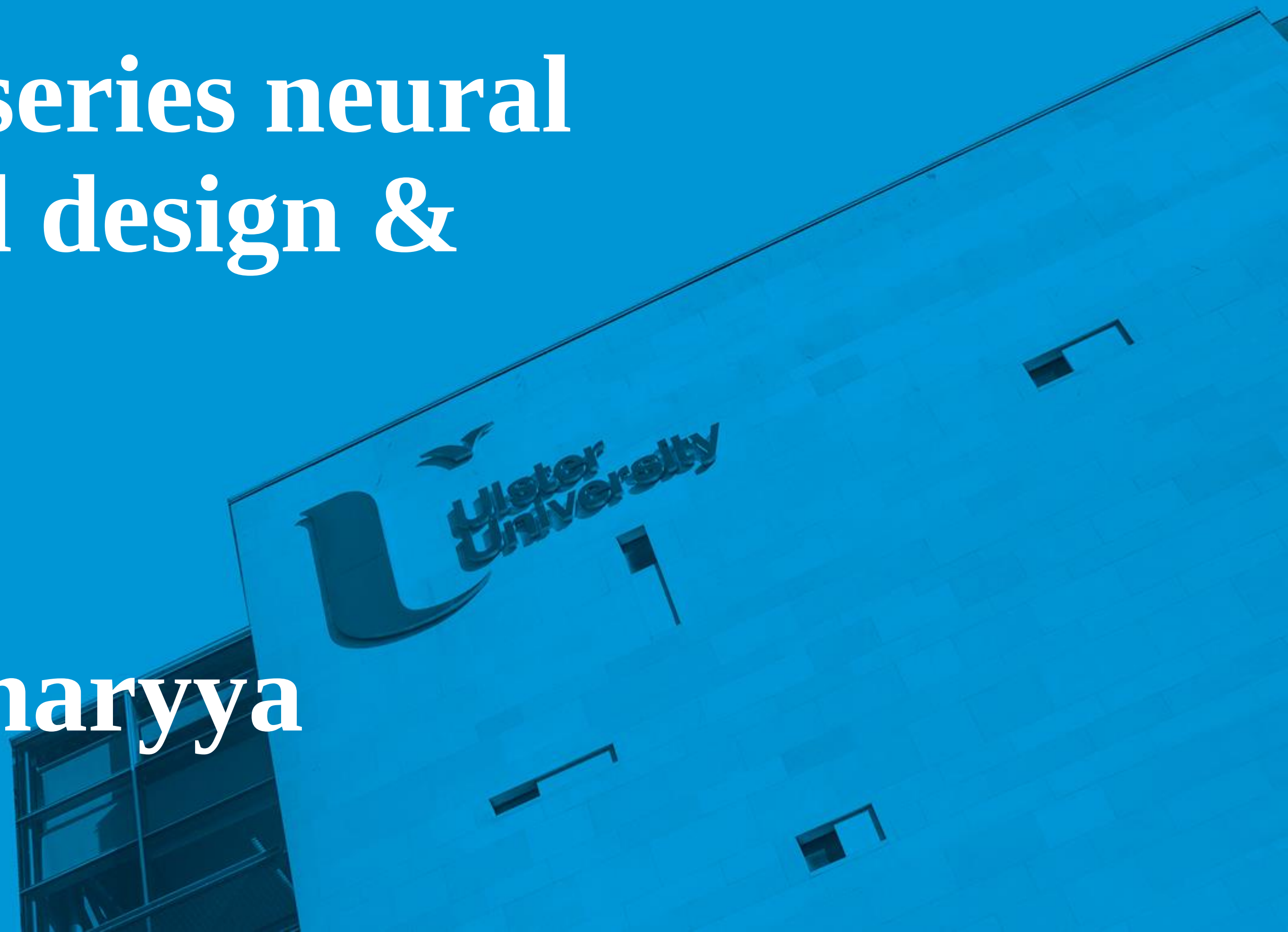

EEG Recording

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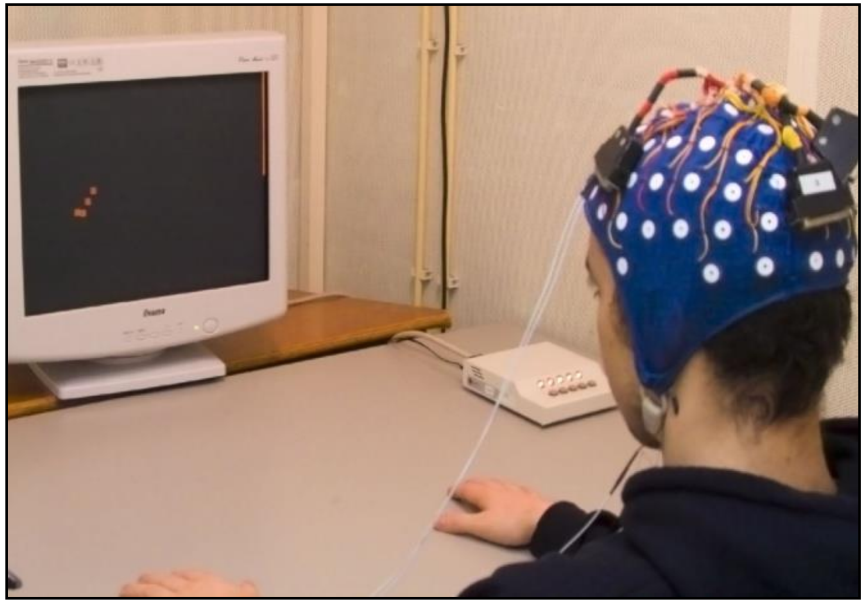
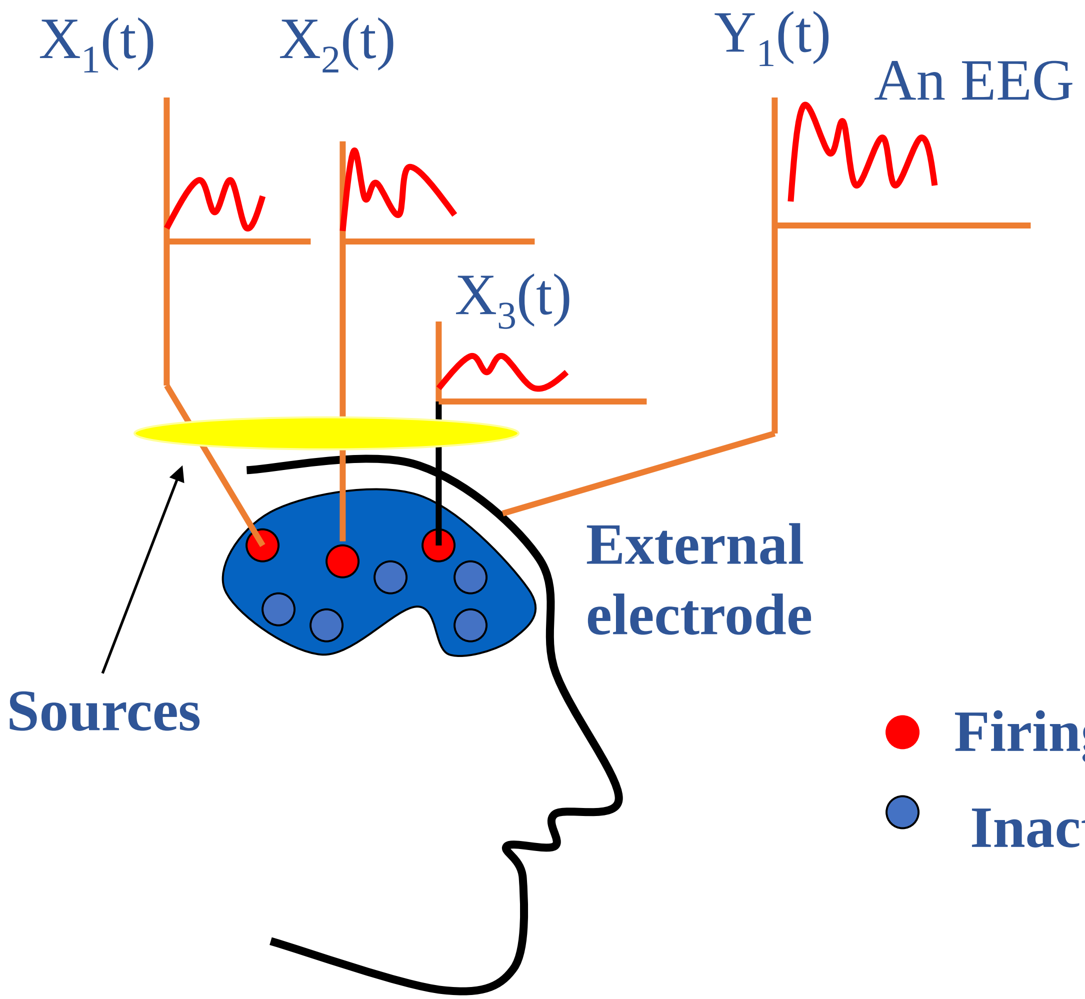
- The neuronal firing inside the brain generates electrical signals.
- These electrical signals picked up from the scalp by metallic electrodes are called EEG signals.

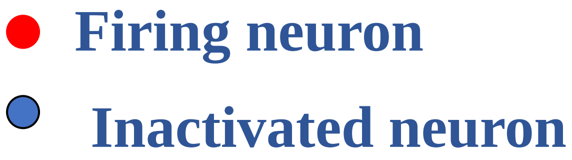


EEG as a Weighted Sum of Independent Neuronal Signals



EEG is presumed to be a linear combination of independent intra-cortical source signals.

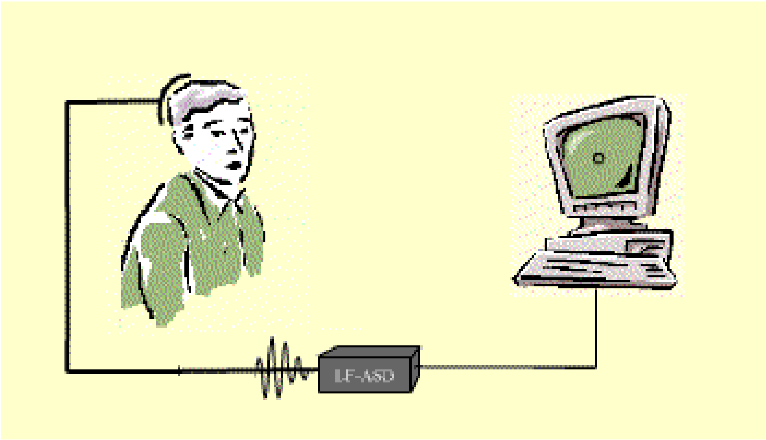
$$Y_1(t) = w_{11}\, X_1(t) + w_{21}\, X_2(t) + w_{31}\, X_3(t)$$



Brain-computer interfacing?

- *" A Brain-Computer Interface is a communication system that do not depend on peripheral nerves and muscles"* [Wolpaw et al. 2000]

- A technology which allows a human to control a computer, peripheral, or other electronic device with thought.

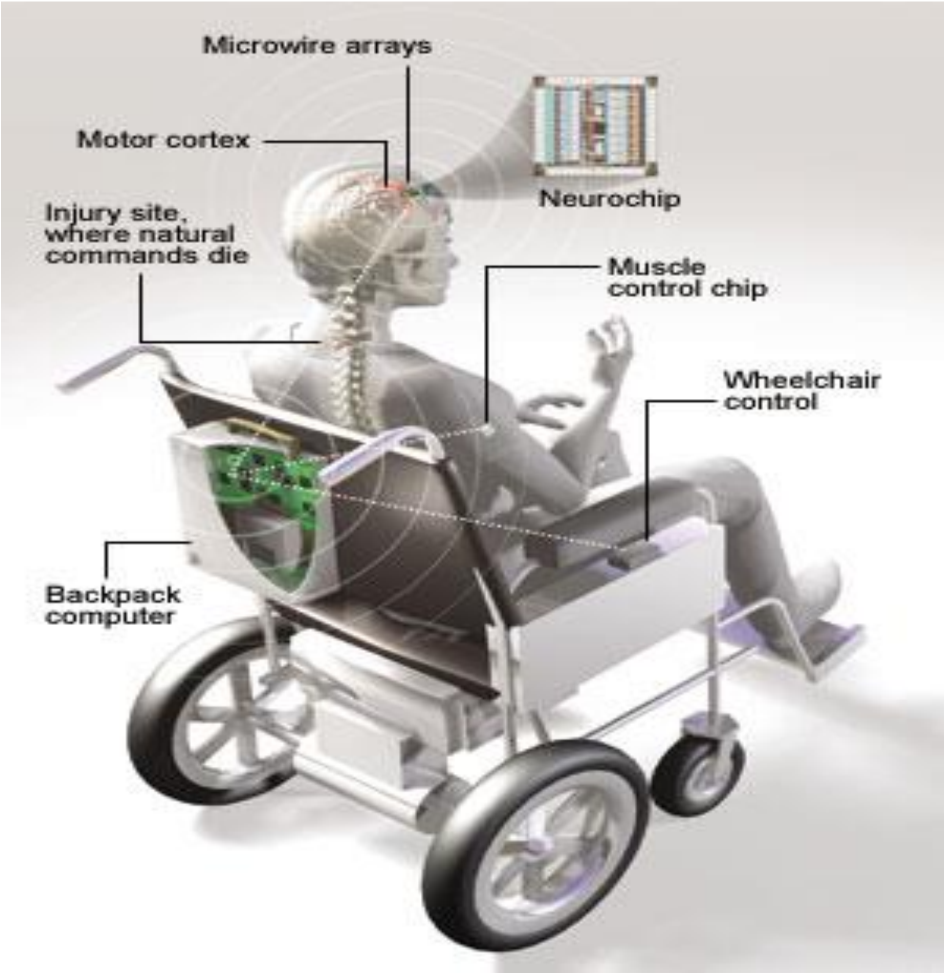


http://www.ece.ubc.ca/~garyb/BCI.htm

Motivation

- is to give disable people to communicate, to operate prostheses, and even to operate wheelchairs using brain signals.

- **Target group:**
  - Amyotropic Lateral Sclerosis
  - Cervical spinal injury
  - Stroke paralysis
  - Celebral palsy
  - Amputee, etc



Nicolelis, 2001

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BCI in Rehabilitation

1. Thought Controlled Wheelchair
2. Upper Limb Prosthesis
3. Cursor Control
4. Virtual Keyboard
5. BCI Speller

BCI in Everyday Life

https://emotiv-website-uploads-live.s3.amazonaws.com/uploads/2019/05/bci-gaming-world-of-warcraft-1.png

https://www.ireviews.com/content/uploads/2017/08/7.jpeg

https://www.army-technology.com/features/feature brain-computer-interfacing-military-mind-
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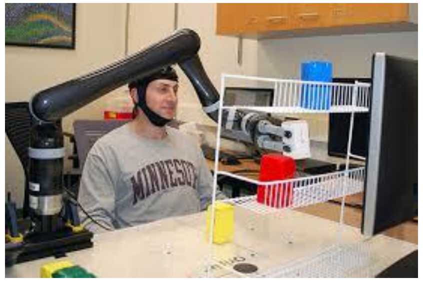


https://cdn.thenewstack.io/media/2016/12/ac3d5887-brain-computer-interface-robotic-arm-1.jpg

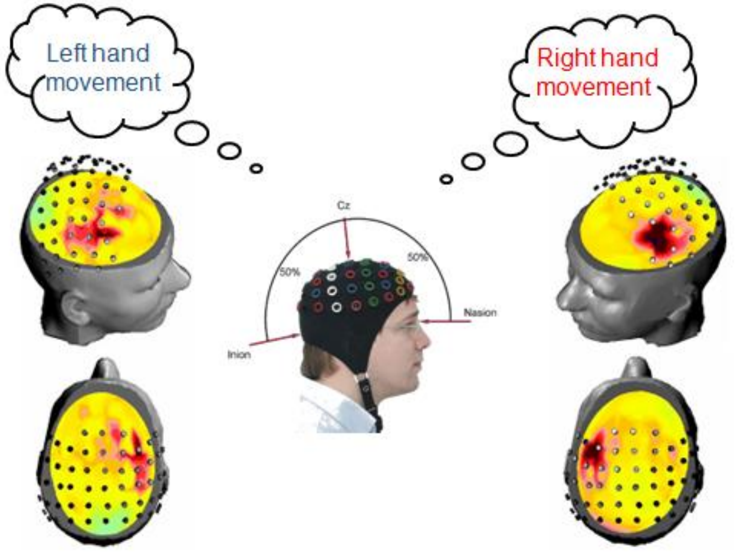
https://cakedigit.com/wp-content/uploads/2017/01/coca.png

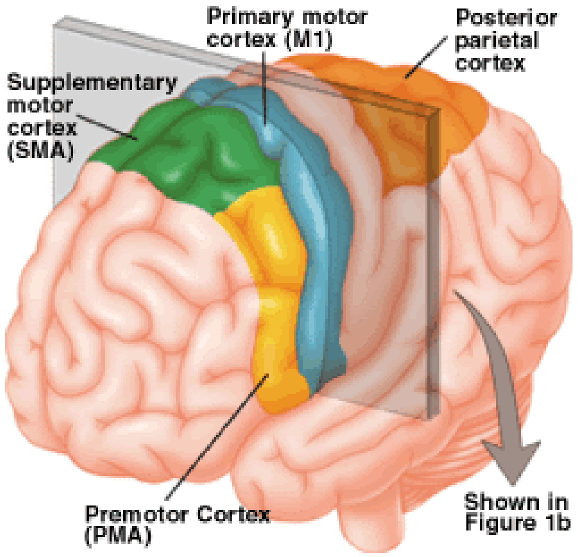
Common Neural Signals

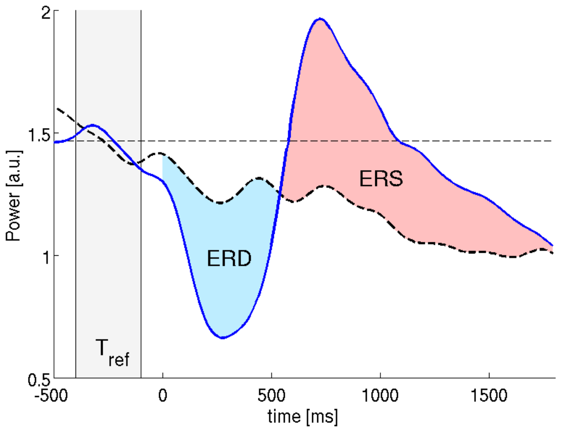
Motor Imagery (ERD/ERS)

- **Rolandic mu rhythm (8-12 Hz)** and the **central beta rhythm (16-24 Hz)**

- **Movement Imagination/Execution**

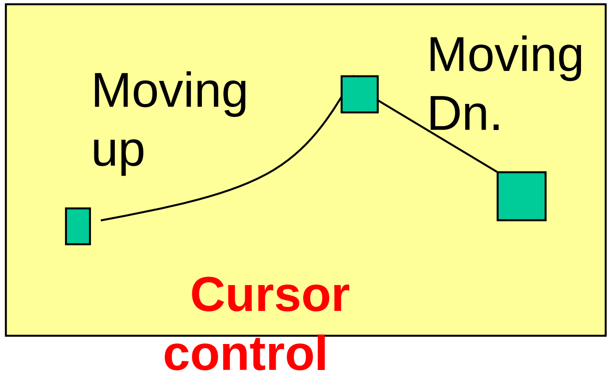


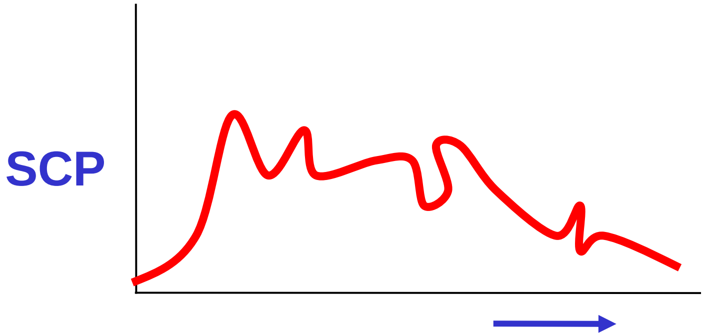


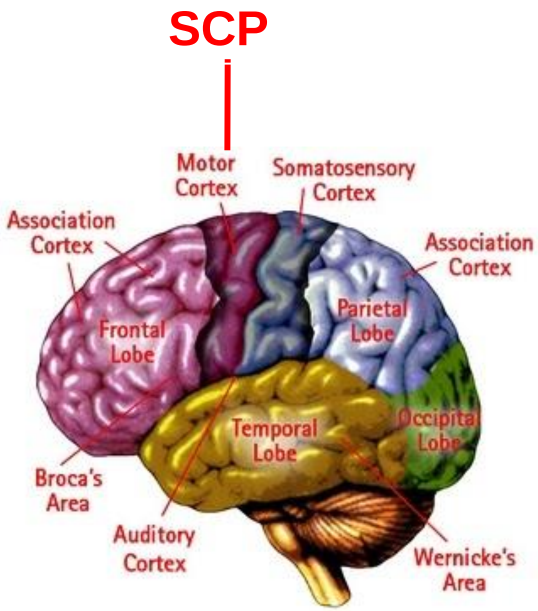


Slow Cortical Potential Operant Conditioning

- **Example: Moving cursor up and down causes a respective growth and fall off in SCP signal.**

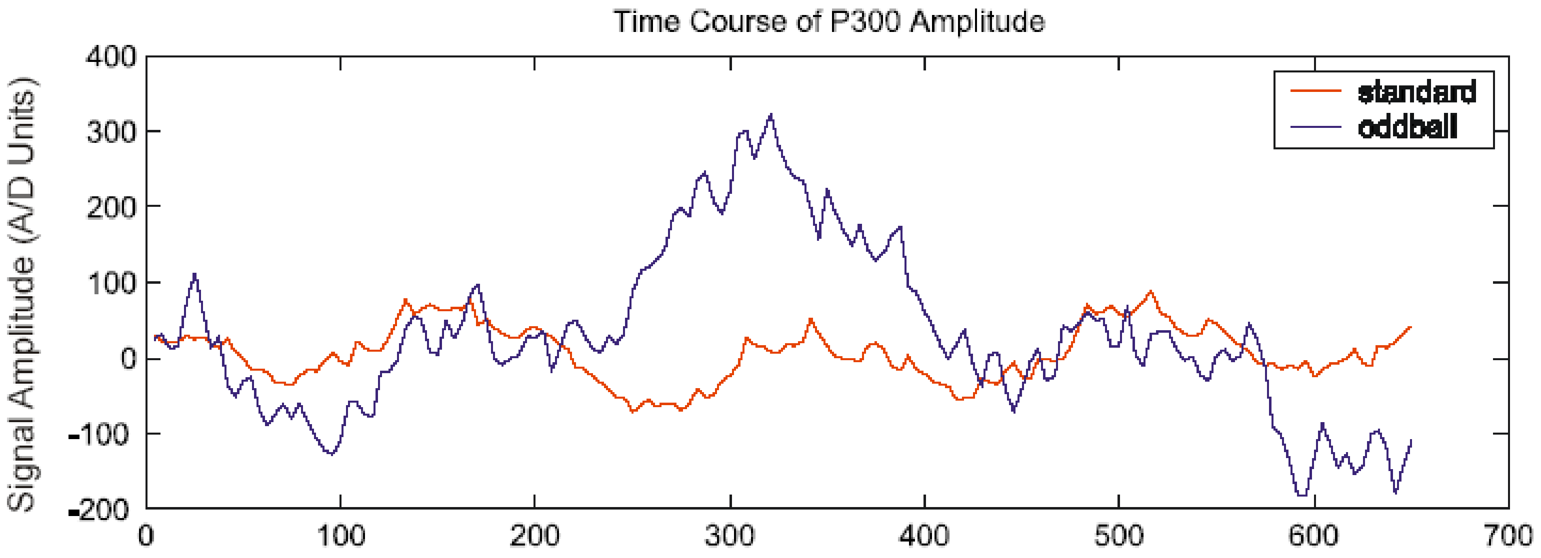






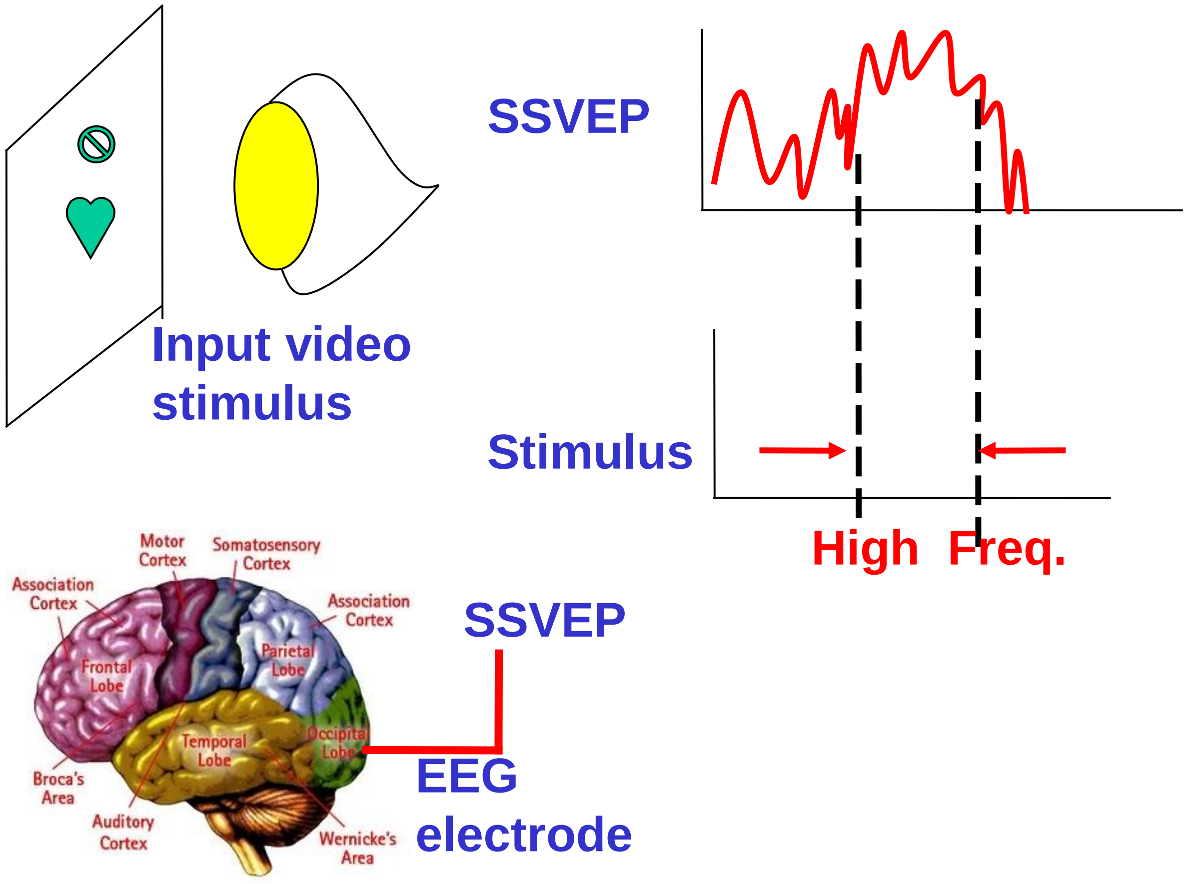
P300

- **Event-related potential (ERP) associated to the presence of uncommon targets or infrequent stimuli to which a user is paying attention**



Steady-State Visual Evoked Potential

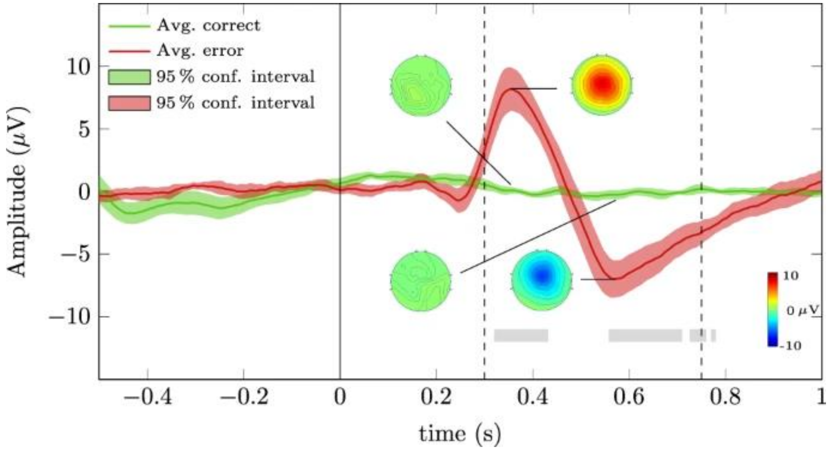
- **SSVEP:** The amplitude of the response is modulated by the frequency of the stimulus.



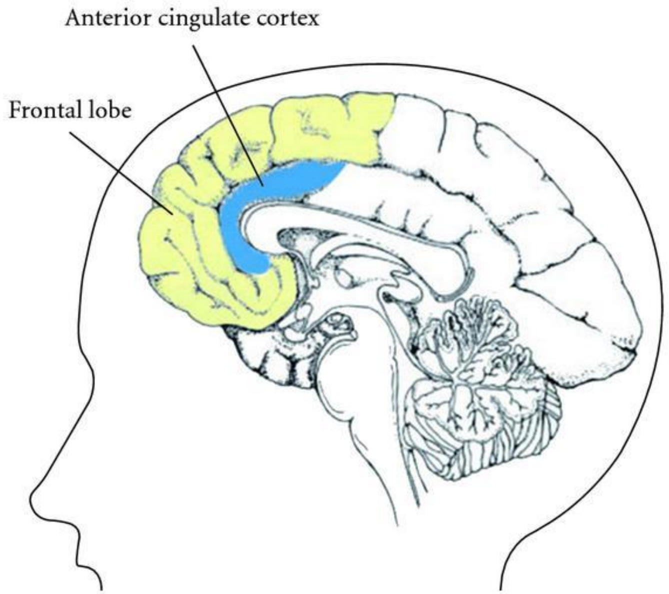
Error Related Potential

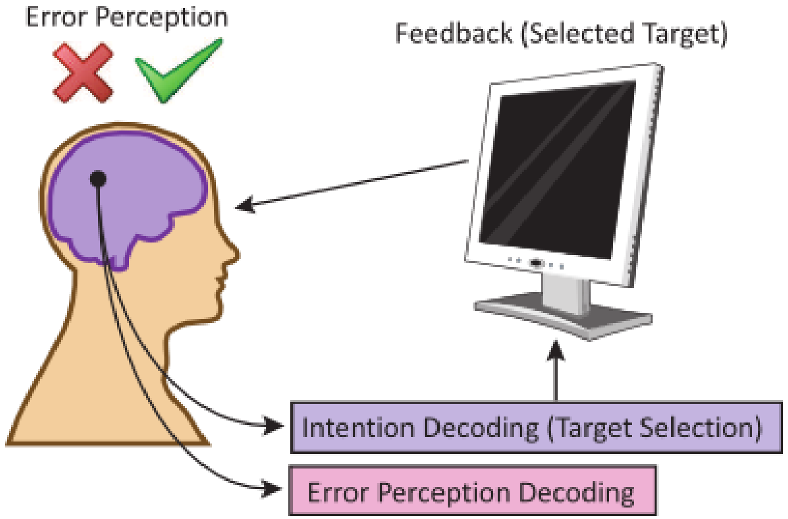
- User’s awareness to erroneous response.

- Typical occurrences that elicits ErrP:
  - Choice reaction tasks
  - Feedback tasks
  - Observation tasks



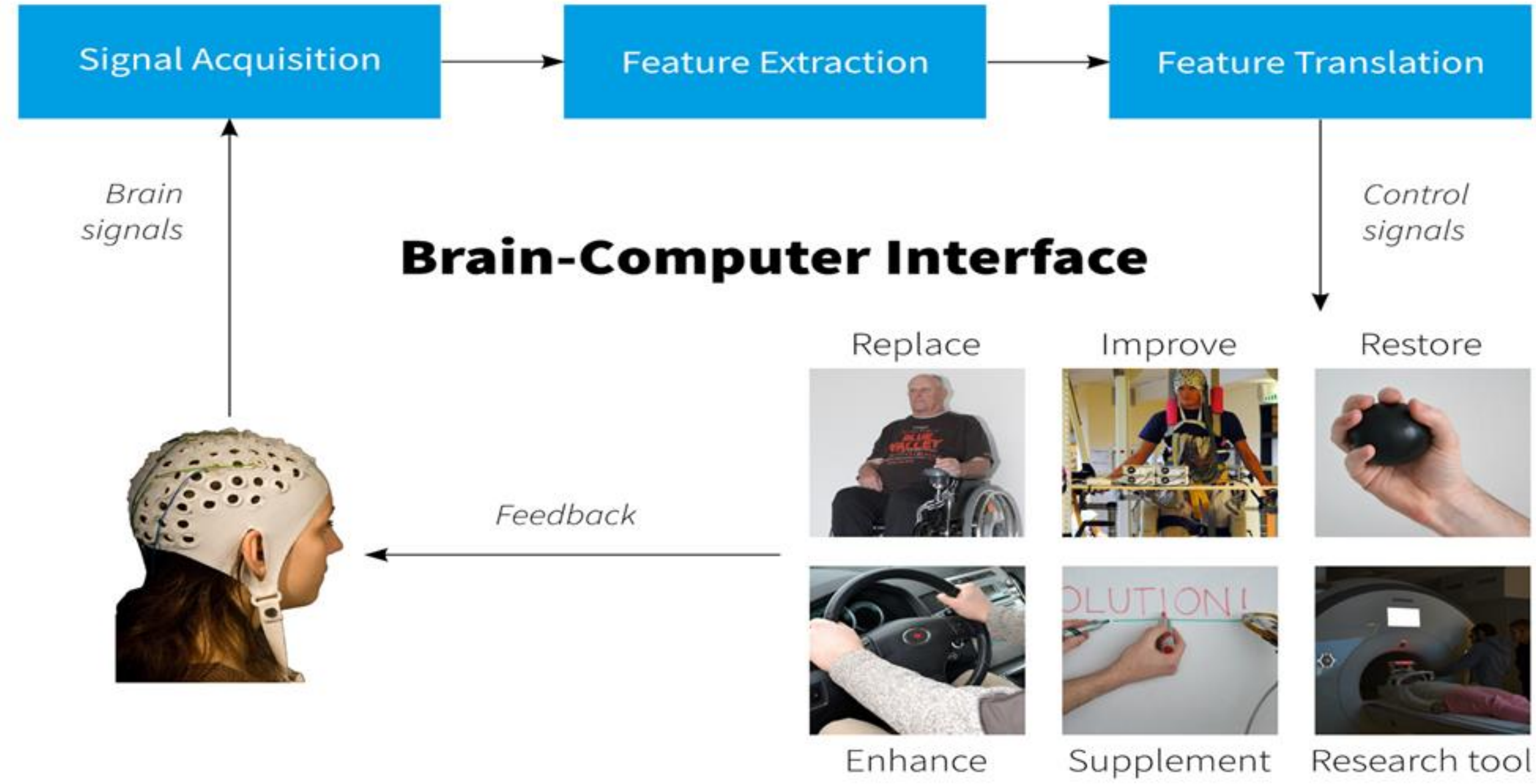
Lopes-Dias et al., Sci. Rep., 2019





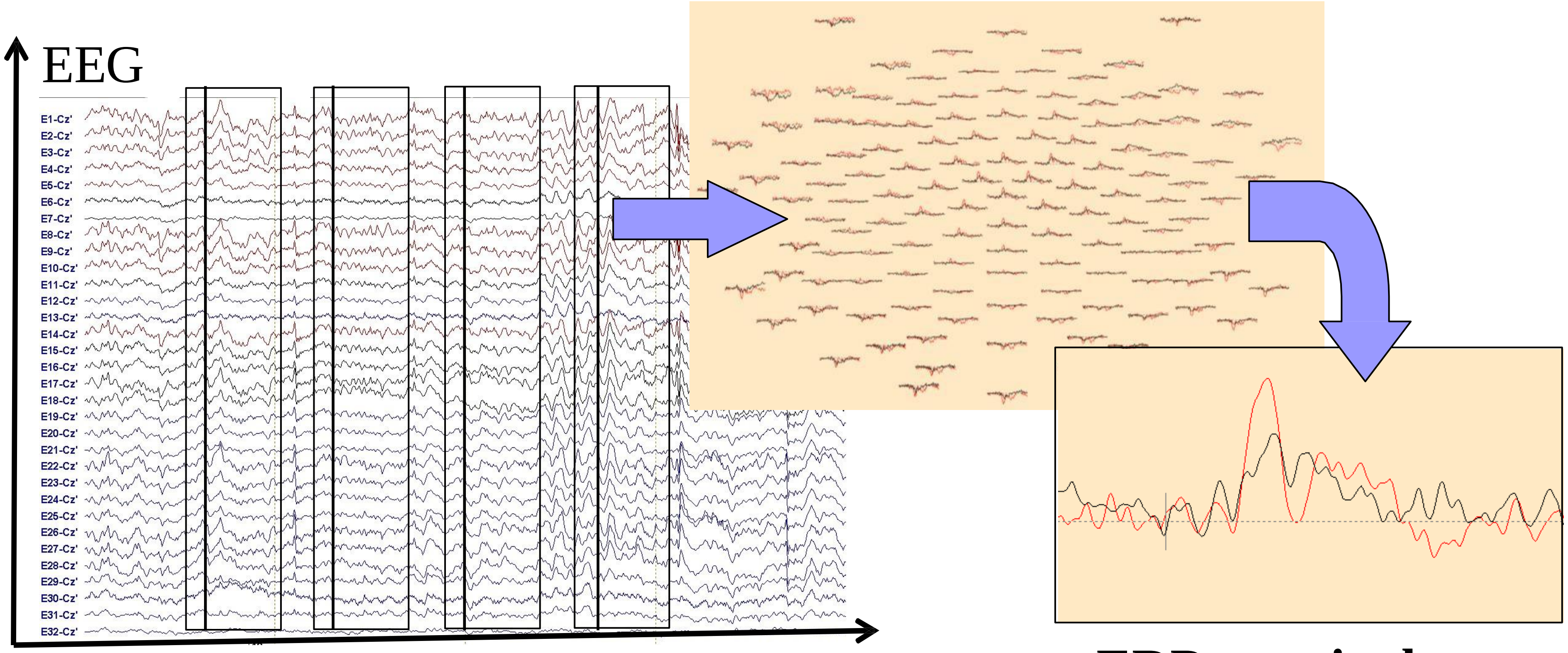
* Spuler, et al., Frontiers Human Neuroscience, 2015

Basic Pipeline



Event Related Potential

Averaged across 100 stimulus presentations



ERP at a single electrode

Event Related Potential

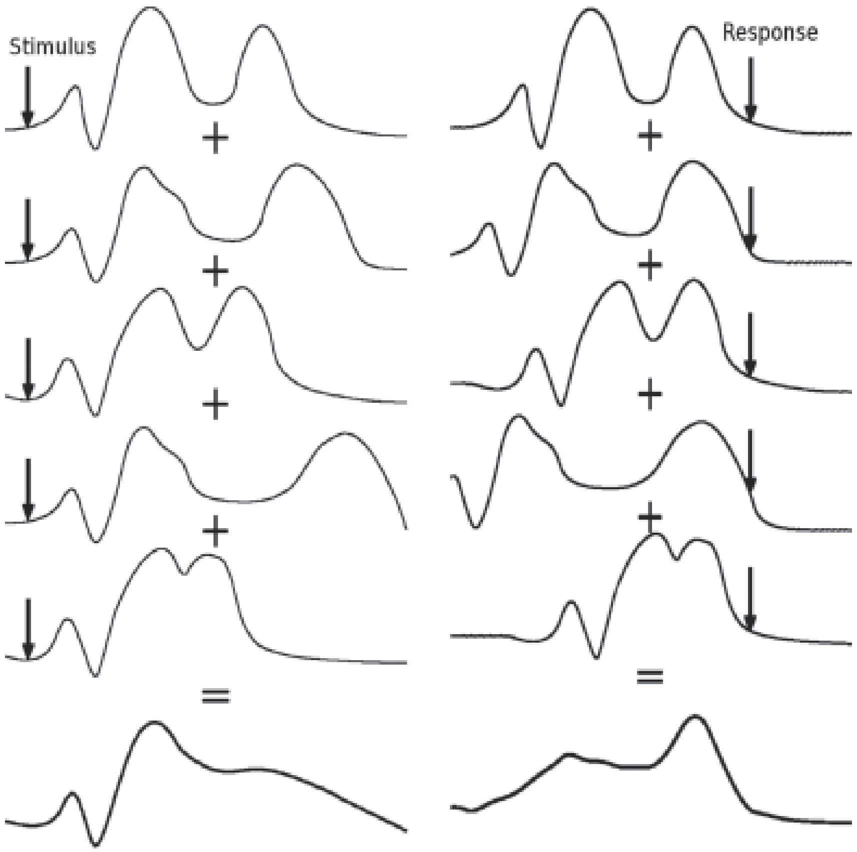
ERP-averaging is based on the following assumptions: (Regan, 1989)

1. The background EEG acts as noise for the ERP-signal
2. The signal waveform is generated by a process that stays stationary from trial to trial
3. The noise, background EEG, is produced by a stationary random process
4. The noise samples are uncorrelated from trial to trial

Possible problems:

- The background EEG is not always random in relation to stimuli.
  - e.g. 50 Hz electric current can create a regular rhythm to the background EEG.
- A psychological process, reflected in ERP-signal, may not remain the same during the entire measurement session, e. g. due to arousal state effects

Stimulus-Locked & Response-Locked ERPs



Stimulus-Locked Response-Locked

Designing Experiments

- Do not underestimate the importance of good experiment design
- Produce meaningful and interpretable results
    - Implications for theories
    - Inspire new research
- Pilot test your experiment behaviourally

Event Markers

- Triggers that are sent from stimulus delivering computer to the EEG amplifier
- Recorded as separate channel
- Encode specific events such as stimulus onset or responses, etc.

https://pressrelease.brainproducts.com/wp-content/gallery/1602_ST/GUI_NavigationBar_Markers.jpg

Designing Experiments

Intra- and Intertrial Timing

- Ideal to have experiment events within a trial separated by several hundred milliseconds

- Intervals between two trials (Inter-trial intervals):
  - Baseline normalisation
  - Frequencies to analyse

- Constant or Variable

- **Number of trials required?**
- Signal-to-Noise Ratio
- Big the effect is
- Type of analysis

- **Electrodes & Sampling Rate-** Dependent on the type of analysis

Python based packages

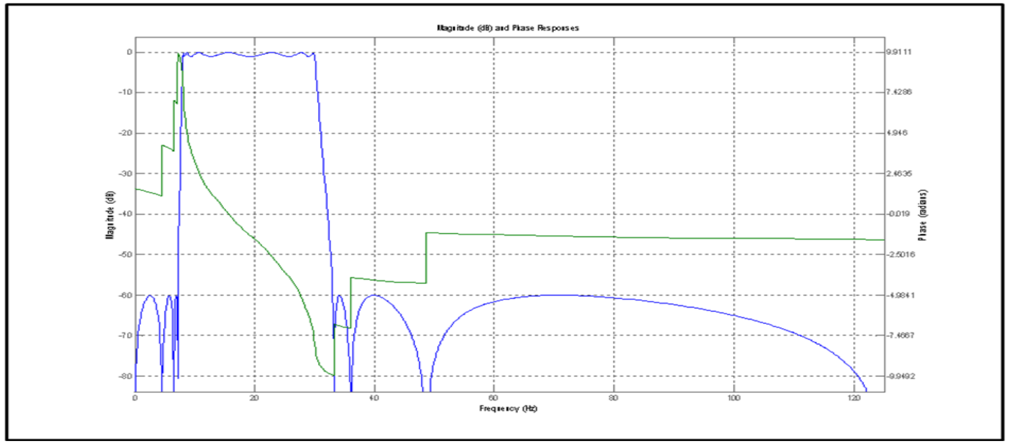
- Numpy
- Scipy
- Scikit-learn
- MNE-Open-source Python package for exploring, visualizing, and analyzing human neurophysiological data: MEG, EEG, sEEG, ECoG, NIRS, and more.

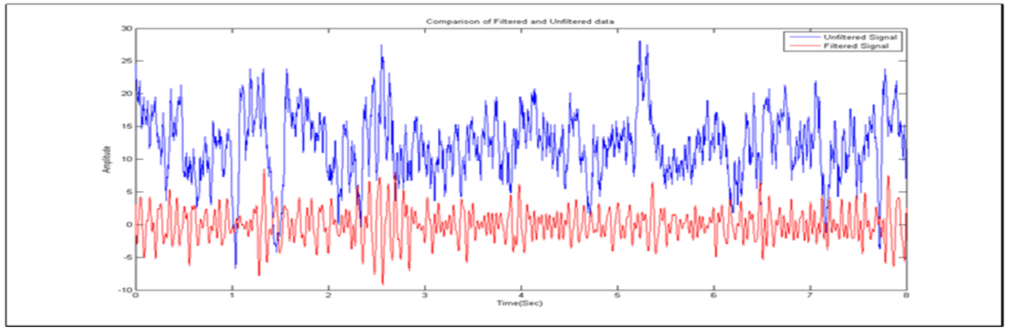
Pre-processing

- Refers to any transformation or reorganisation of signals before analysing the data and after collecting the data.
- Steps involved:
  - Filtering
  - Epoch extraction
  - Trial Rejection
  - Spatial Filtering
  - Re-referencing
  - Interpolating bad electrodes

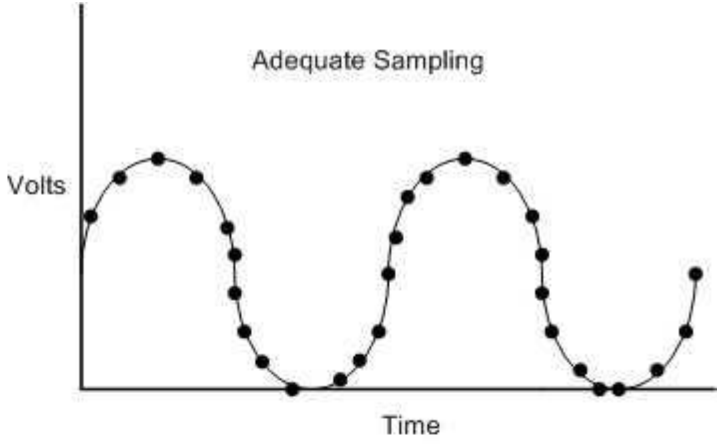
Pre-processing: Filtering

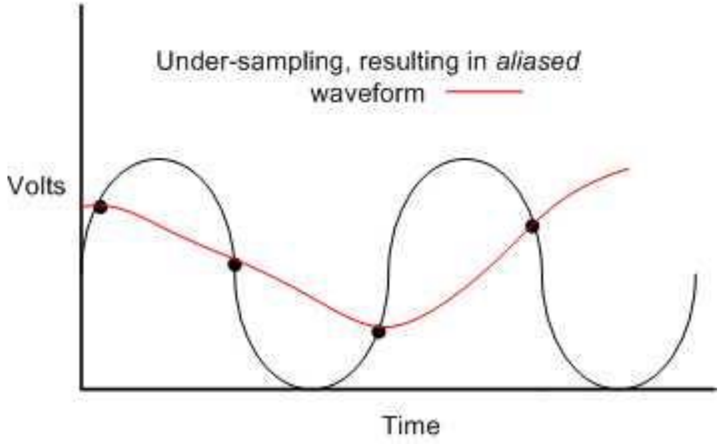
- Remove high frequency artefacts, low frequency drifts
- Notch filters at 50/60 Hz to attenuate electrical line noise
- Recommended to apply a High-pass filter at 0.1 or 0.5Hz to minimize slow drifts
- Band-pass, Band-stop, High, Low Filters
- FIR and IIR filters
  - FIR filters are more stable; less likely to introduce nonlinear phase distortions
  - Computational costs higher to IIR
- scipy.signal (https://docs.scipy.org/doc/scipy/reference/signal.html)





Pre-processing: Downsampling





- Nyquist Theory – minimum digital sampling frequency must be > twice the maximum frequency in analogue signal

Pre-processing: Spatial Filtering

- Bipolar: the voltage difference between two electrode pairs
- Laplacian

$$V_i^{Lap} = V_i^{ER} - \sum_j g_{ij} V_j^{ER} \quad \text{where} \quad g_{ij} = \left(d_{ij} \sum_j \frac{1}{d_{ij}} \right)^{-1}$$

- Common Average Referencing (CAR)

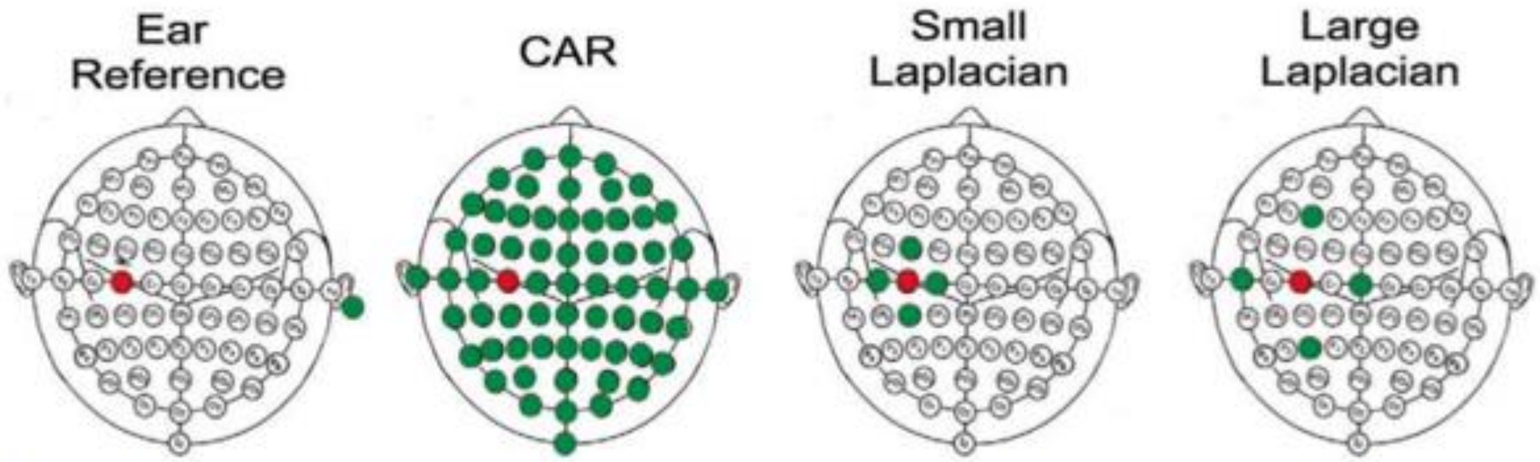
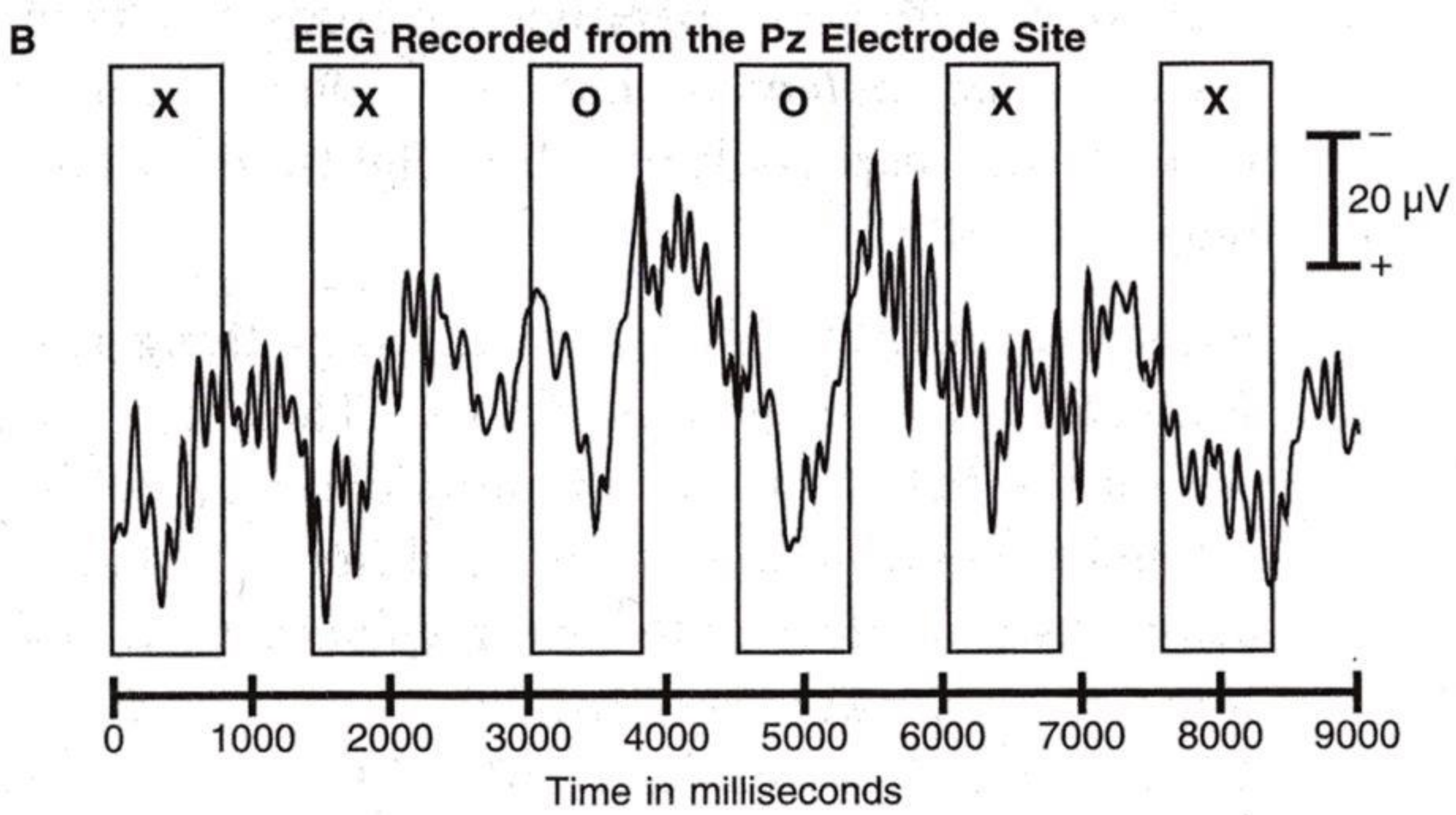


Figure 3. For a clinical EEG array, a mean or weighted mean of green electrodes would be subtracted from the red electrode for each spatial filter listed [7].

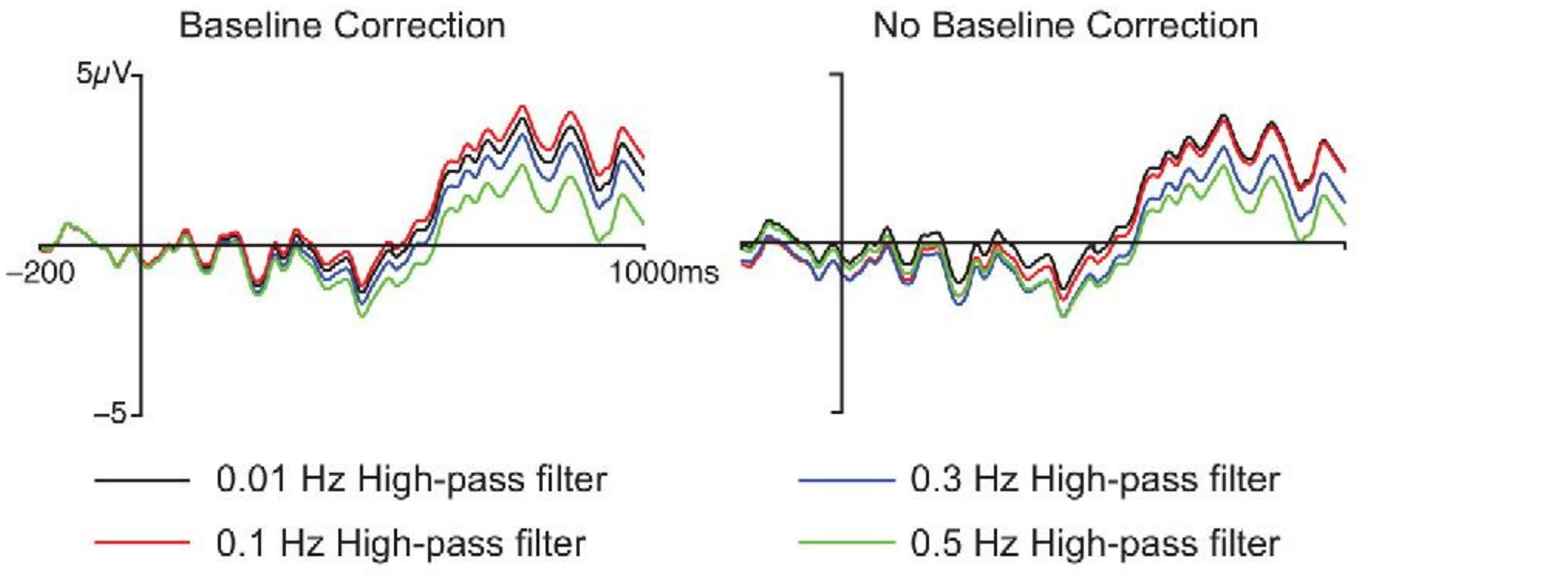
McFarland, 1997

Pre-processing: Epoching



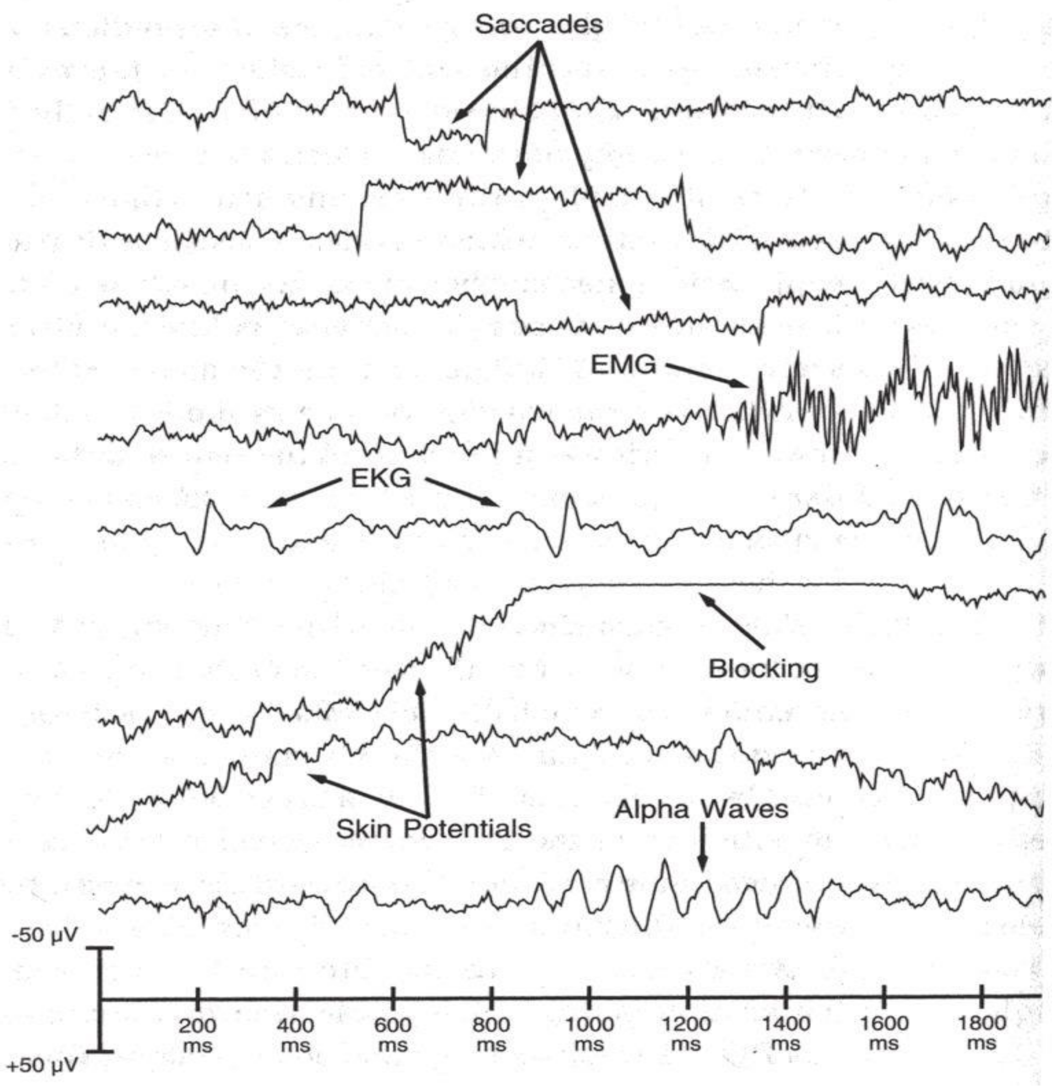
Pre-processing: Baseline Correction

- Baseline correction is a linear operation because we are just computing the average of the points from the baseline period and subtracting this average from each point in the waveform.



Tanner 2016, Journal of Neuroscience Methods

Artefact Removal



Blinks

Eye-movements

Muscle activity

EKG

Skin potentials

Alpha waves

Artefact Removal

- **Blinking**
  - Avoid contact lenses
  - Build ‘blink breaks’ into your paradigm
  - If subject is blinking too much – tell them

- **EMG**
  - Ask subjects to relax, shift position, open mouth slightly

- **Alpha waves**
  - Ask subject to get a decent night’s sleep beforehand
  - Have more runs of shorter length – talk to subject in between
  - Jitter ISI – alpha waves can become entrained to stimulus

Artefact Removal-EOG/Blinks

- most common contaminants of the EEG signal.

Linear Regression

- The main assumption in this approach is that each EEG channel can be expressed as the sum of noise-free EEG signal and a fraction of the source artifact available through EOG electrodes.
- Let S be the recorded EEG signal which can be expressed as the sum of noise-free EEG signal E and EOG or eye blink signal B multiplied by a weight matrix W.

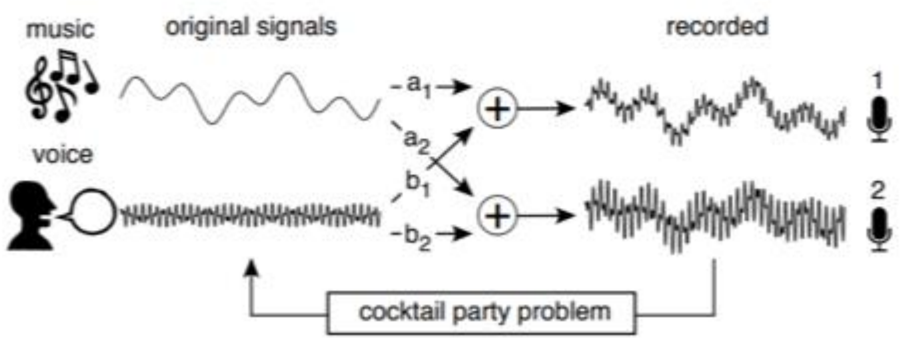
$$S = WB + E$$

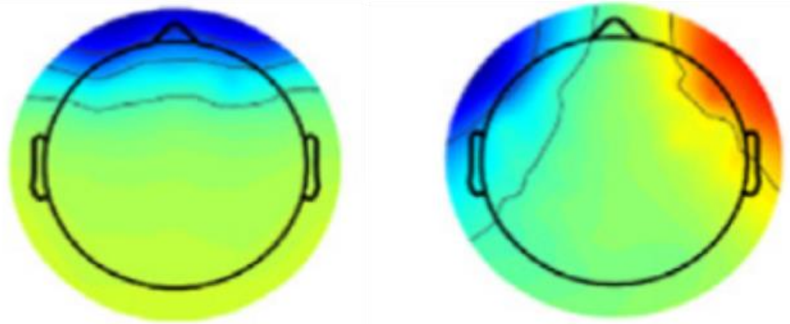
W describes the contribution of the EOG artifact in each EEG channel

Artefact Removal-EOG/Blinks

ICA

- Independent component analysis (ICA) is a blind source separation (BSS) technique that is widely used in an array of signal processing applications.
- Once the components have been identified, to remove the EOG artifacts, one can visually determine which independent component corresponds to eye-blinks or movements based on the following criteria.

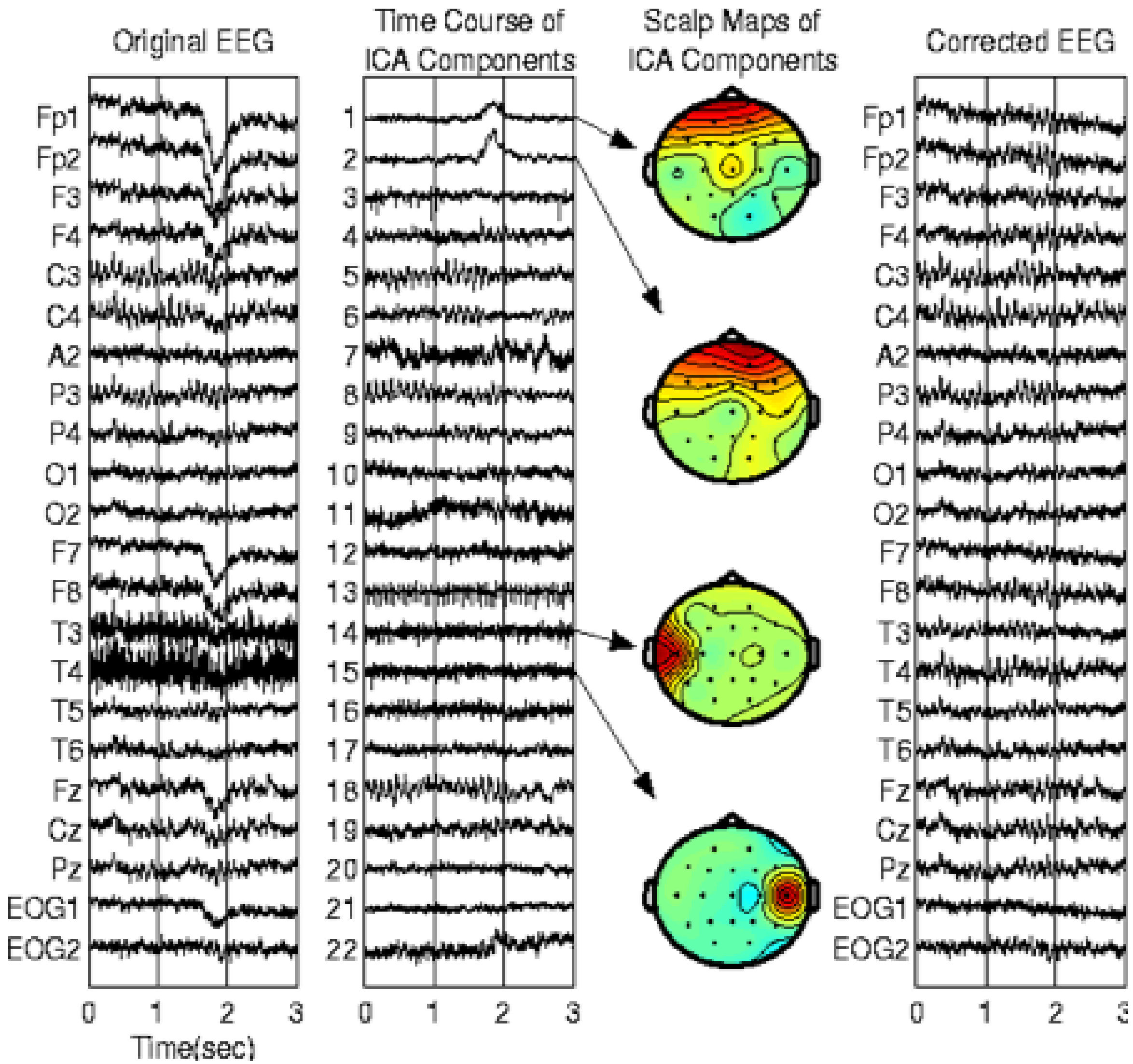




Presence of frontal topography (for blinks, shown on left) and bilateral with opposite sign frontal topography (for horizontal eye-movements, shown in right) in scalp map (adapted from here).

Artefact Removal-EOG/Blinks

ICA

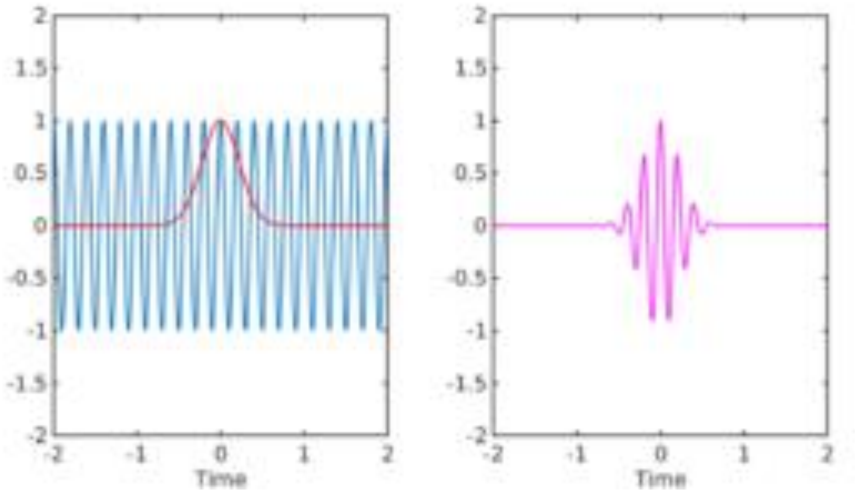


- mne.preprocessing.ICA
- (https://mne.tools/stable/generated/mne.preprocessing.ICA.html)

Time-Frequency Domain Analysis

Morlet Wavelet

- Wavelets overcome limitations of methods such as the Fourier transform by enabling a view of changes across both time and frequency.
- shape of a sinusoid, weighted by a Gaussian kernel, and they can therefore capture local oscillatory components in the time series.
- Wavelets have variable resolution in time and frequency.

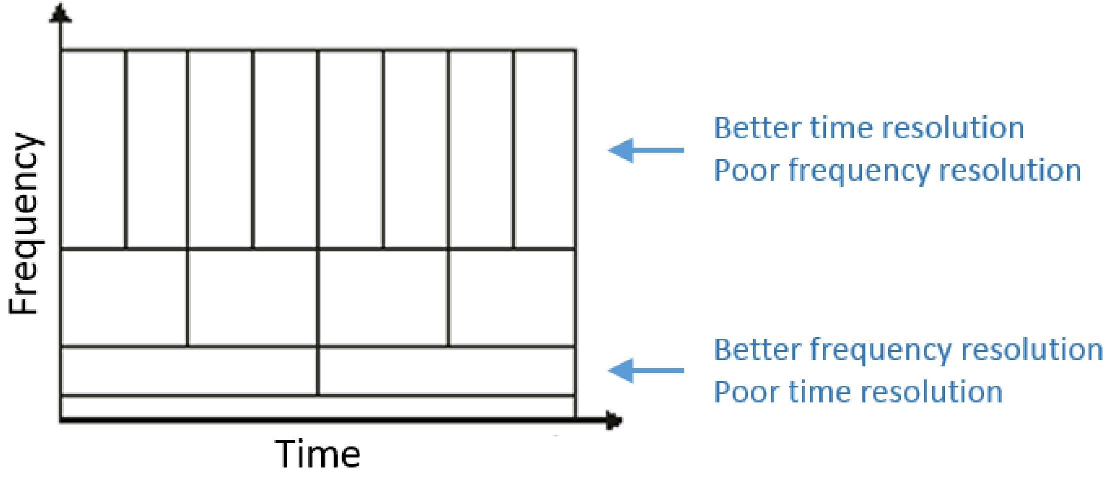


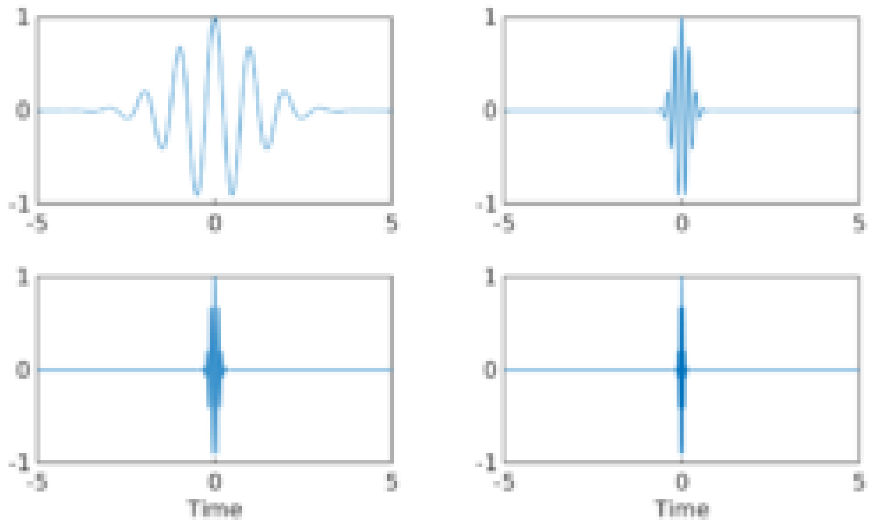
$$\psi(t) = e^{2j\pi f t} e^{\frac{-t^2}{2\sigma}}$$

Time-Frequency Domain Analysis

Morlet Wavelet

- Wavelet transformation then essentially involves convolving the complex wavelet with the EEG signal and moving it along the time axis (known as **translation**) and doing this with wavelets of varying frequencies (known as **scaling**).
- **higher frequency wavelets** can achieve **better localization in time**, while low frequency wavelets lose some information in time as they are stretched out.





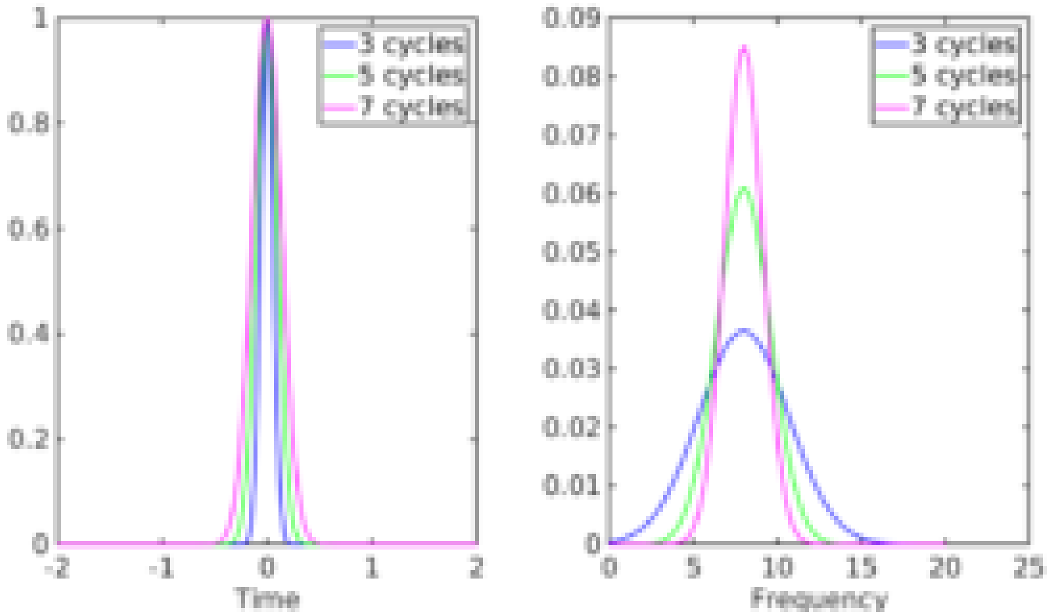
wavelets of frequency 1, 5, 10 and 20 Hz

Time-Frequency Domain Analysis

$$\sigma = \frac{n}{2\pi f}$$

Morlet Wavelet

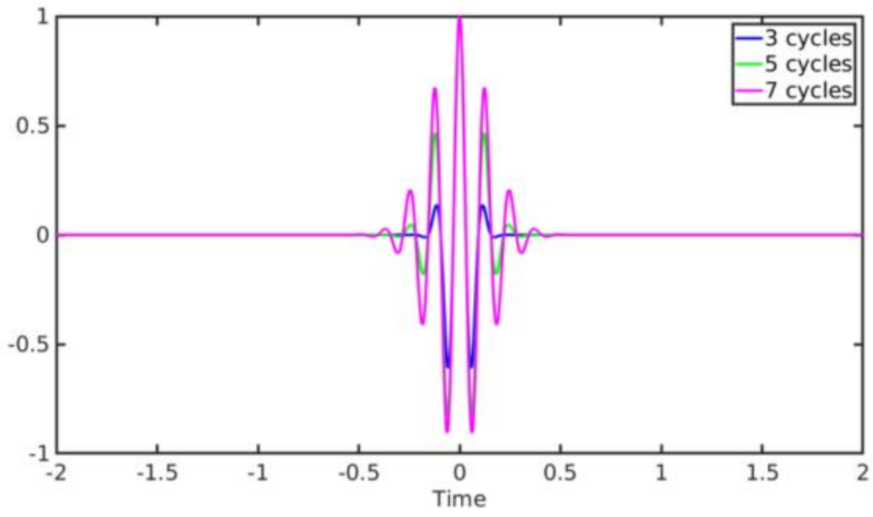
- Most important parameter-**number of cycles**
- As the number of cycles is increased the width of the Gaussian increases.
- When we take the FFT of these Gaussians, we see that the Gaussian with lower number of cycles is spread more in the frequency domain compared to the Gaussian with higher number of cycles.



Time-Frequency Domain Analysis

Morlet Wavelet-Choosing the number of cycles (*n*)

- the wavelet with higher *n* has wider spread than wavelet with lower *n*, which can be interpreted as poorer temporal localization as *n* increases.
- For temporal-focussed analysis, choose **lower n**
- For frequency-focussed analysis, choose **higher n**



mne.time_frequency.tfr_morlet
mne.time_frequency.tfr_array_morlet
(https://mne.tools/stable/time_frequency.html)

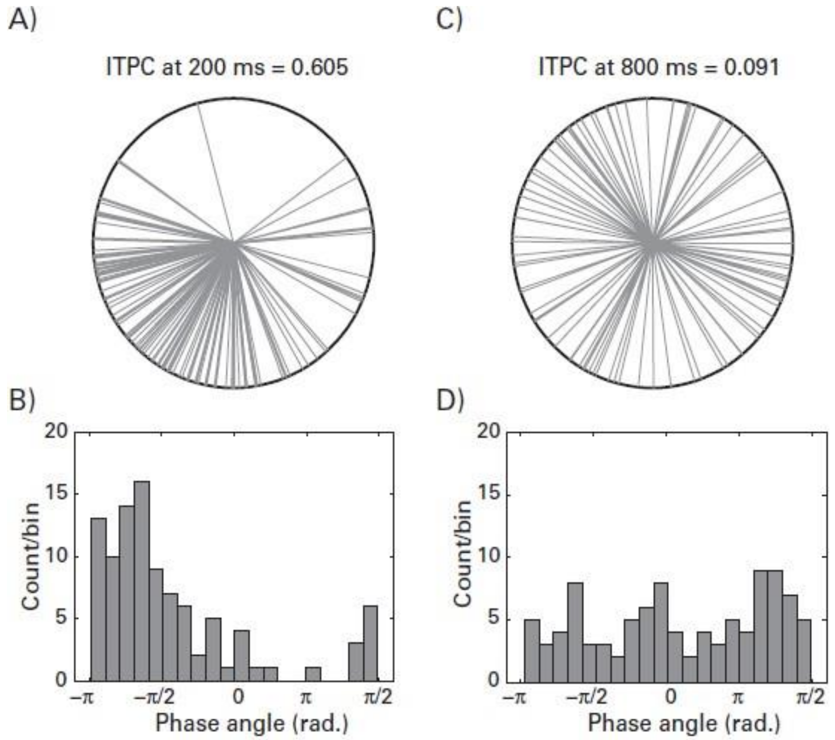
Inter-trial Phase Clustering (ITPC)

Average the activity at each time point across trials to form an event-related potential (ERP)

Average the frequency-band-specific power at each time point across trials

Phase values cannot be averaged together in the same way that voltage values or power values can be averaged

Basis for phase-based connectivity methods



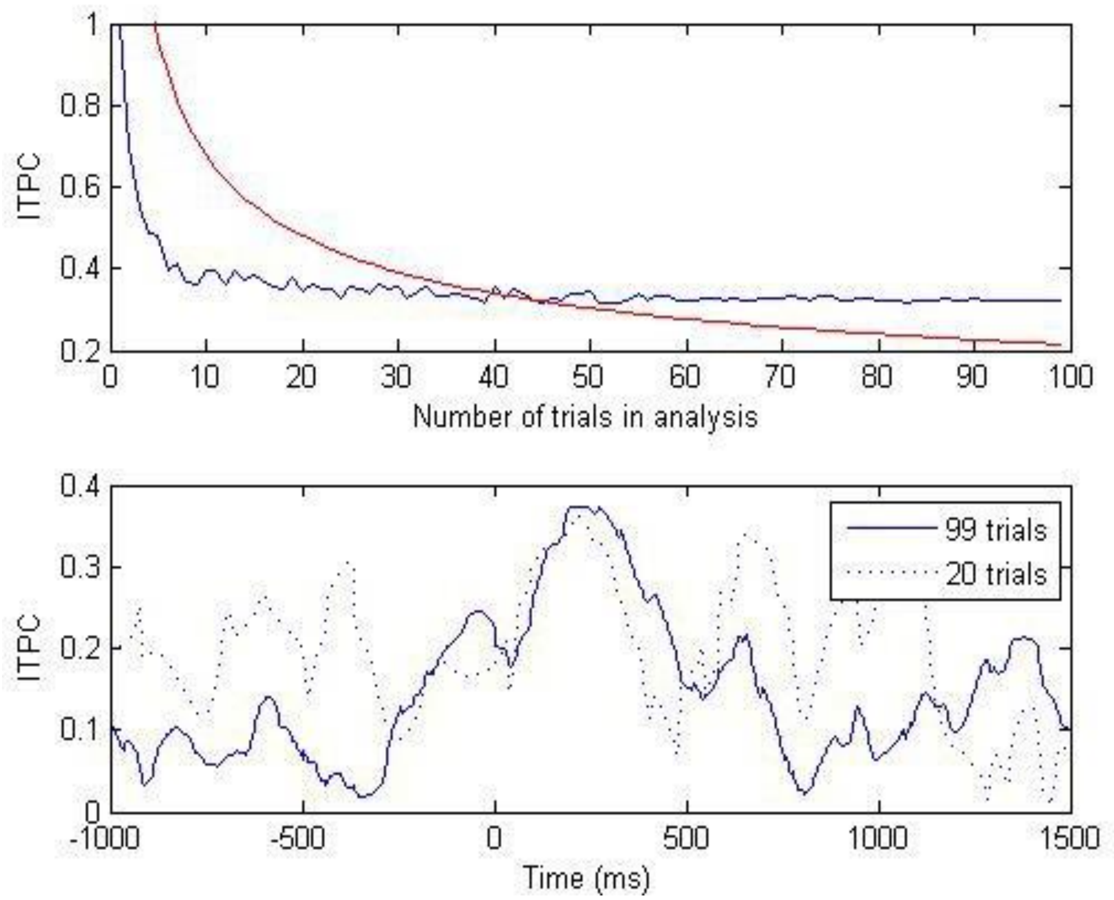
Inter-trial Phase Clustering (ITPC)

- ITPC measures the extent to which a distribution of phase angles at each time-frequency-electrode point across trials is nonuniformly distributed in polar space
- ‘phase-locking value’, ‘phase coherence’
- Measured by computing average vector, and then take the length of that average vector
- Individual vectors have unit length, average vector has a length < 1
- Further apart are the 2 vectors, their average length is smaller
- Length of average vector reflects the closeness of the two unit length vectors
- ITPC is the length
- ITPC = 0 means completely uniformly distributed phase angles
- ITPC = 1 completely identical phase angles

$$\mathrm{ITPC}_{tf} = \left| n^{-1} \sum_{r=1}^{n} e^{ik_{tfr}} \right|$$

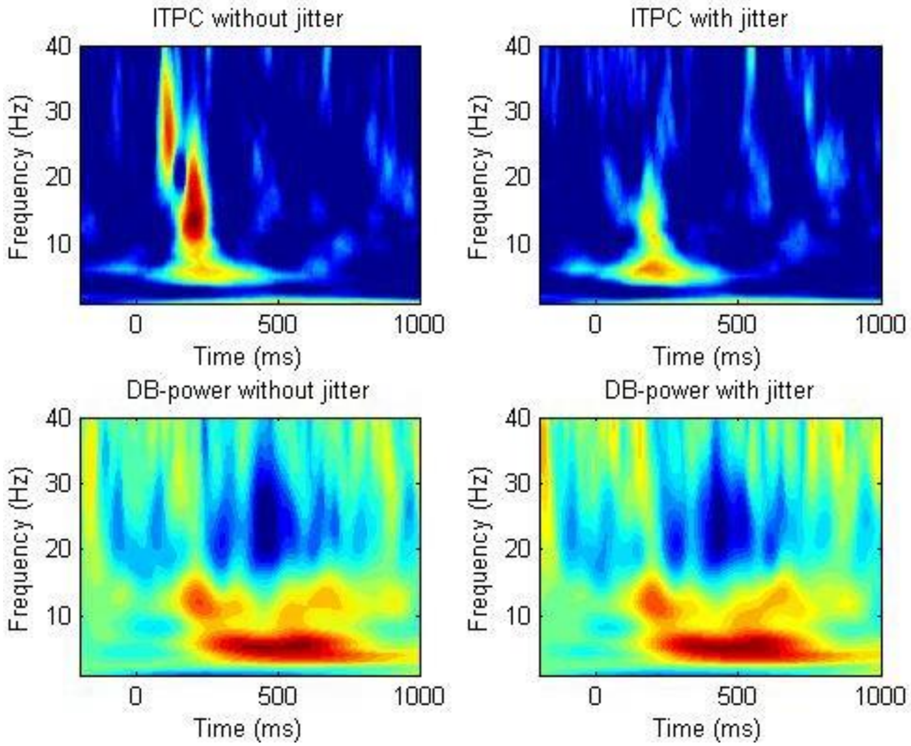
ITPC-Trial Count

- Small number of trials inflates ITPC
  - Especially problematic when comparing across conditions with different trial counts
- ~30 trials o.k.
- High-frequency activity may require even more trials



ITPC-Temporal Jitter

- Most problematic when examining higher frequencies
- consider monitor refresh rate



ITPC-Phase and Power

- Phase is more influenced by power when power is low
  - Check SNR or plot
- When power is high, phase is independent of power