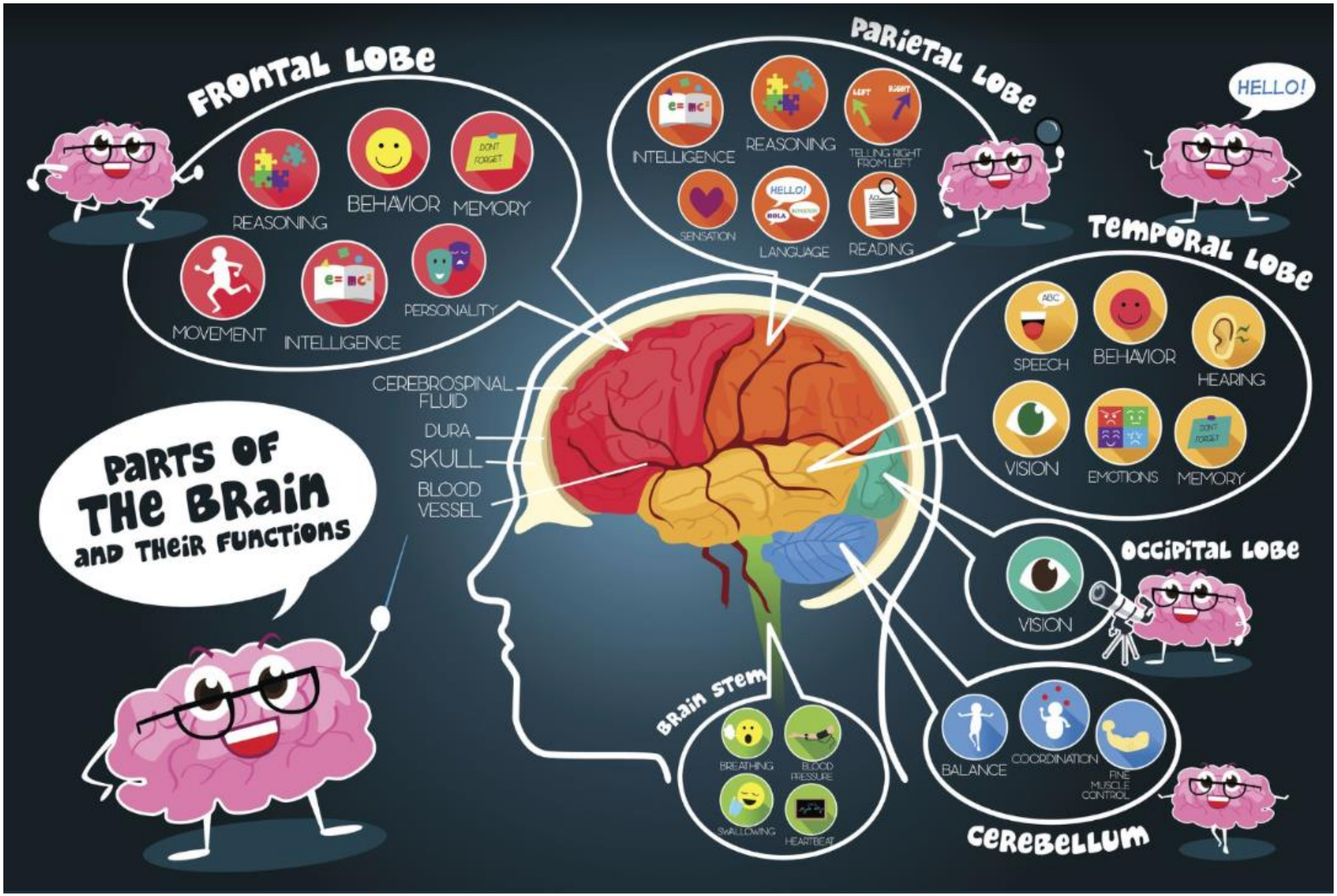
Investigating time series neural data: Experimental design & signal processing practices

Dr Saugat Bhattacharyya

Content

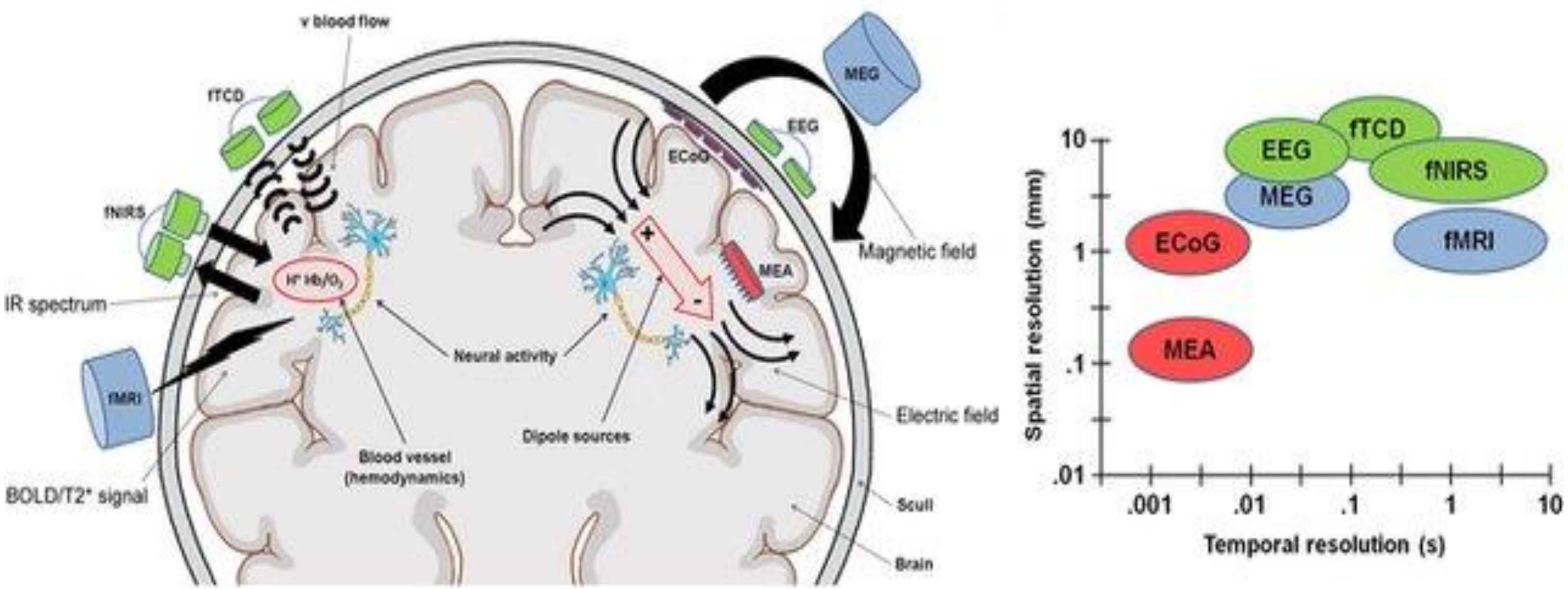
- EEG Signal Analysis
  - Common Pre-processing methods
  - Time-Domain
  - Time-frequency
- Brain Computer Interfacing- An Introduction
- Collaborative BCI

Activity in the Brain



https://community.esri.com/t5/human-brain-webgis-blog/parts-of-the-brain-and-their-function/ba-p/892955

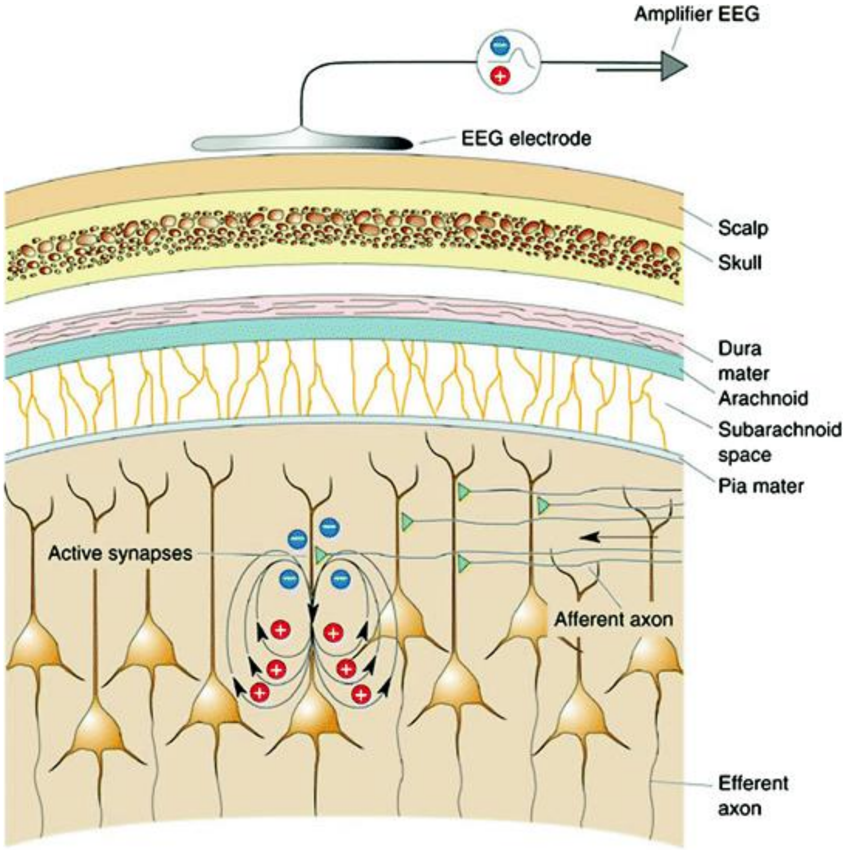
Recording Neural Activity



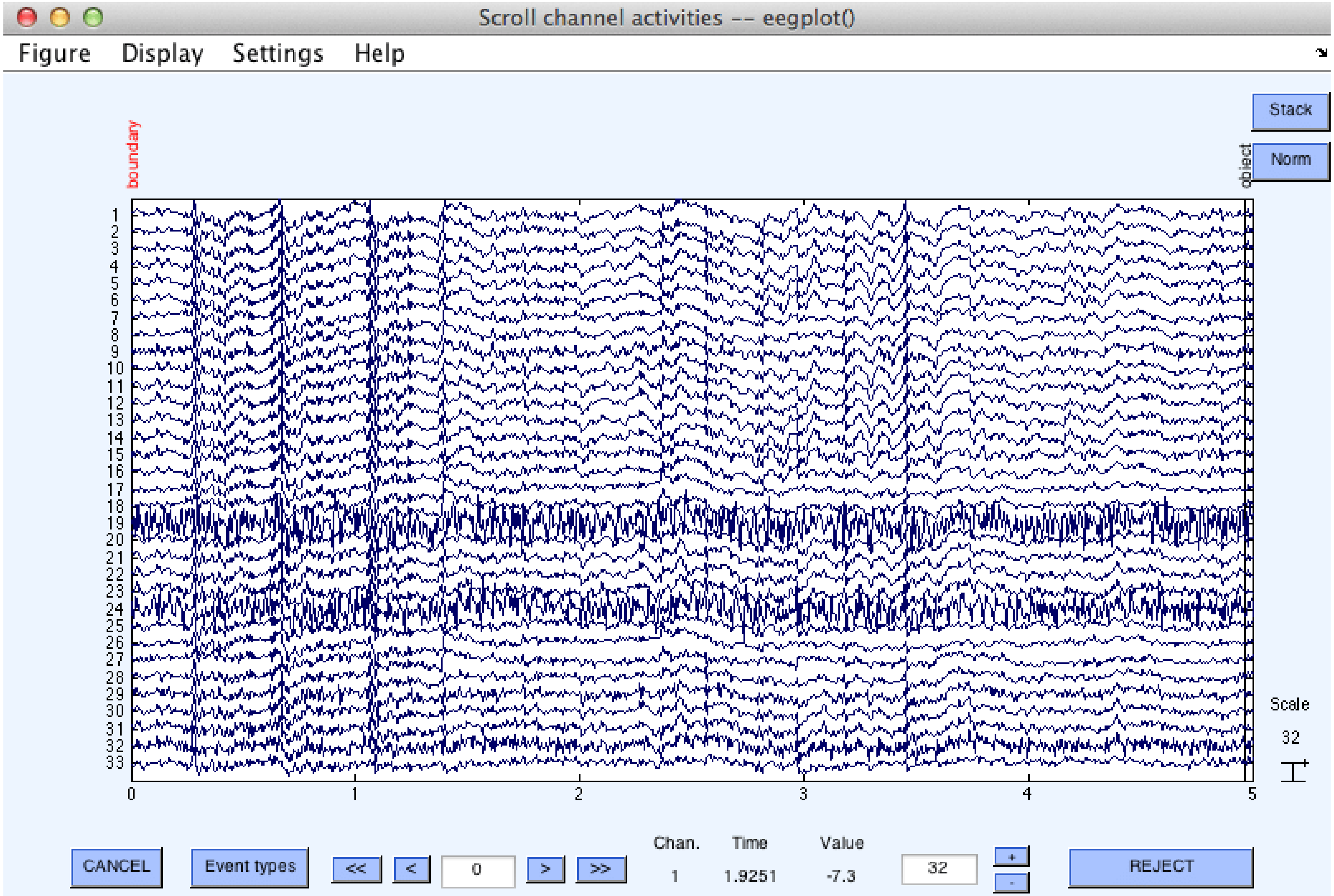
Trambaillo, Falk. 2018

Existence of EEG

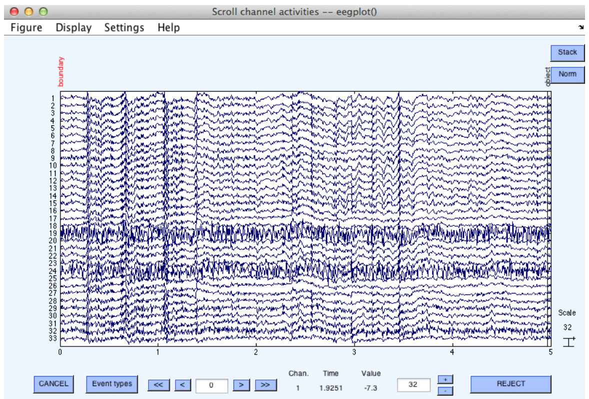
- The neuronal firing inside the brain generates electrical signals.
- These electrical signals picked up from the scalp by metallic electrodes are called EEG signals.
- Summation of excitatory and inhibitory postsynaptic potentials



What do EEG look like?



Basic Pipeline

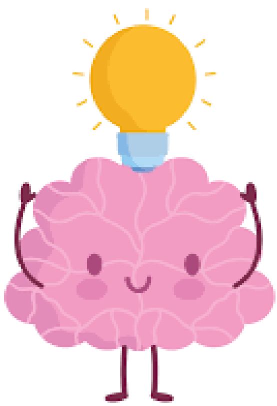


Pre-processing

Processing (Analysis)

Time Cosuming
Tedious
Signal Processing
Do it well, Do it once

Hypothesis driven
Exploratory
Often done multiple times



EEG Frequency Chart

Waveform	Frequency Range (in Hz)	Amplitude (in μV)	Occurrence
Gamma rhythm	30-50		Excitement
Beta rhythm	18-30	< 10	Alert/eyes open, arousal, anterior scalp
Alpha rhythm	8-13	0-40	Adults, older children, relaxed wakefulness/eye closed, parietal, occipital temporal regions
Mu rhythm	7-11	0-20	Asymmetric, asynchronous between 2 sides at times unilateral, central parietal, attenuates with contra-lateral extremity movement, thought of movement, or tactile stimulation; no reaction to eye opening and closing
Theta rhythm	4-7	40-60	Childhood, light sleep, temporal areas through adolescence
Delta rhythm	0.5-4	40-200	Sleep
Delta rhythm	0.5-3	40-200	Infancy, deep sleep, coma
Lambda & K complex & sleep spindles	Not defined solely in terms of rhythm		Deep sleep

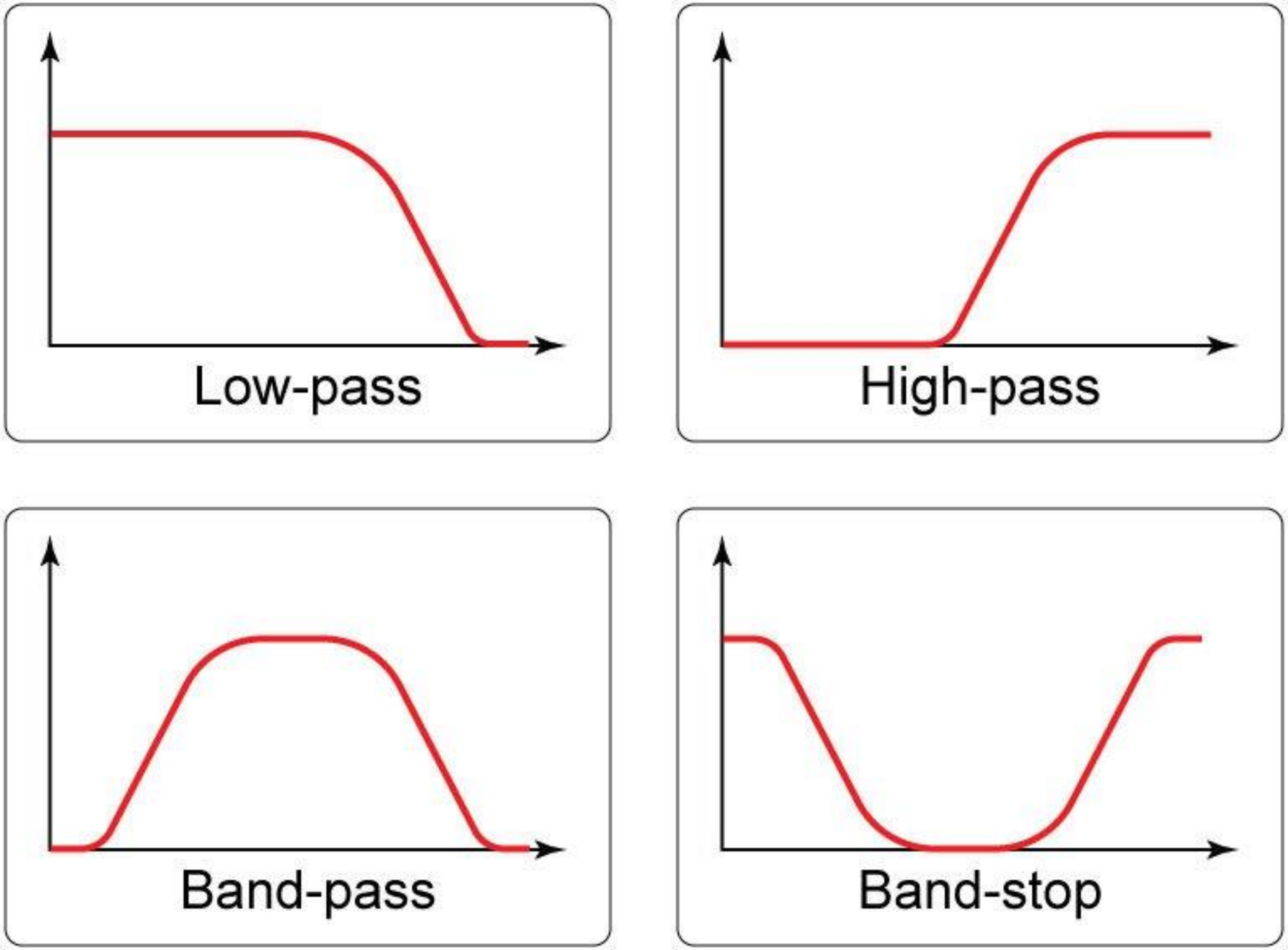
Possible Pre-processing Steps

- Import Data and Channel Locations
- Filter the data
- Downsample
- Extract Data: Epoch the data around important events
- Baseline correction: Subtract pre-stimulus baseline
- Adjust marker values
- Manual trial rejection
- Identify bad channels
- Re-reference the data
- Run ICA to clean data

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: Filtering



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)

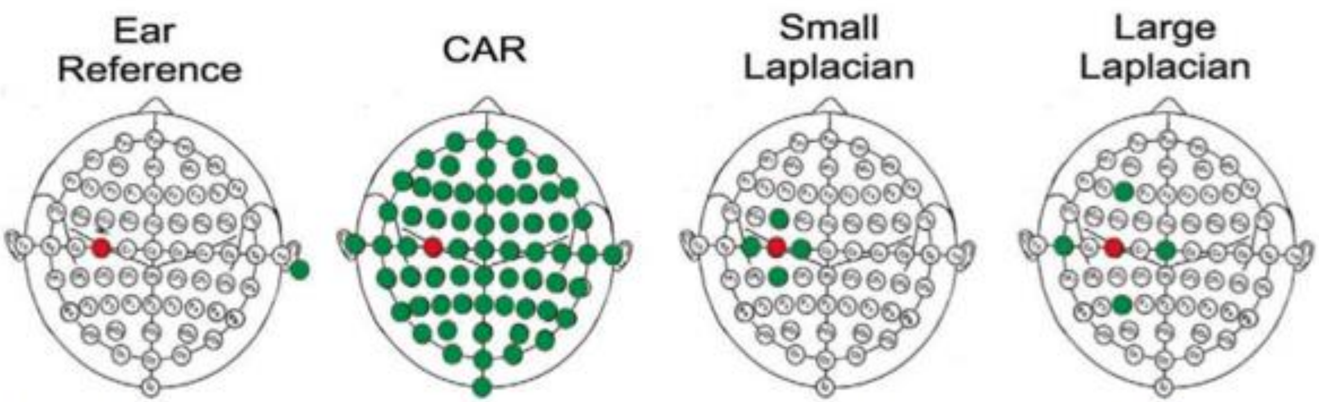
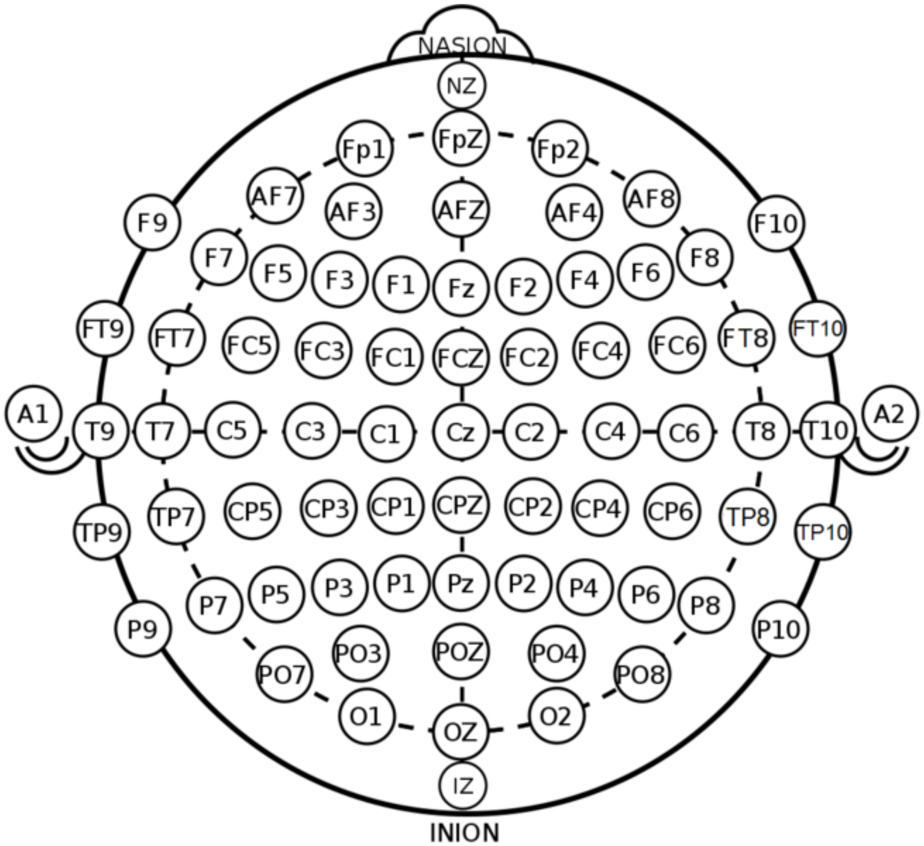


Figure 3. For a clinical EEG array, a mean or weighted mean of green electrodes would be subtracted from the red electrode for each spatial filter listed [7].

McFarland, 1997

Pre-processing: Spatial Filtering

Small Laplacian

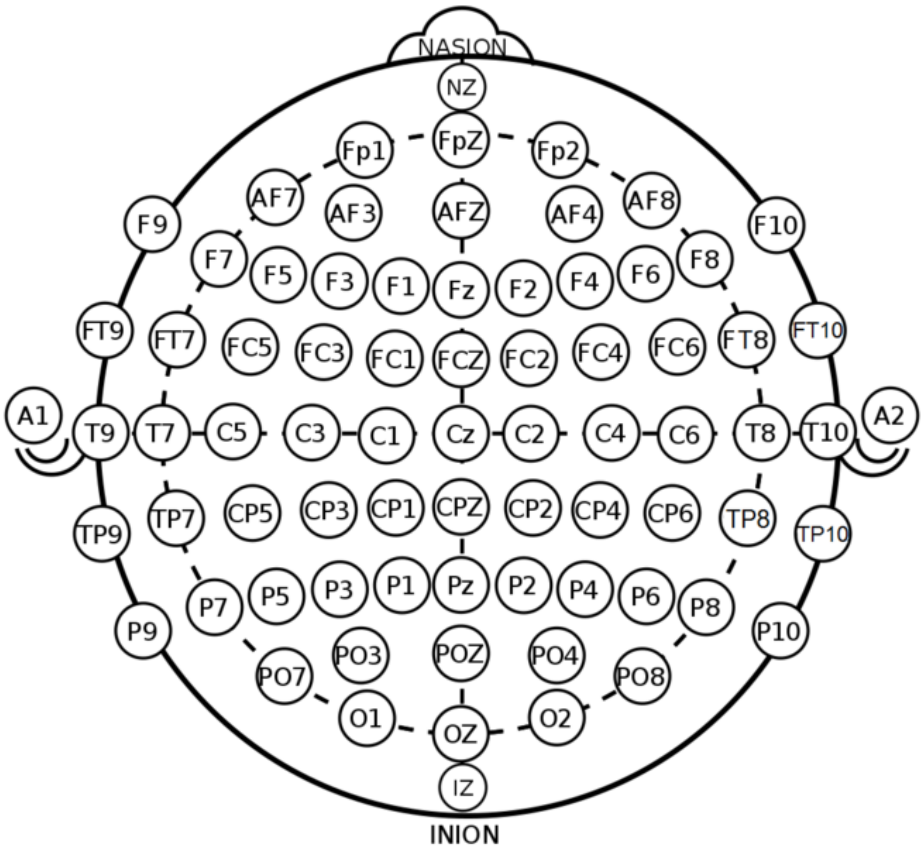


Cz= Cz-1/8*(FC1+FCz+FC2+C2+CP2+CPz+CP1+C1)

FC3=??

Pre-processing: Spatial Filtering

Small Laplacian

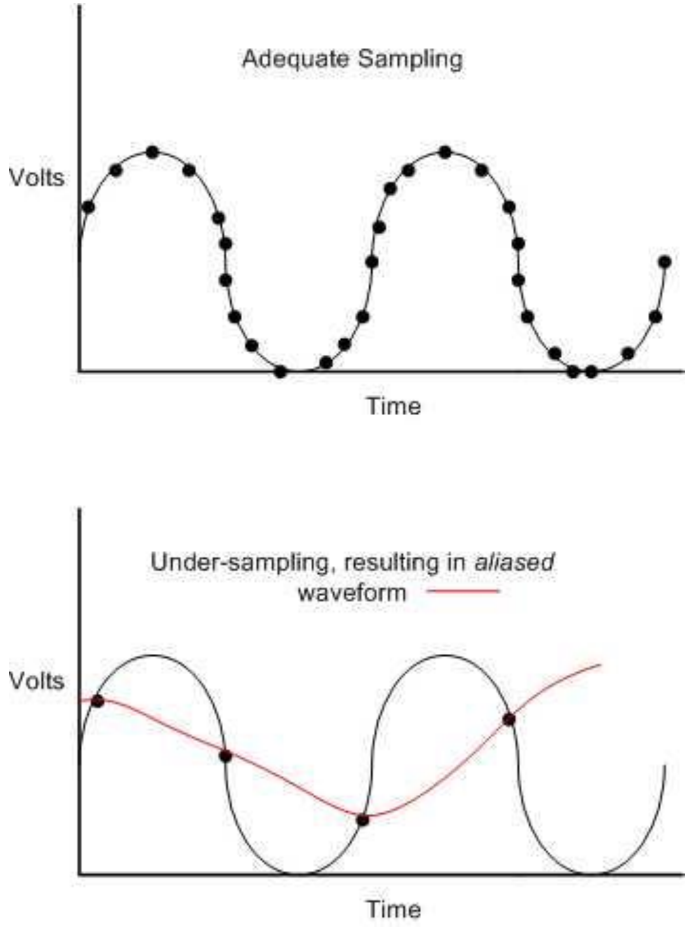


Cz= Cz-1/8*(FC1+FCz+FC2+C2+CP2+CPz+CP1+C1)

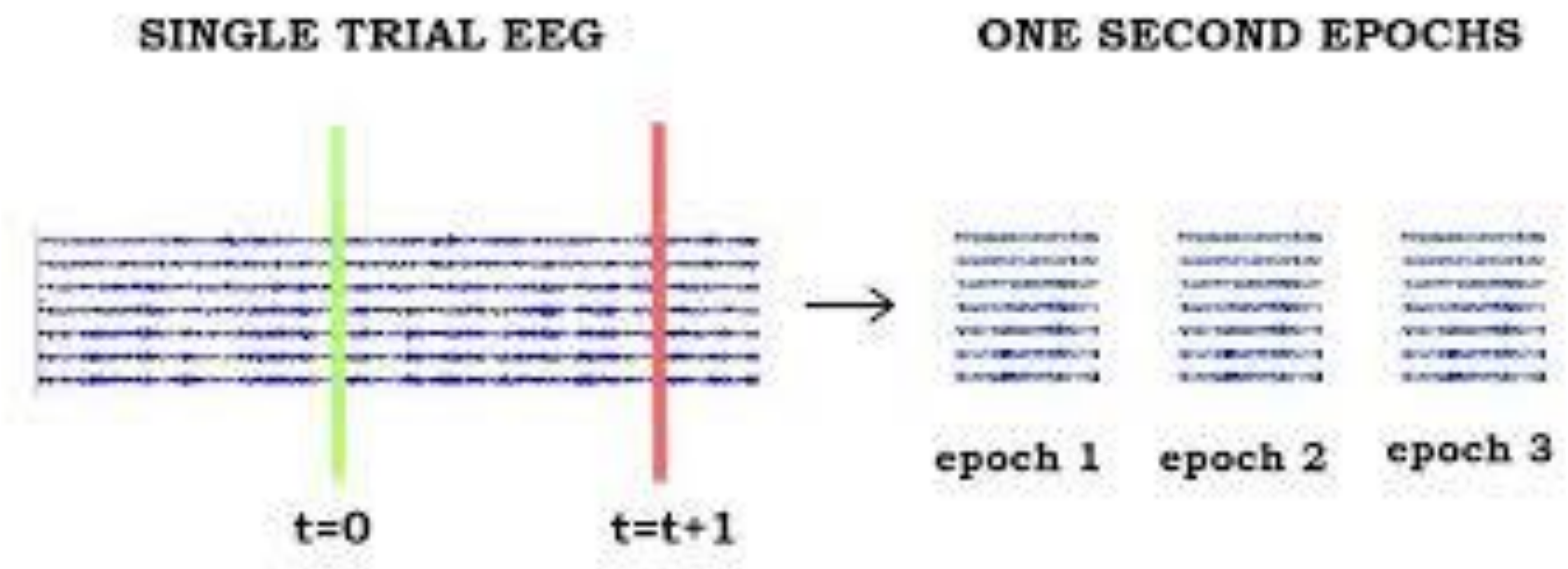
FC3= FC3-1/8*(FC5+F5+F3+F1+FC1+C1+C3+C5)

Pre-processing: Downsampling

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

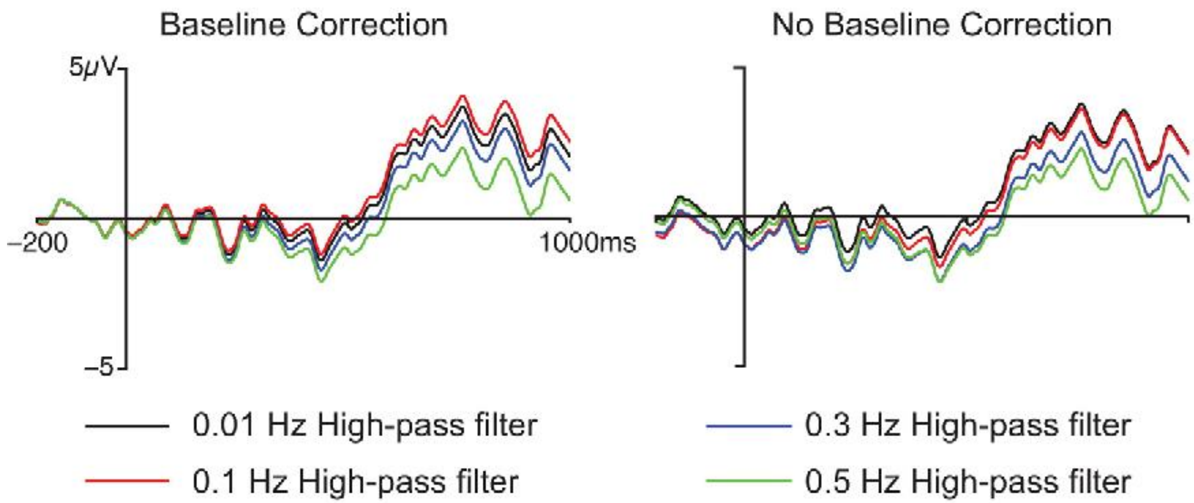


Pre-processing: Epoching



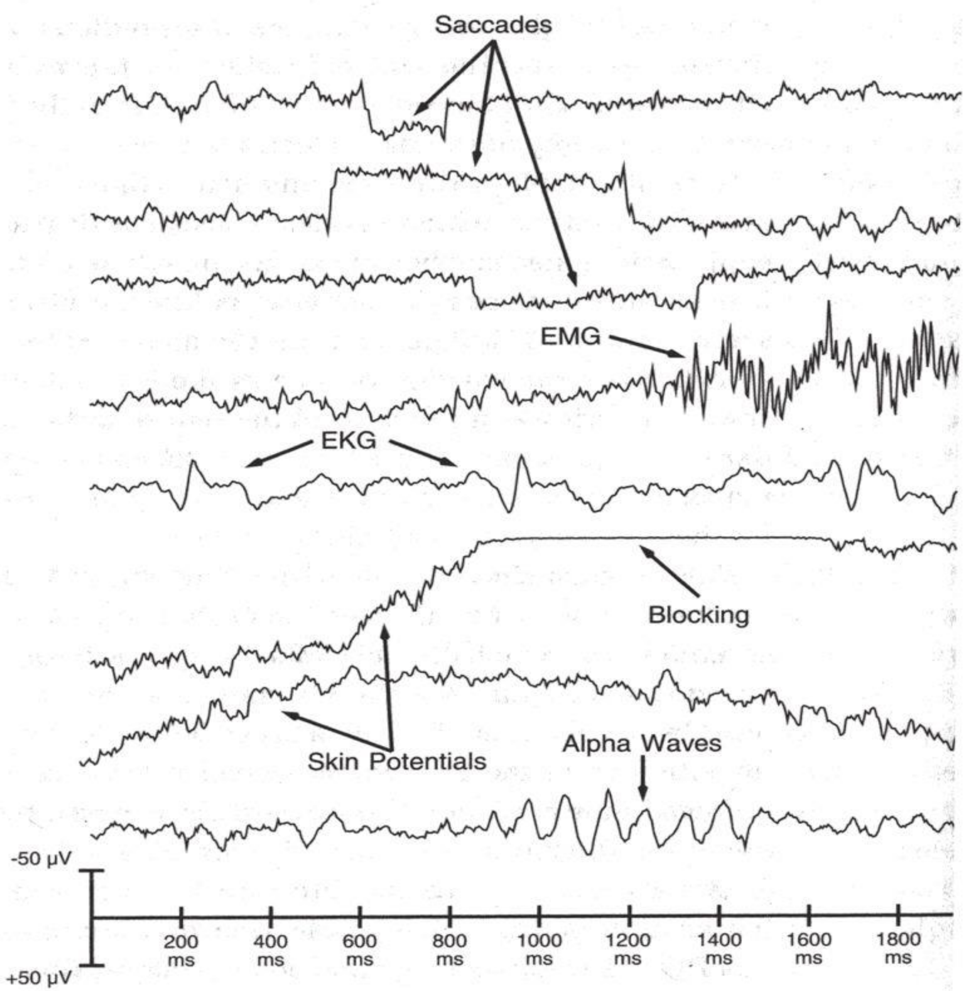
Pre-processing: Baseline Correction

- 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

Preprocessing: Artefact Removal



Blinks

Eye-movements

Muscle activity

EKG/ECG

Skin potentials

Alpha waves

Preprocessing: 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*.

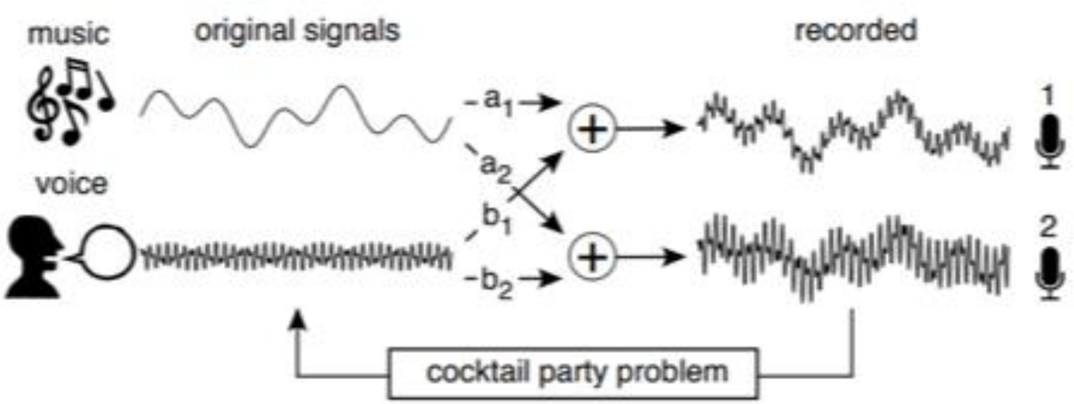
$$S = WB + E$$

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

Artefact Removal-EOG/Blinks

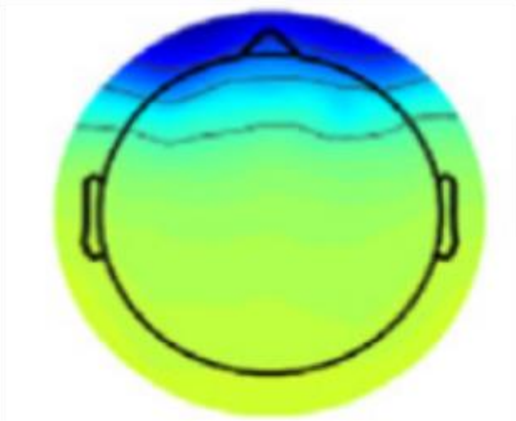
ICA

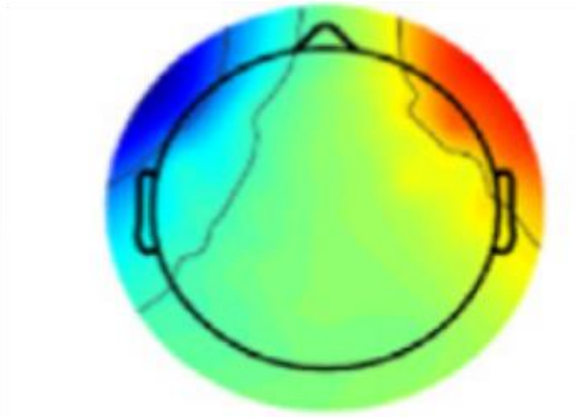
- Independent component analysis (ICA) is a blind source separation (BSS) technique that is widely used in an array of signal processing applications.
-
- Once the components have been identified, to remove the EOG artifacts, one can visually determine which independent component corresponds to eye-blinks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



Artefact Removal-EOG/Blinks

ICA

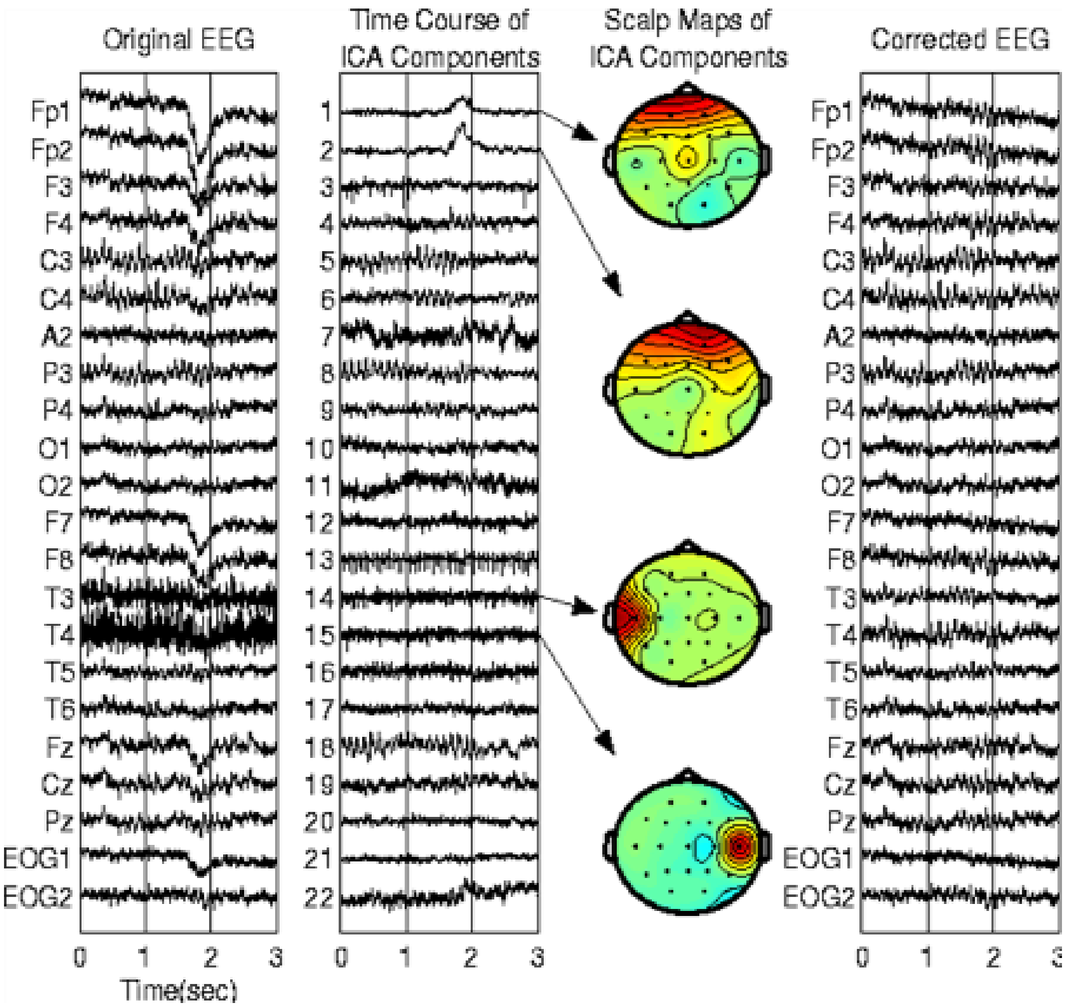




Presence of frontal topography (for blinks, shown on left) and bilateral with opposite sign frontal topography (for horizontal eye-movements, shown in right) in scalp map

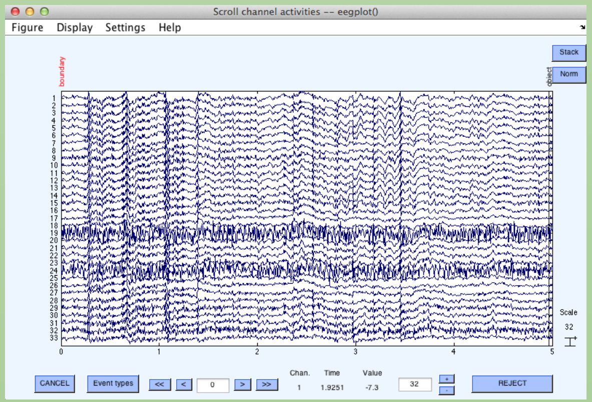
Artefact Removal-EOG/Blinks

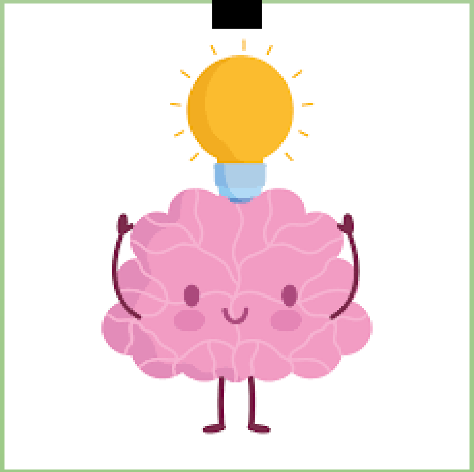
ICA



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

Basic Pipeline





Pre-processing

Processing (Analysis)

Processing

- Time Domain Analysis
  - Event Related Potentials

- Frequency Domain Analysis

- Time-Frequency Analysis
  - Wavelet Transform

Event Related Potentials (ERPs)

- electrical brain responses to events/ stimuli based on time-locked EEG portions

- can measure the time course of processing in tens of ms

- can reveal brain areas related to cortical processing
  - scalp current density and source modeling analyses
  - time-frequency analyses

- allow us to observe how processing changes with development and how it relates to later cognitive outcome

ERPs-Assumptions

ERP-averaging is based on the following assumtions:

(Regan, 1989)

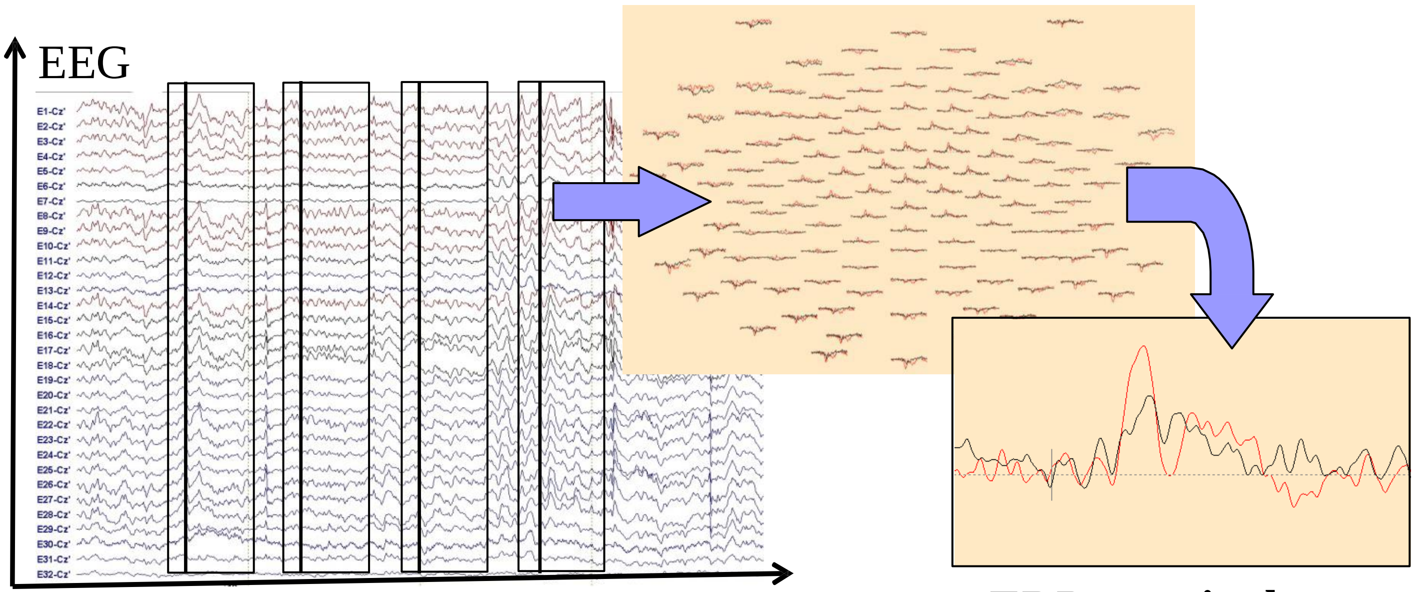
1. The background EEG acts as noise for the ERP-signal
2. The signal waveform is generated by a process that stays stationary from trial to trial
3. The noise, background EEG, is produced by a stationary random process
4. The noise samples are uncorrelated from trial to trial

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

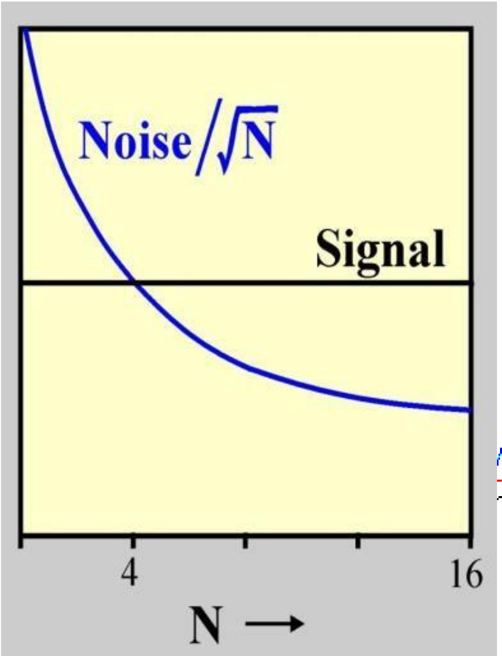
ERPs-Example

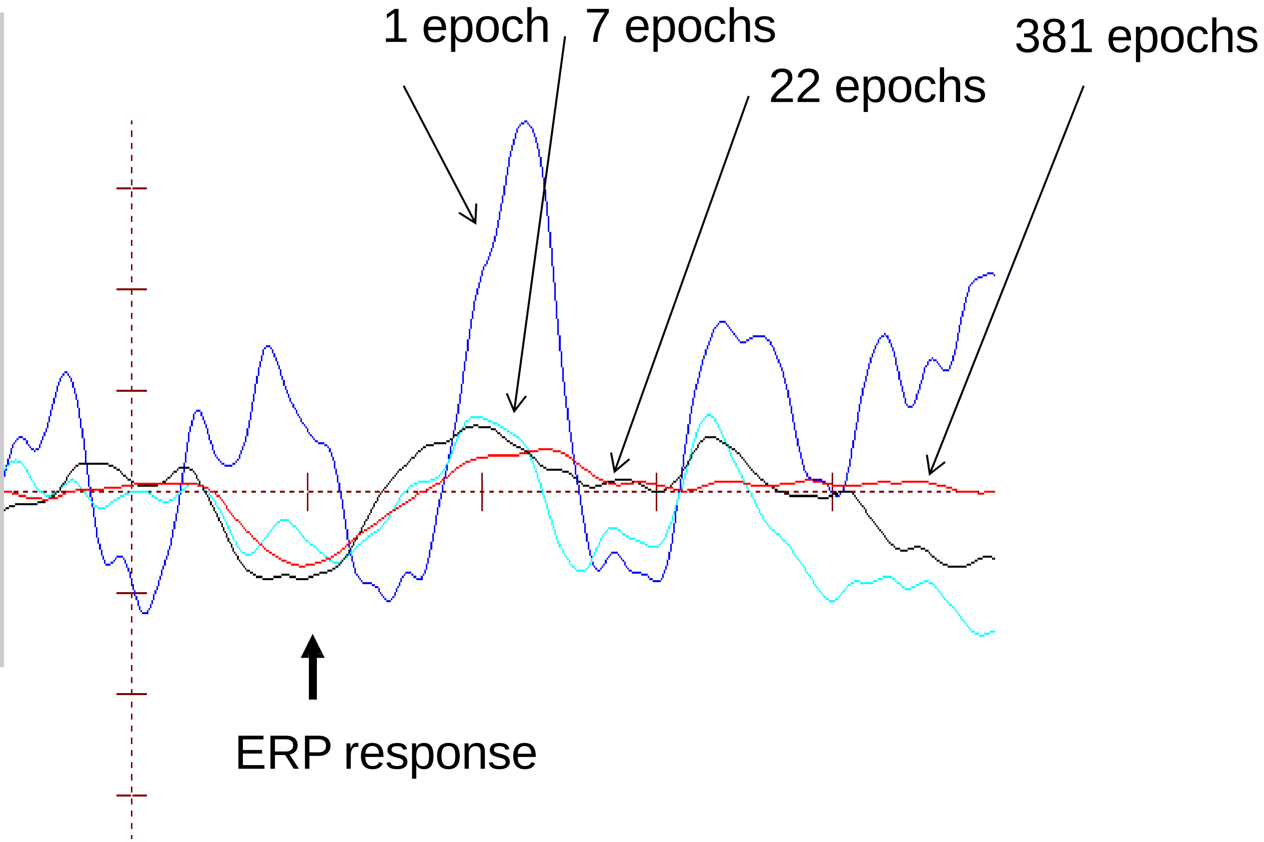
Averaged across 100 stimulus presentations



ERP at a single electrode

Effect of nr of stimulus presentations on the signal-to-noise ratio /SN

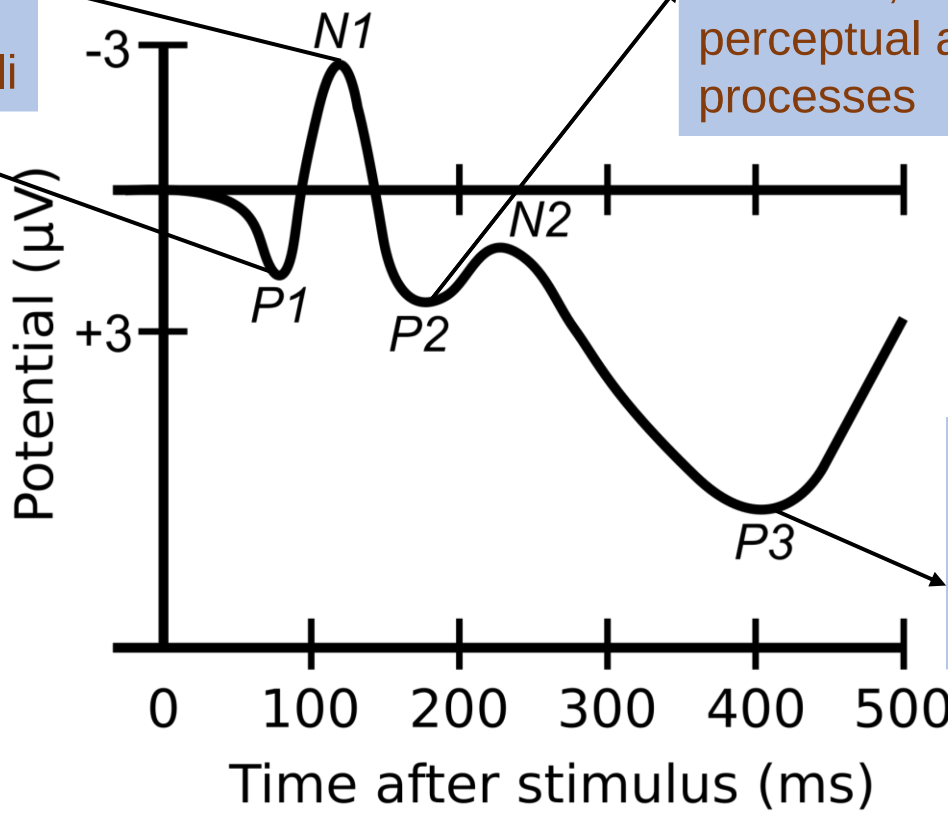




ERP Waveforms

usually larger for attended stimuli than for unattended stimuli

Feature analysis, Goal-directed action selection, higher order perceptual and motivational processes



Attentional resource allocation, memory-updating

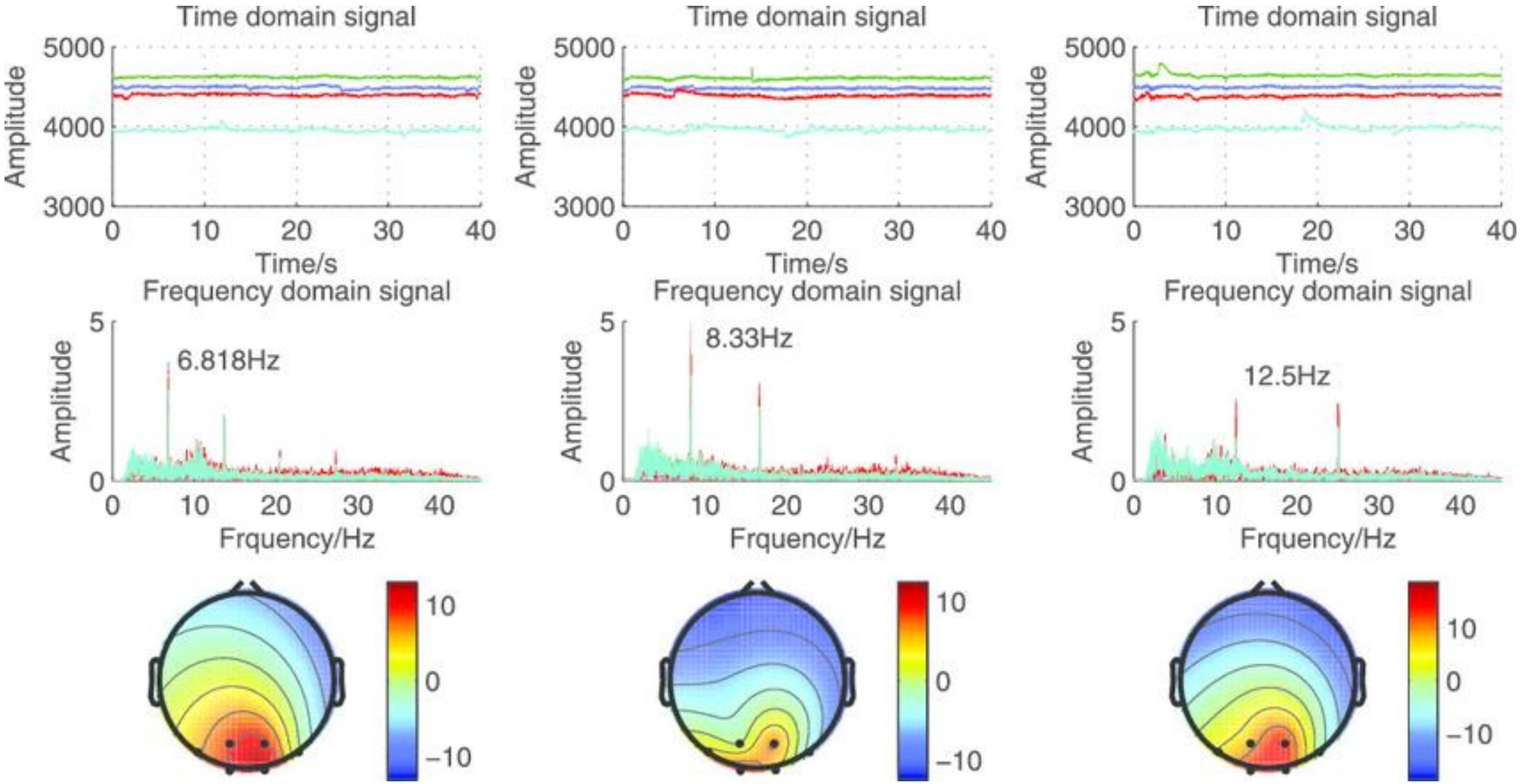
*Definition based on APA dictionary of psychology

Frequency Domain

Fourier Transform:

$$F(j\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}dt$$

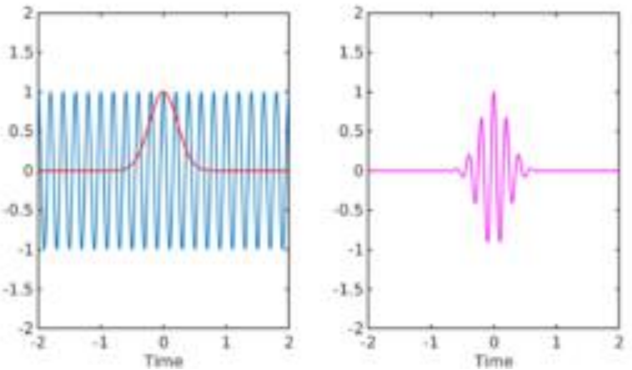
Fourier Transform



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.

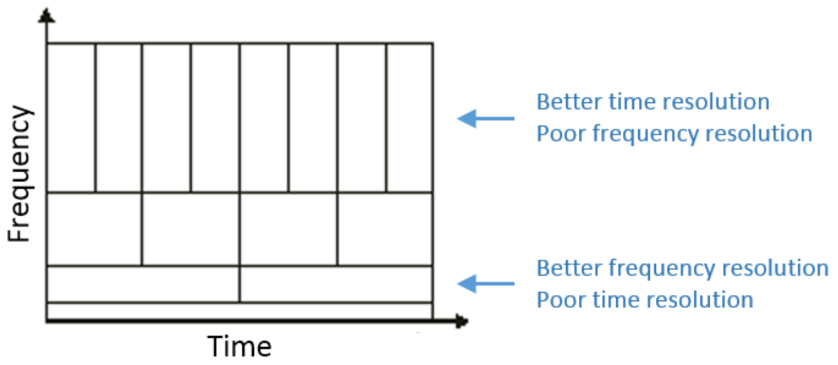


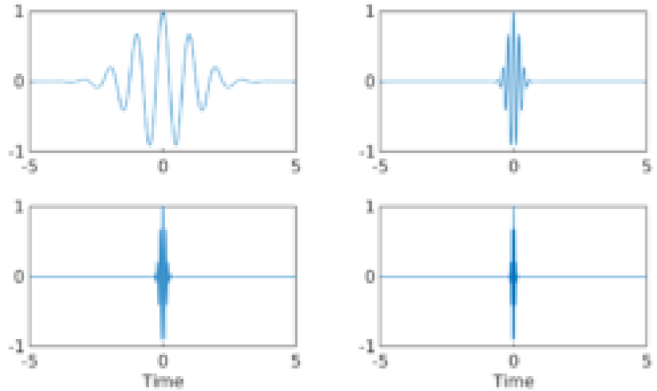
$$\psi(t) = e^{2j\pi f t} e^{\frac{-t^2}{2\sigma}}$$

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.





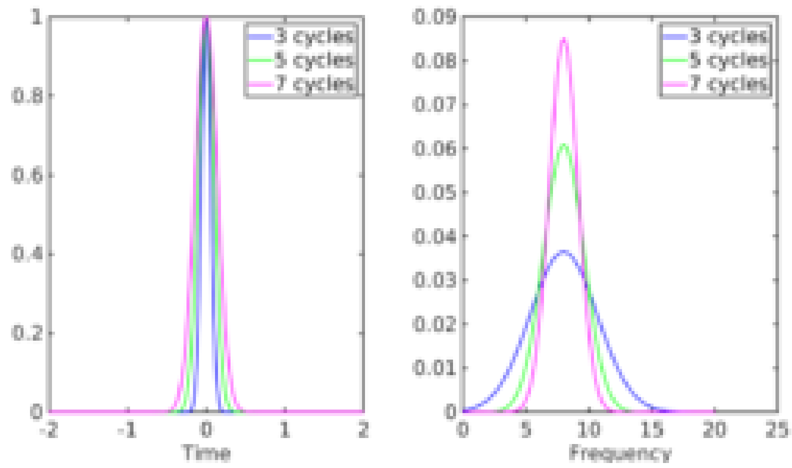
wavelets of frequency 1, 5, 10 and 20 Hz

Time-Frequency Domain Analysis

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.

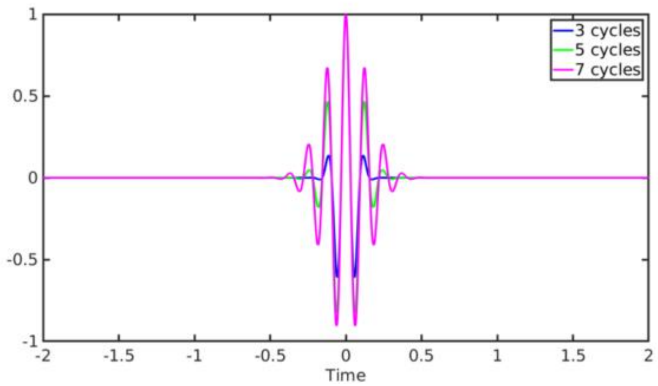
$$\sigma = \frac{n}{2\pi f}$$



Time-Frequency Domain Analysis

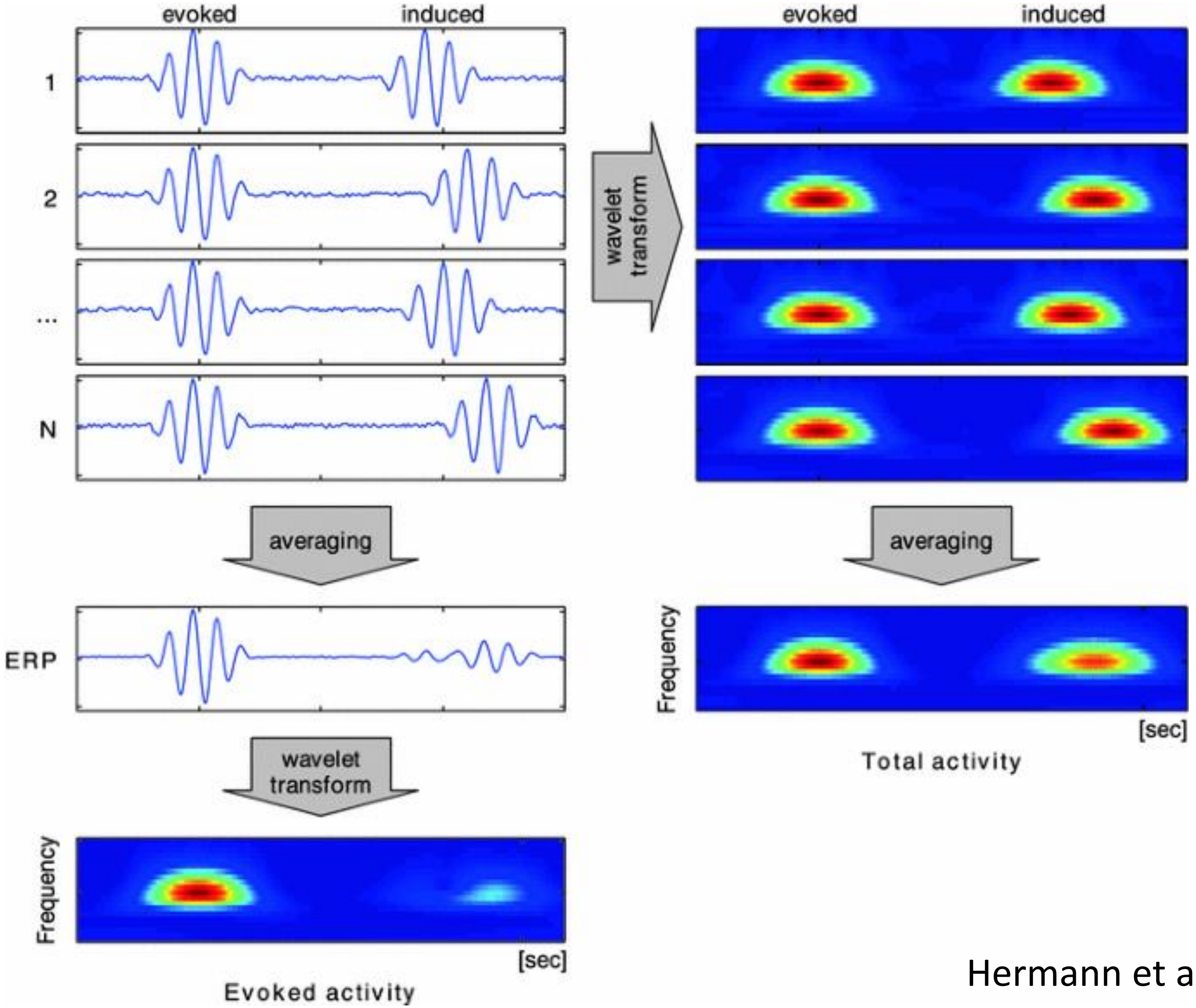
Morlet Wavelet-Choosing the number of cycles (*n*)

- 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)

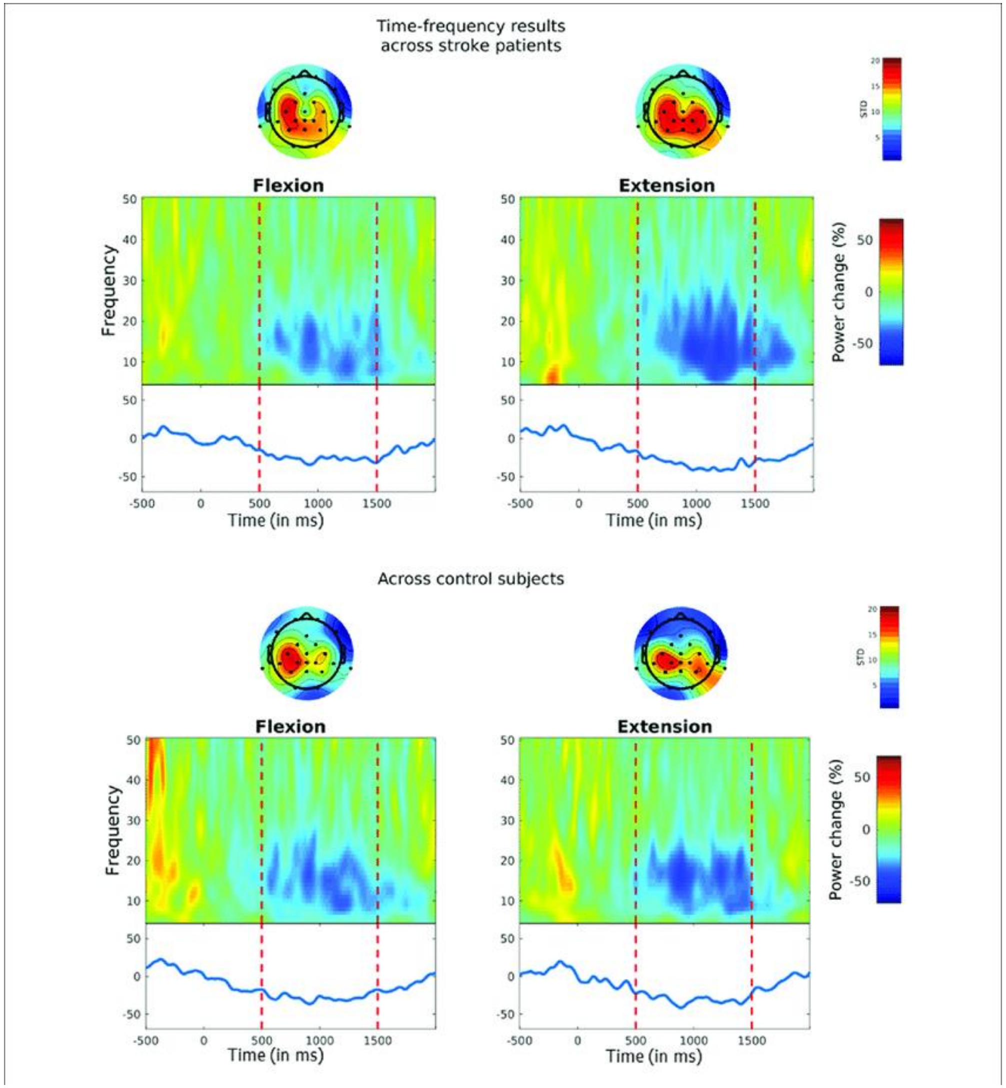
Interpreting TF analysis



Hermann et al, 2013

Interpreting TF analysis

Event-related desynchronization (ERD) during MI. Time-frequency (TF) plots show the percentage change in power from baseline (i.e. from −0.5 s to 0 s) for MI flexion trials (left panels) and MI extension trials (right panels). MI started at time point zero and was performed for 1.5 s. Vertical lines indicate the chosen time interval for the statistical analysis (i.e. from 0.5 s to 1.5 s). The solid blue line on the bottom reflects MI-related power changes within the 10–25 Hz SMR frequency range.



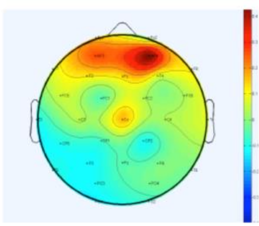
Spychala et al, 2020

Representation of EEG analysis

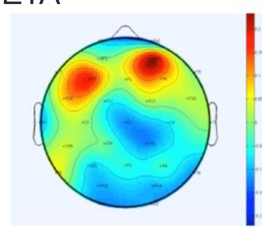
Topographical maps
➔ plot EEG data on a map of the brain.
Data is interpolated between electrodes.

ERP maps ➔ potential changes

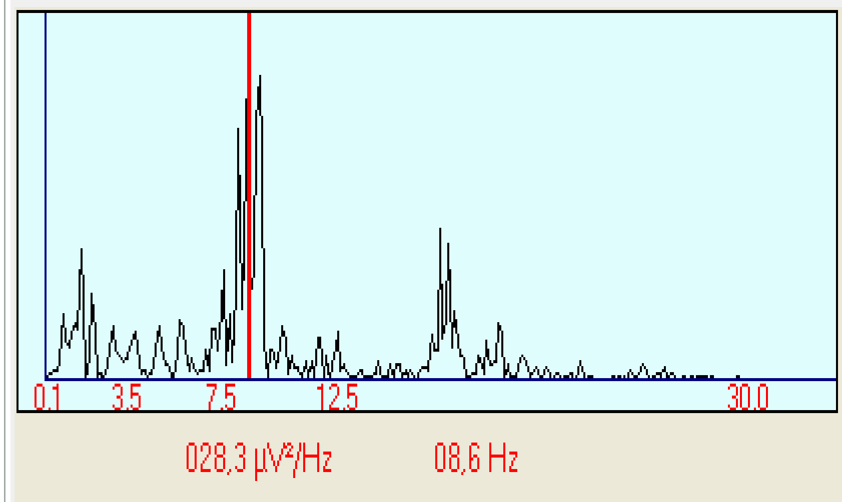
ALPHA



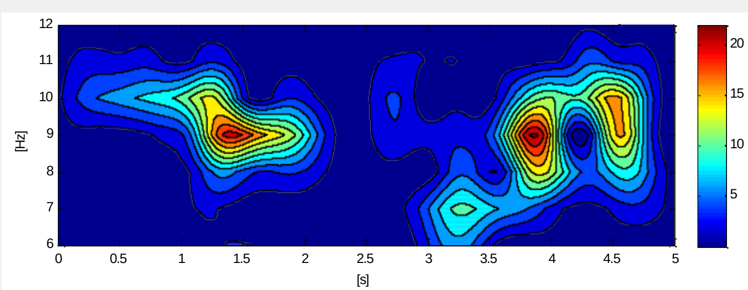
BETA



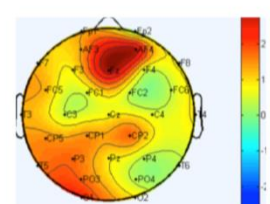
Spectral maps ➔ frequency changes



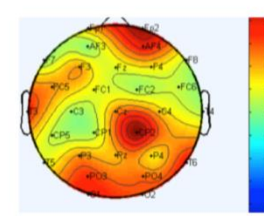
Time-frequency maps
➔ time-frequency changes



Statistical maps
➔ statistical comparisons (e.g. conditions, techniques)



t-map ALPHA



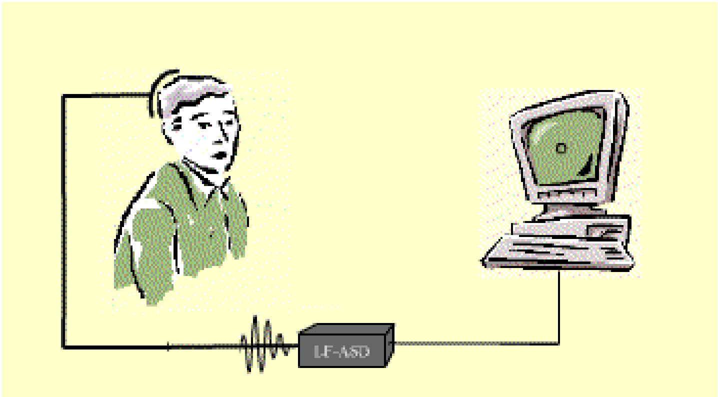
t-map BETA

Brain-Computer Interfacing

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.



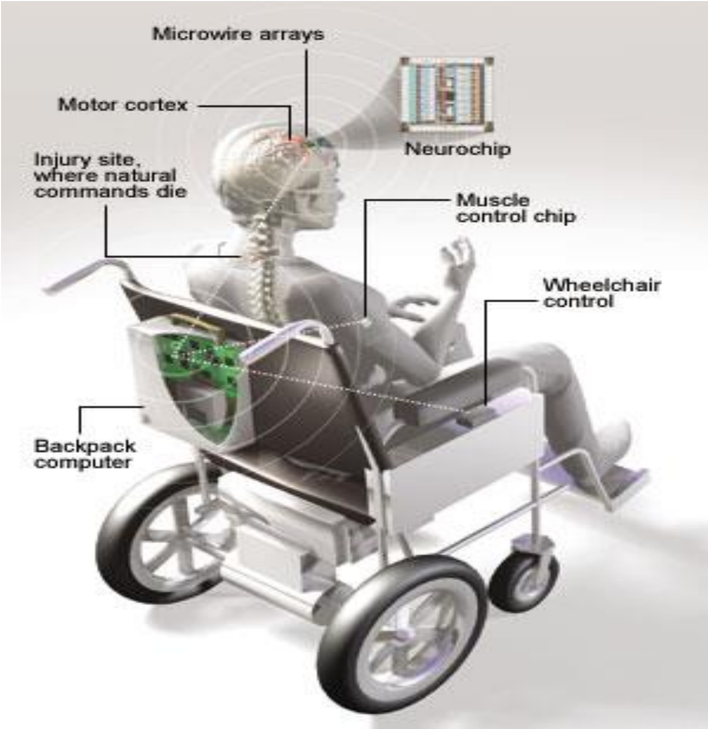
http://www.ece.ubc.ca/~garyb/BCI.htm

Motivation

Ulster University

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

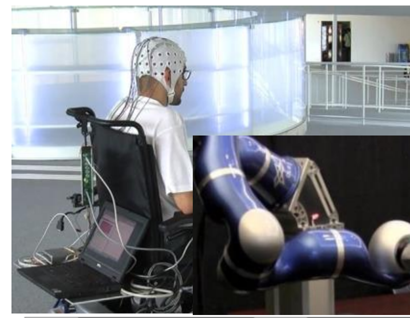
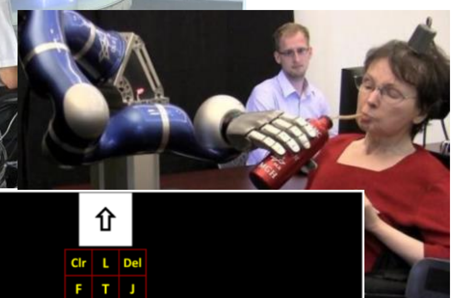
- **Target group:**
  - Amyotropic Lateral Sclerosis
  - Cervical spinal injury
  - Stroke paralysis
  - Celebral palsy
  - Amputee, etc

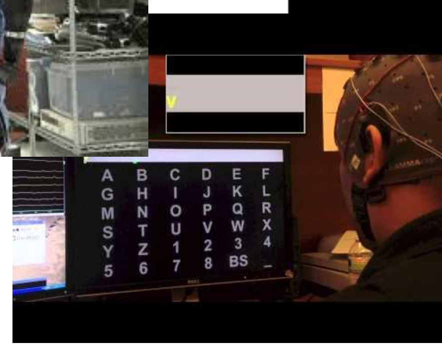
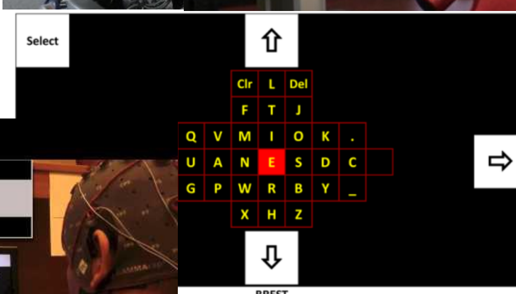


Nicolelis, 2001

BCI in Rehabilitation

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

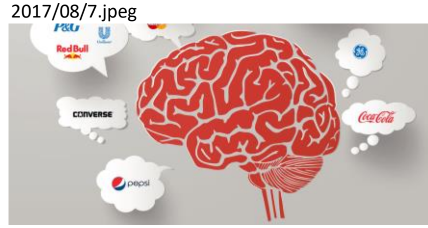



BCI in Everyday Life

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

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

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

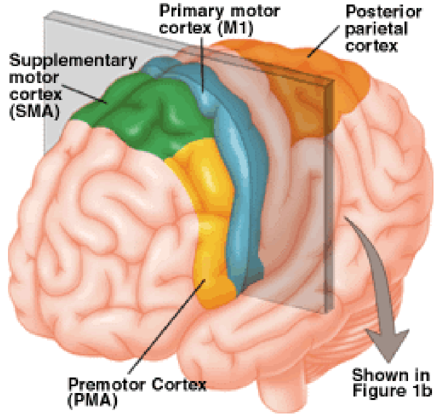


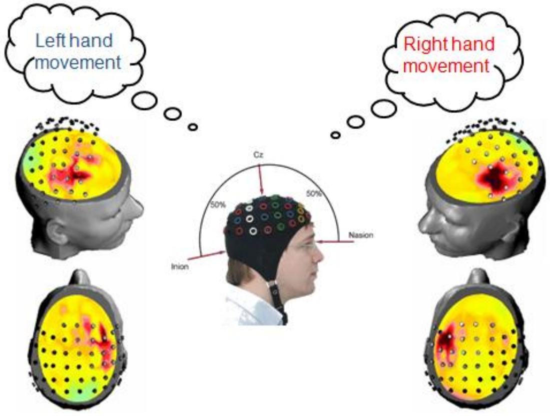
https://cakedigit.com/wp-content/uploads/2017/01/coca.png

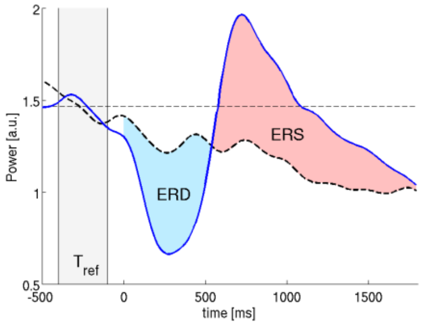
https://www.army-technology.com/features/featurebrain-computer-interfacing-military-mind-control/attachment/featurebrain-computer-interfacing-military-mind-control-4/

Motor Imagery (ERD/ERS)

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

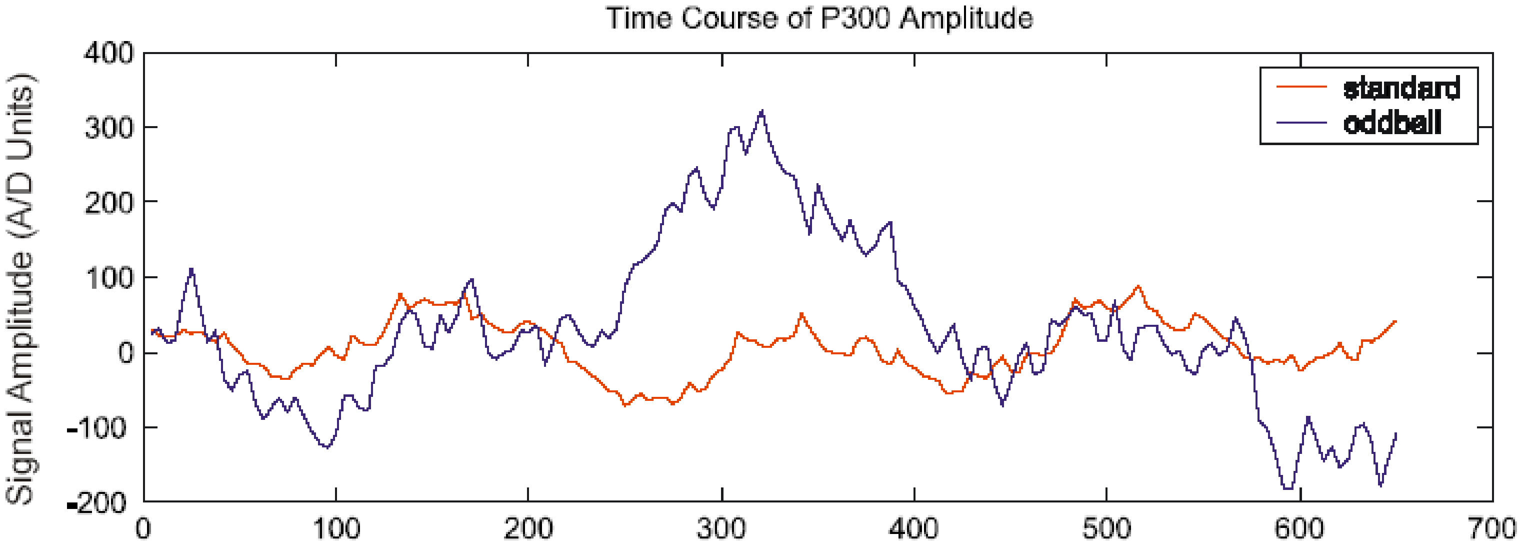






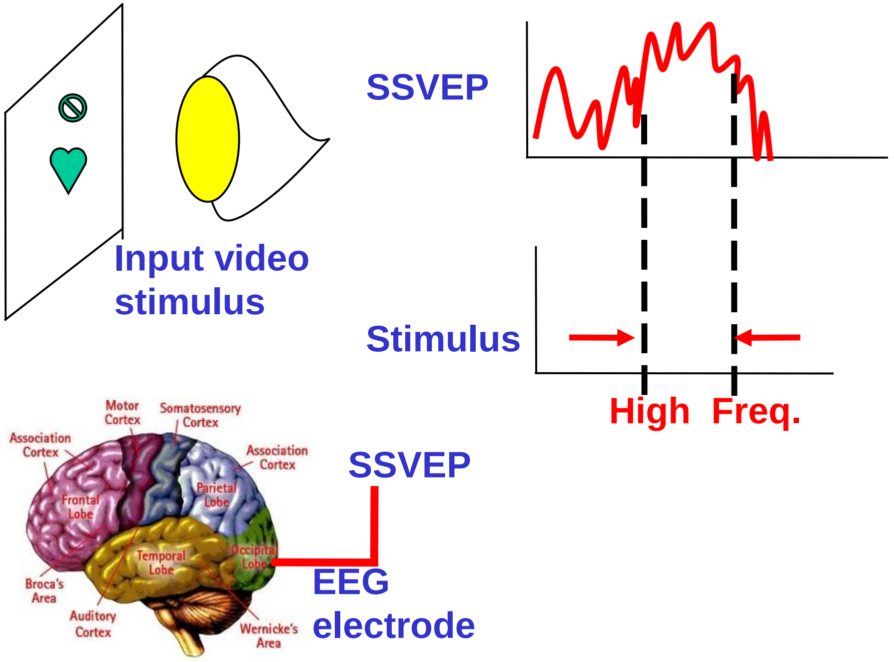
P300

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



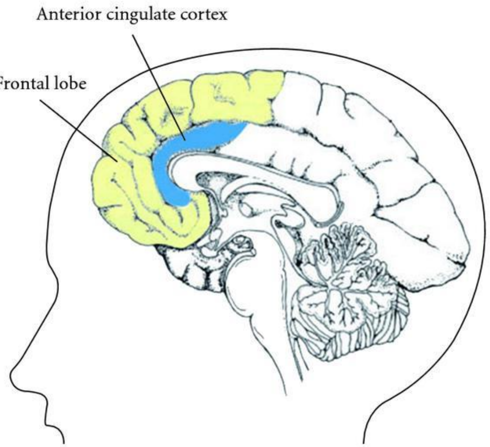
Steady-State Visual Evoked Potential

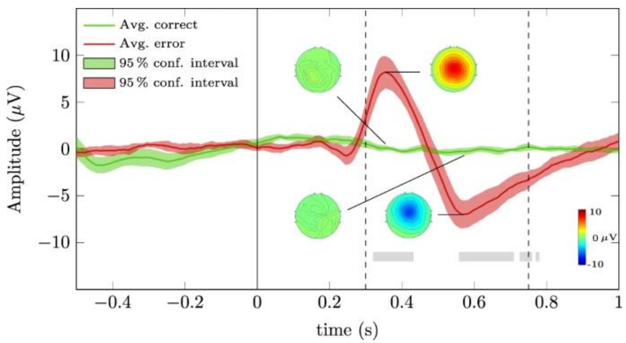
- **SSVEP:** The amplitude of the response is modulated by the frequency of the stimulus.



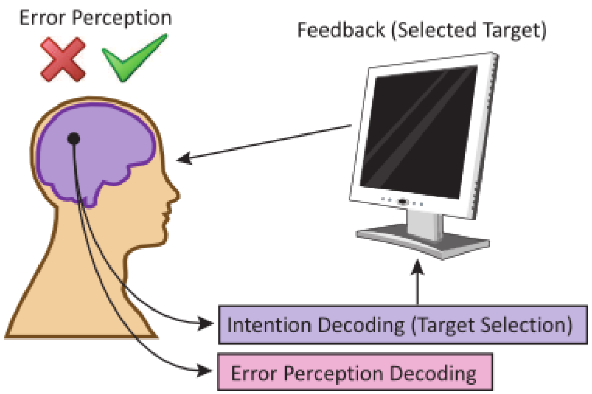
Error Related Potential

- User's awareness to erroneous respo
- Typical occurrences that elicits ErrP:
  - Choice reaction tasks
  - Feedback tasks
  - Observation tasks



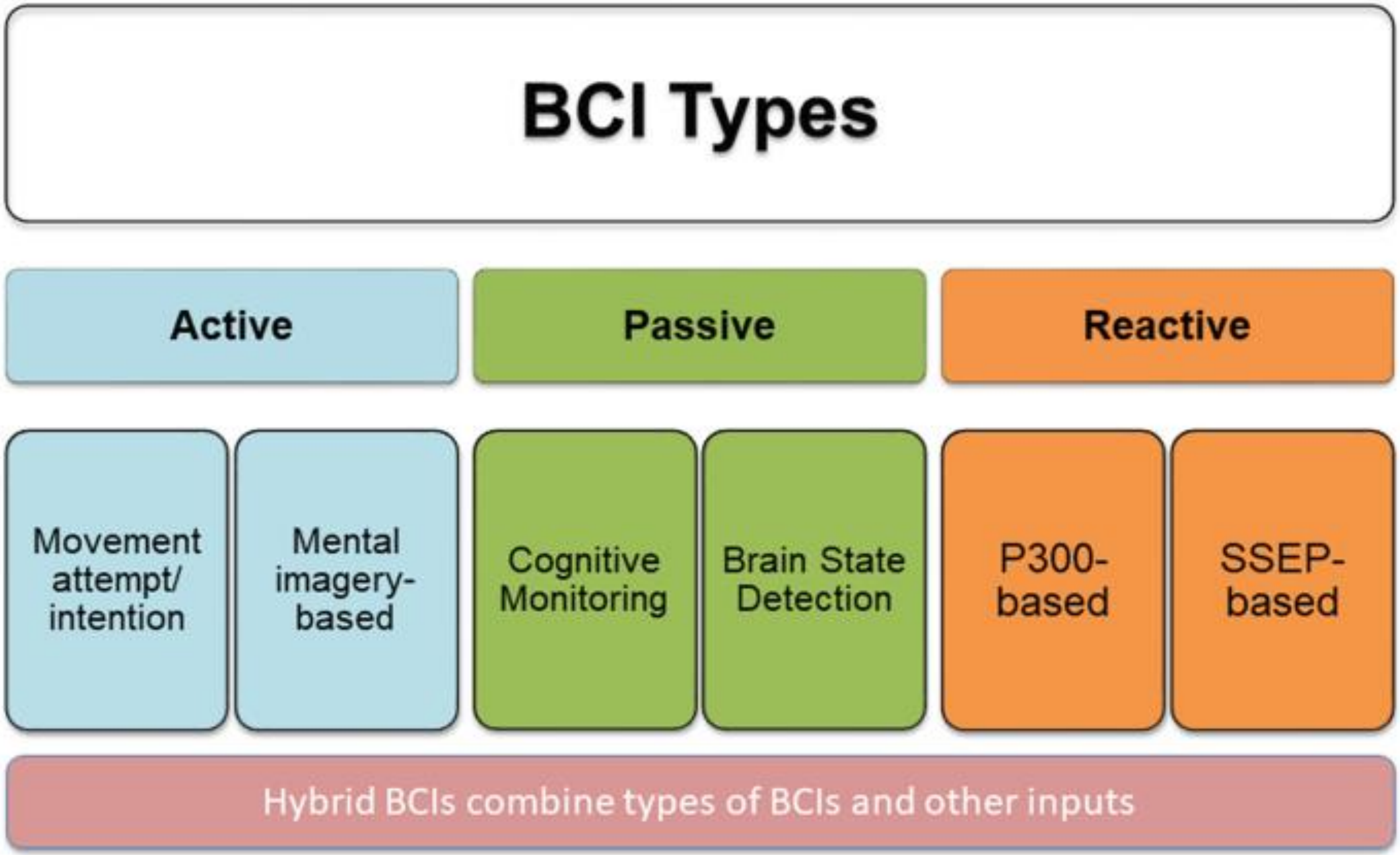


Lopes-Dias et al., Sci. Rep., 2019

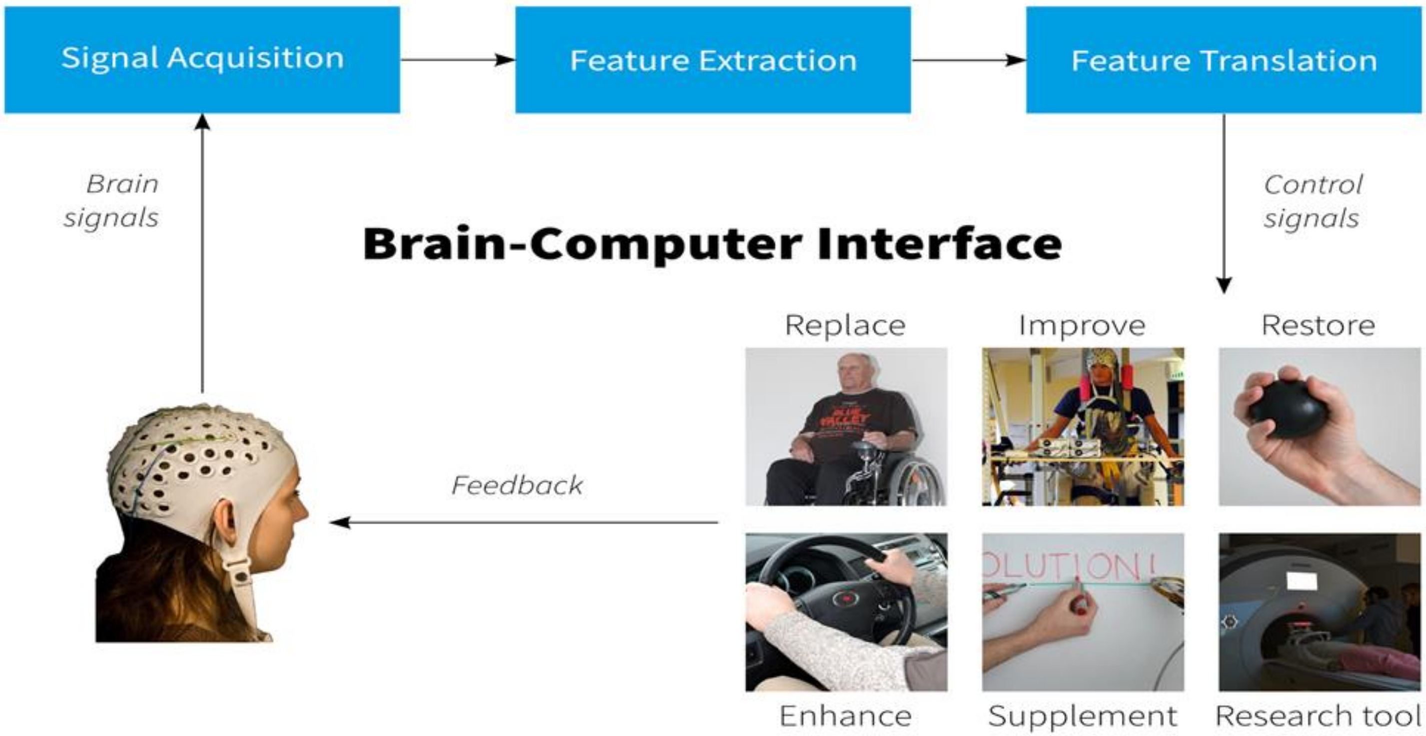


* Spuler, et al., Frontiers Human Neuroscience, 2015

BCI Types


BCI Types
Active
Passive
Reactive
Movement attempt/ intention
Mental imagery-based
Cognitive Monitoring
Brain State Detection
P300-based
SSEP-based
Hybrid BCIs combine types of BCIs and other inputs

A Generic BCI system



Designing Experiments

Ulster University

- 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

Collaborative BCI

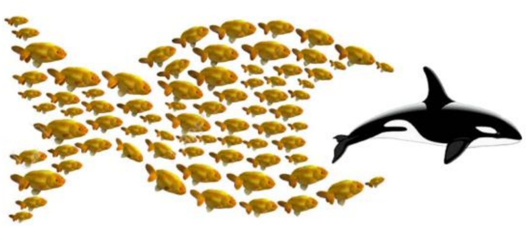
Ulster University

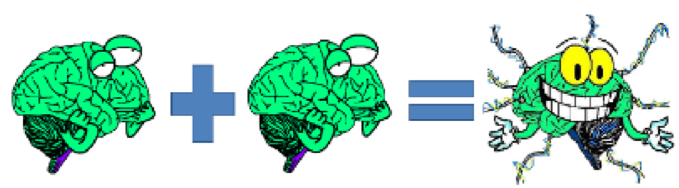
Individual Decision Making

- **Decision accuracy could degrade with:**
    - Limited processing time
    - Quantity and complexity of data
    - Irrelevant information, audiovisual clutters/distractors
    - High-stakes, time-pressured situations
- **Mental state of the operator also affects decision accuracy**
    - Fatigue/alertness
    - Mental workload
    - Attention level

Groups

- **Most animals and humans live within groups. Why?**
- **A group can do things that individuals alone can't:**
  - Augmented action capabilities: Members of a group can join forces to do something that is beyond the strength or endurance of a single individual
  - Increased sensing capabilities: A group has a much higher probability of finding resources and noticing danger
  - Increased cognition and intelligence: groups show emergent cognition and intelligent behaviours which are more powerful than those of the individual members.





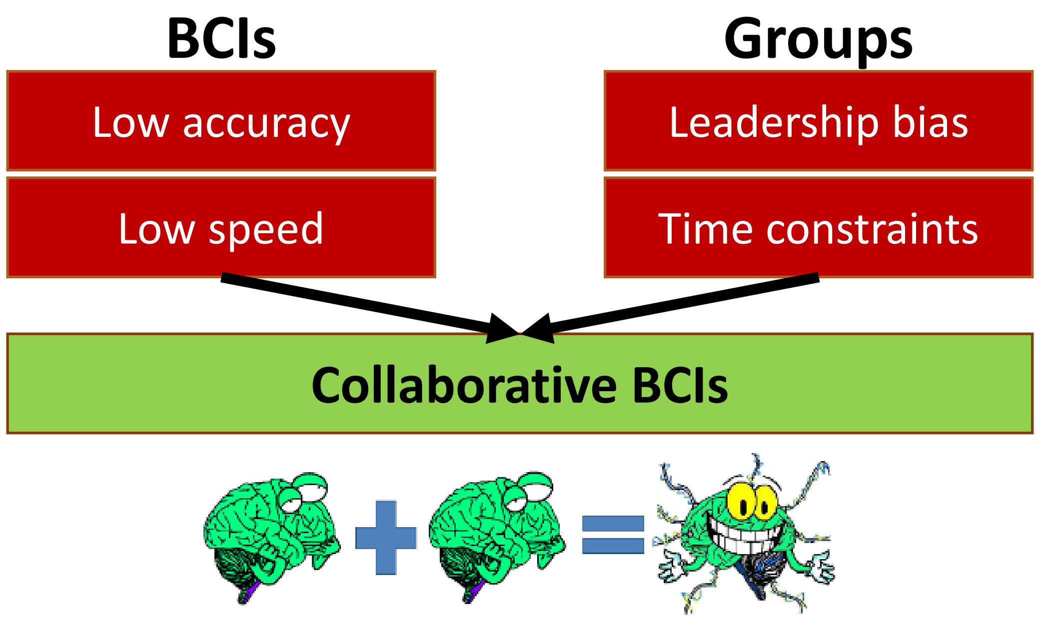
Collaborative Decision Making

- **Power of crowds:** groups have augmented wisdom. This is why human decisions are routinely made by committees (where members' knowledge, intelligence, experience and creativity are melded to improve outcomes).

- **Groups could fail:** under- and over-confidence biases, reduced member effort, time constraints, strong leadership, …

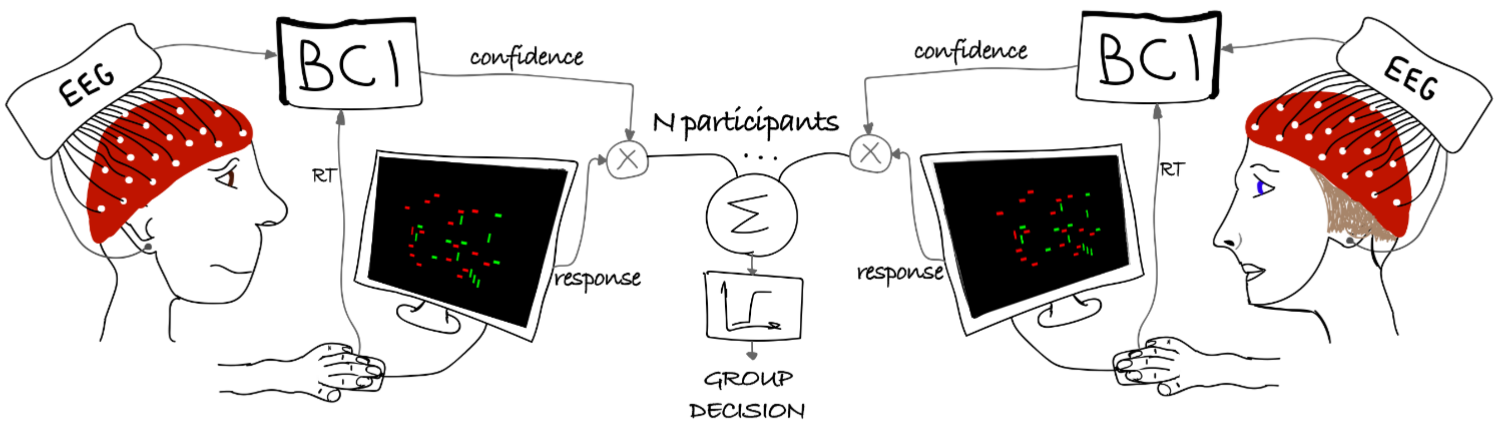
Collaborative BCIs (cBCIs)

- Use data from multiple brains
- First studies in the 2010s with simple perceptual tasks (faces/cars)



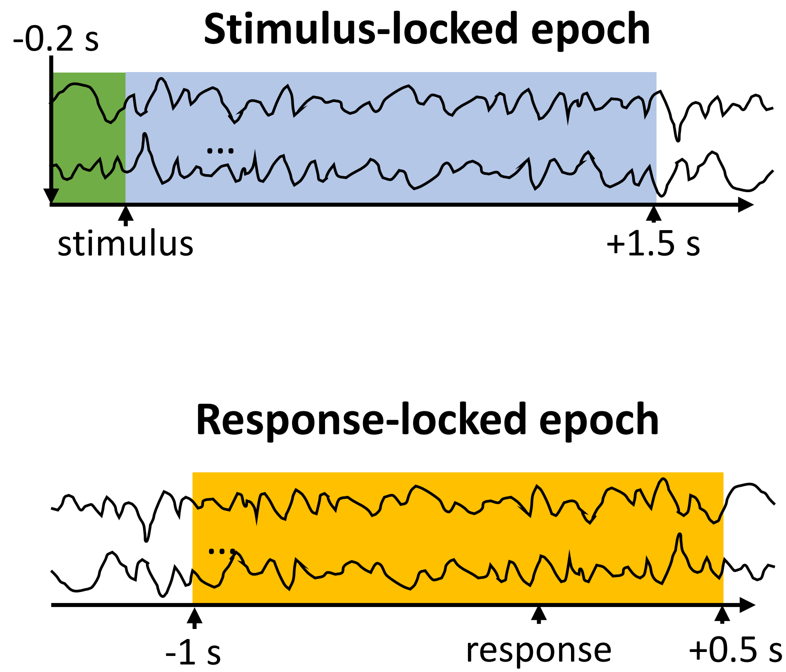
Our cBCIs Framework

- Users report individual decisions
- Brain signals used to decode the decision confidence of each participant
- Group decisions made by weighing individual decisions according to the confidence estimates



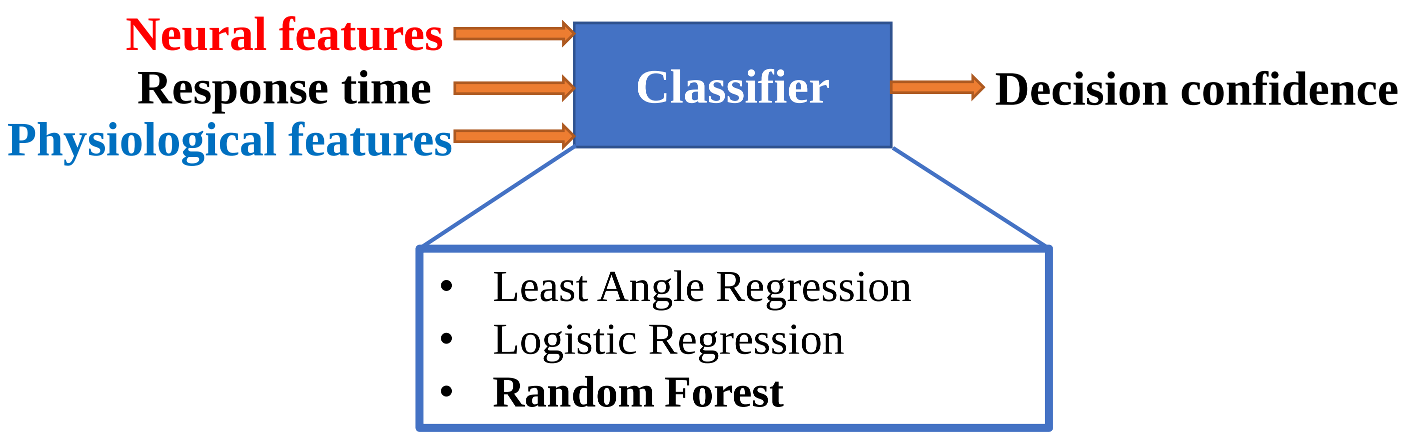
Data recording and processing

- **EEG Data** (64 electrodes)
- **Reference to earlobes**
- **Band-pass filter** 0.15-40 Hz
- **EOG correction**
- **Epoching**
- **Baseline correction**



Confidence estimation

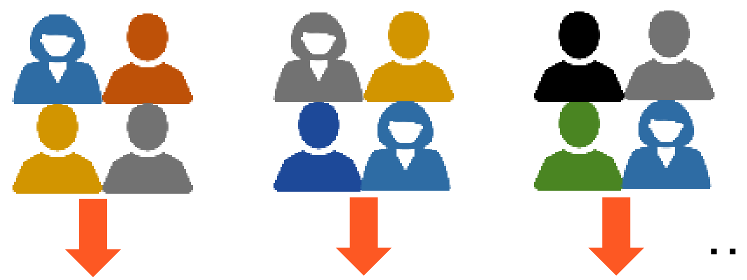
- Training epochs grouped on the basis of the correctness of the decision of the user
  - Label = -1 for correct decisions
  - Label = +1 for incorrect decisions



Group simulation

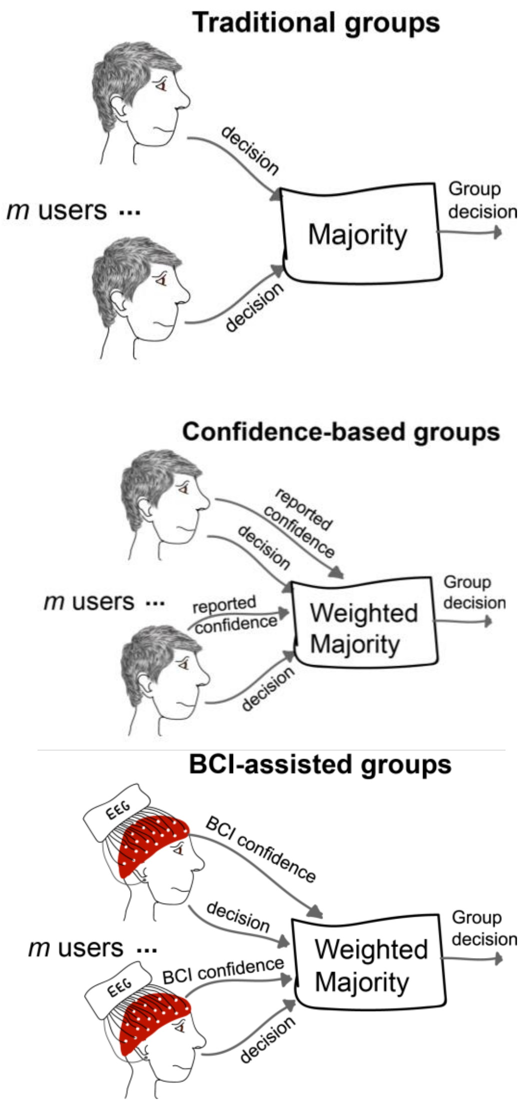
Individuals perform the **same experiment**

Individual data combined offline in **all possible groups** of a given size m



Average performance of m-sized groups

Aggregating individual opinions



One head = One vote

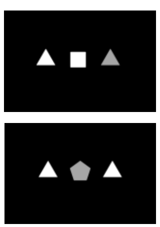
Confidence reported by the participants

Confidence decoded from the EEG

Bringing collaborative BCIs out of the lab

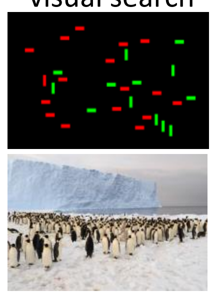
2014

Visual matching



2015

Traditional and realistic visual search



2016

Realistic speech perception

Radio messages

2017

Face recognition for surveillance applications

Multi-viewpoint

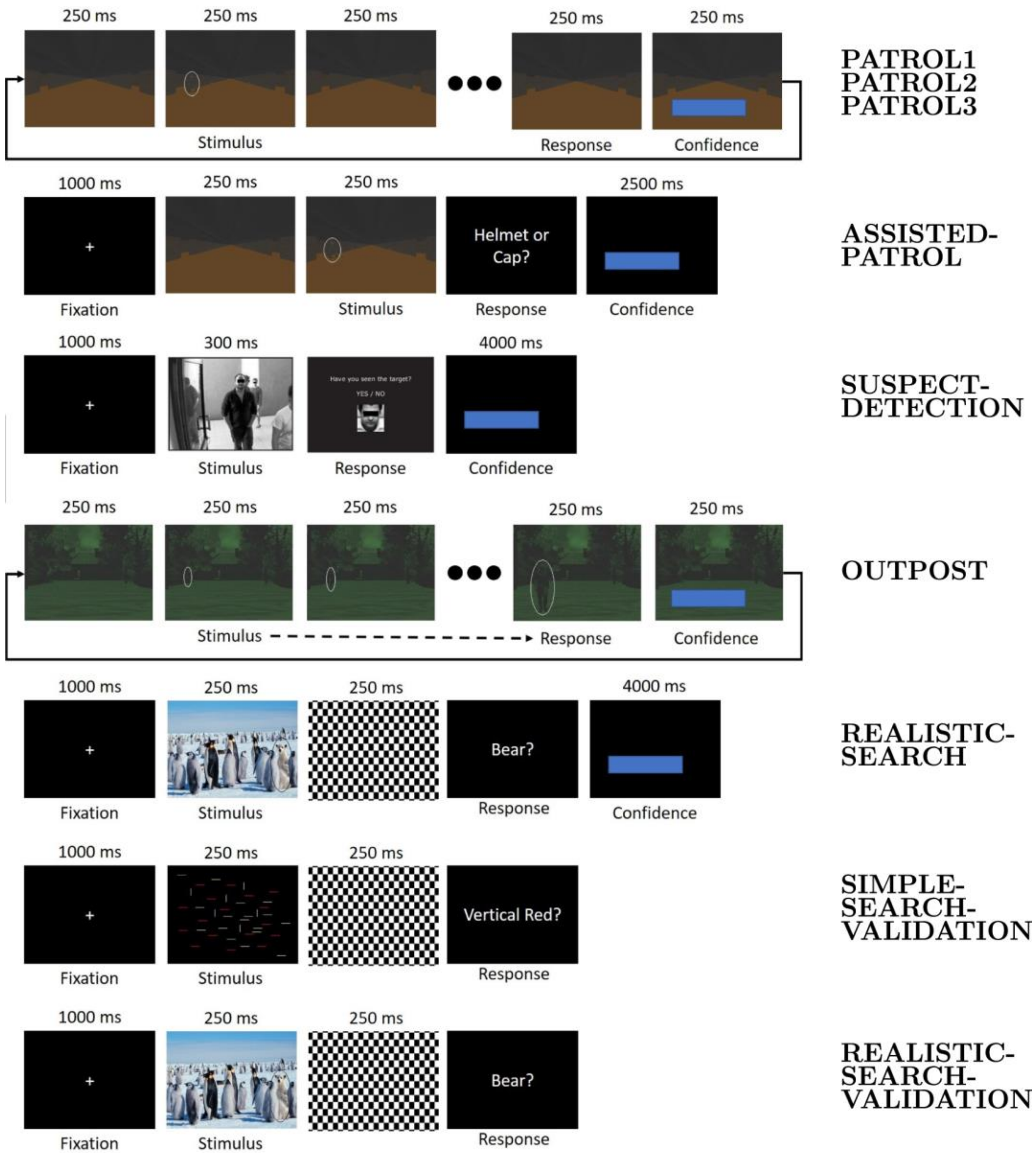
2018

Target detection with video feeds

Controlled ← **Environment** → **Realistic**

Thanks to DSTL, UK MOD

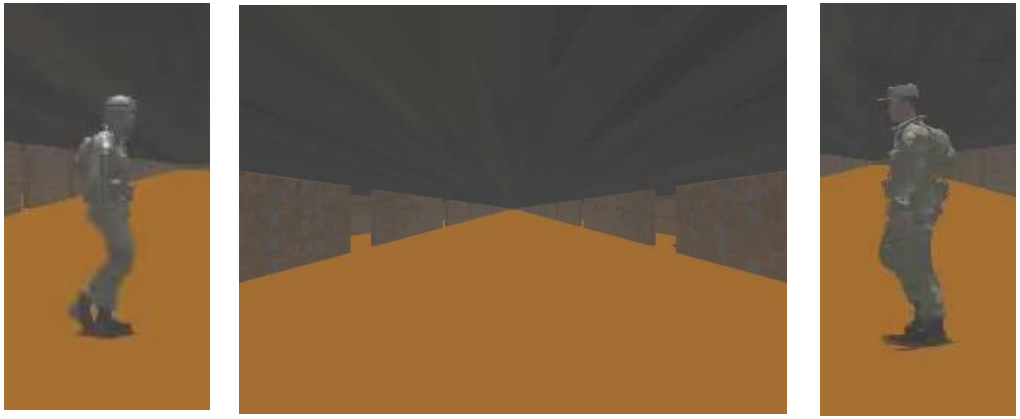
Stimuli



Fernandez-Vargaz et al., 2021

Dynamic, realistic environment

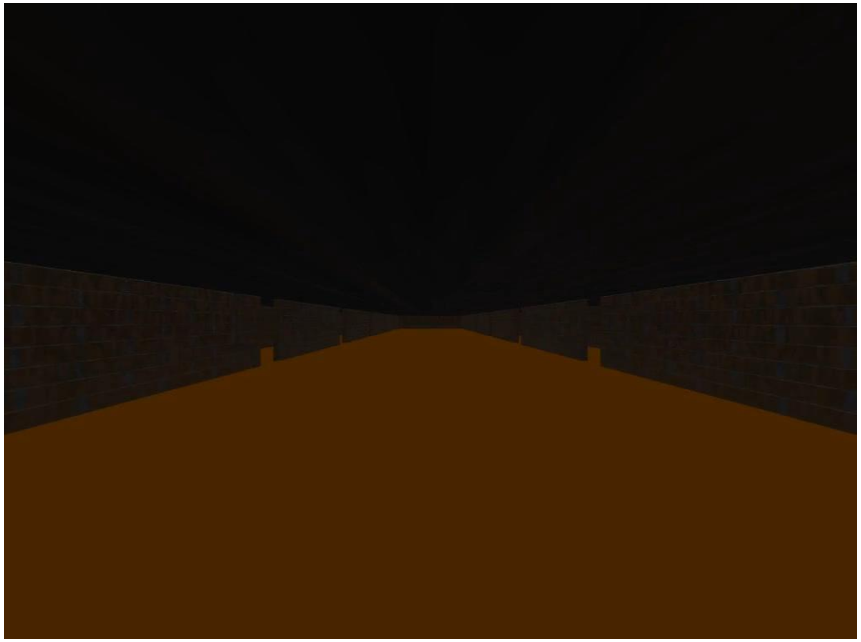
- We used Unity3D to generate a **dynamic environment** where a soldier is walking along a corridor with multiple doorways present on both sides
- Task: Decide whether the characters appearing wear a helmet or a cap



Bhattacharyya et al., NER'19

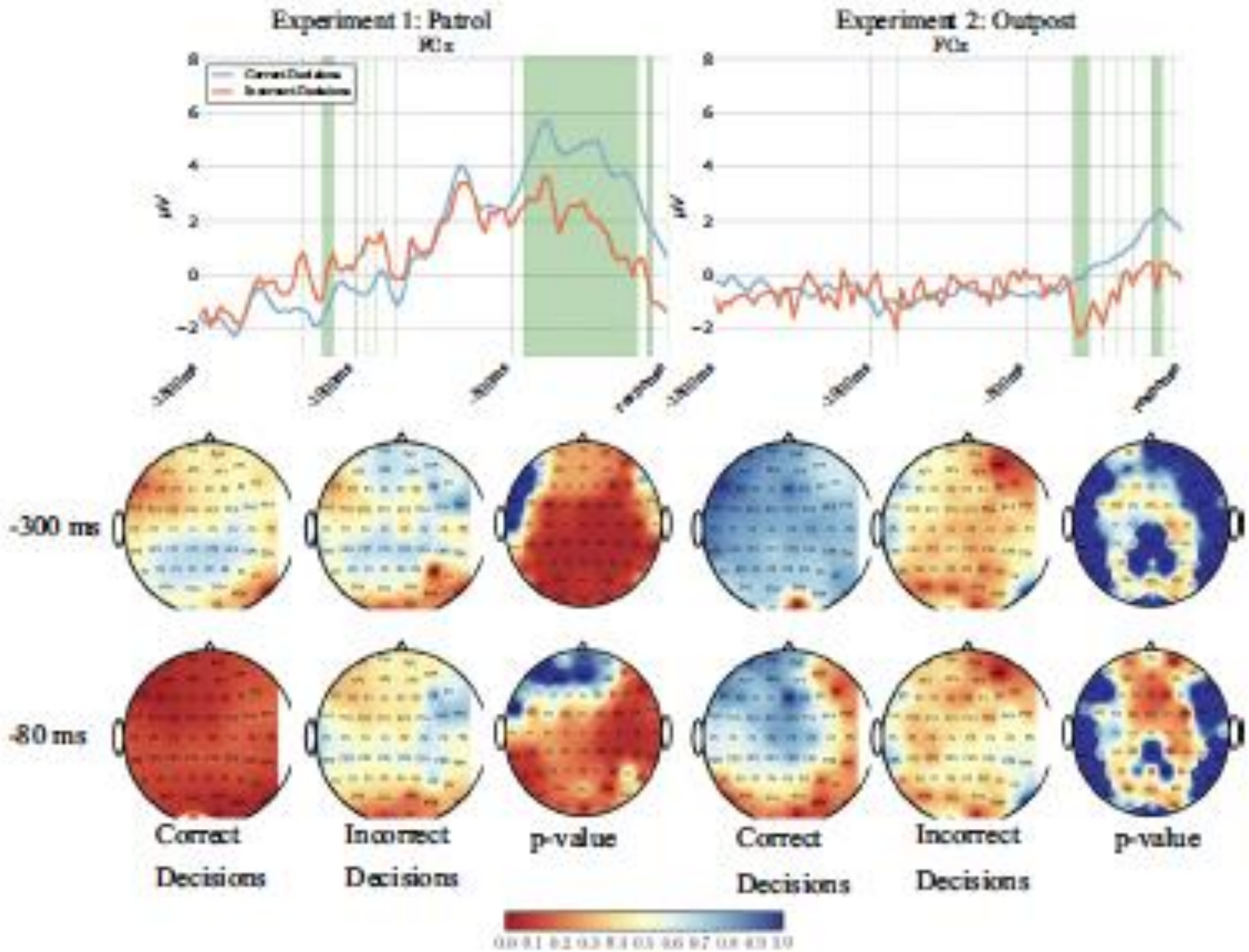
Brightness increased by 40% for presentation purposes.

Your turn! Count the caps



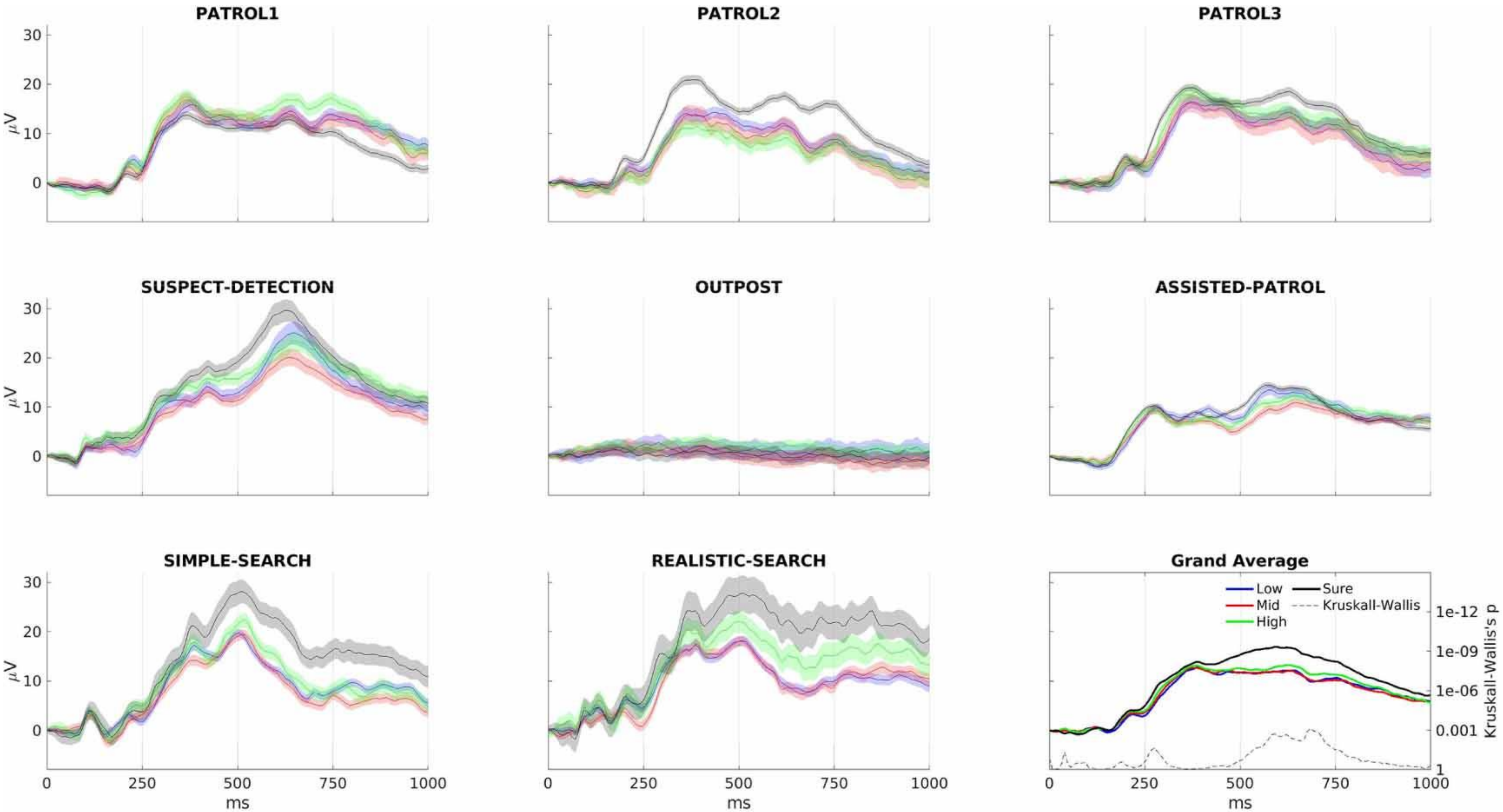
Brightness increased by 40% for presentation purposes.

Existence of brain markers for correct and incorrect decisions



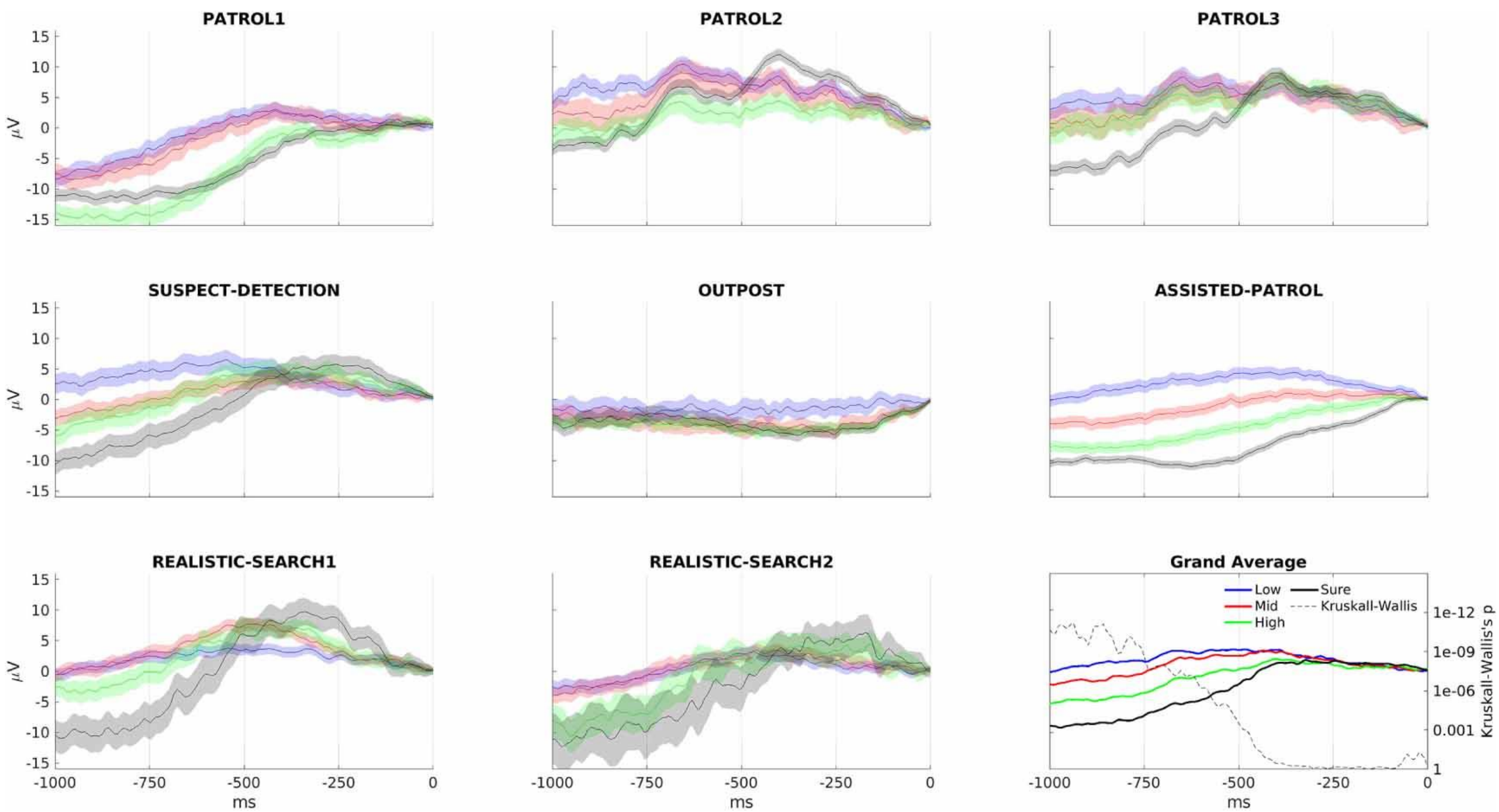
Existence of brain markers for confidences

Stimuli-Locked Event



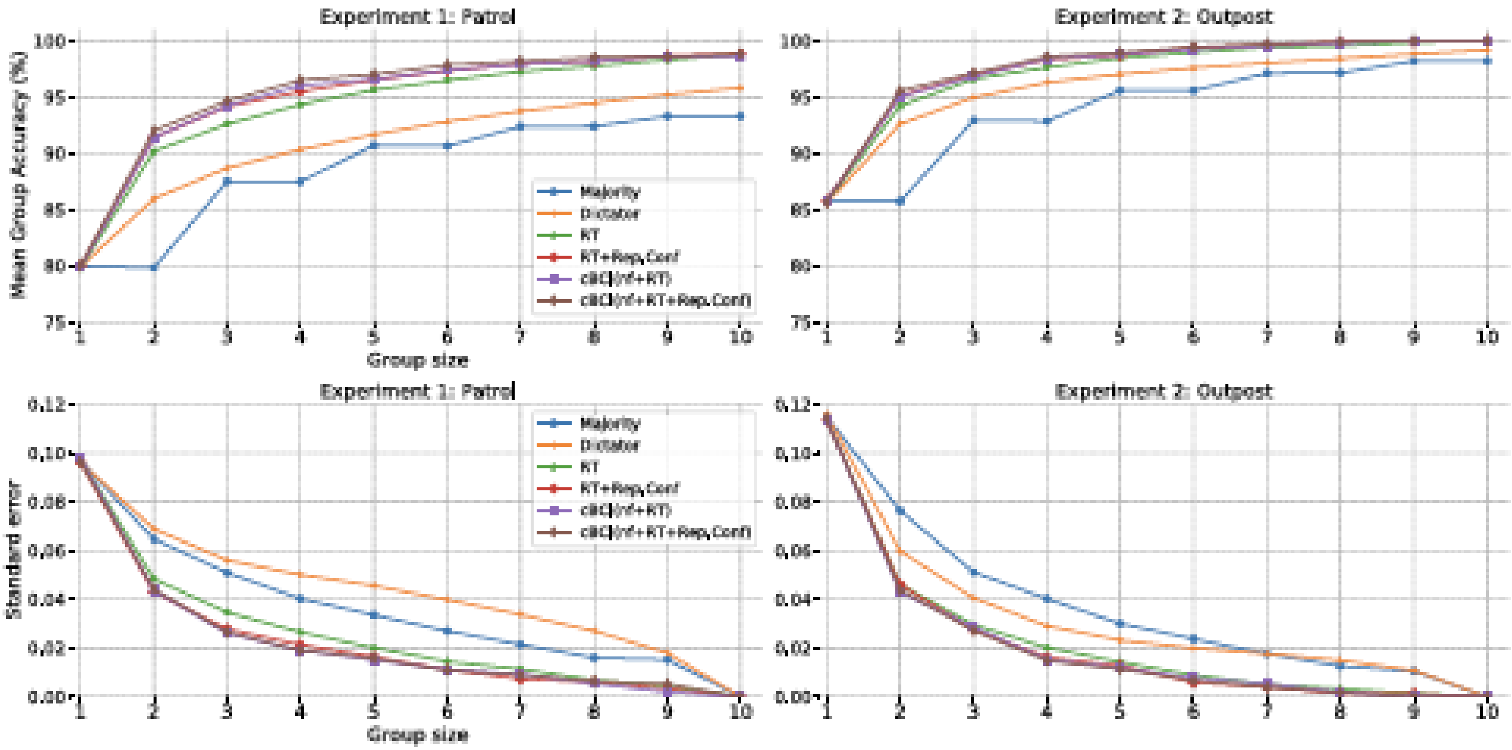
Existence of brain markers for confidences

Response-Locked Event



Difference in Behaviour…

Reflected on cBCI performance…

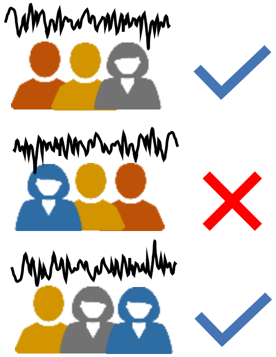


Bhattacharyya et al., 2021

What’s next?

Non-binary decision-making

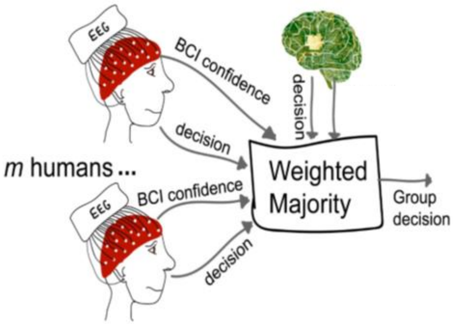
Decision-making in **multisensory** environments



BCI-based **group selection**

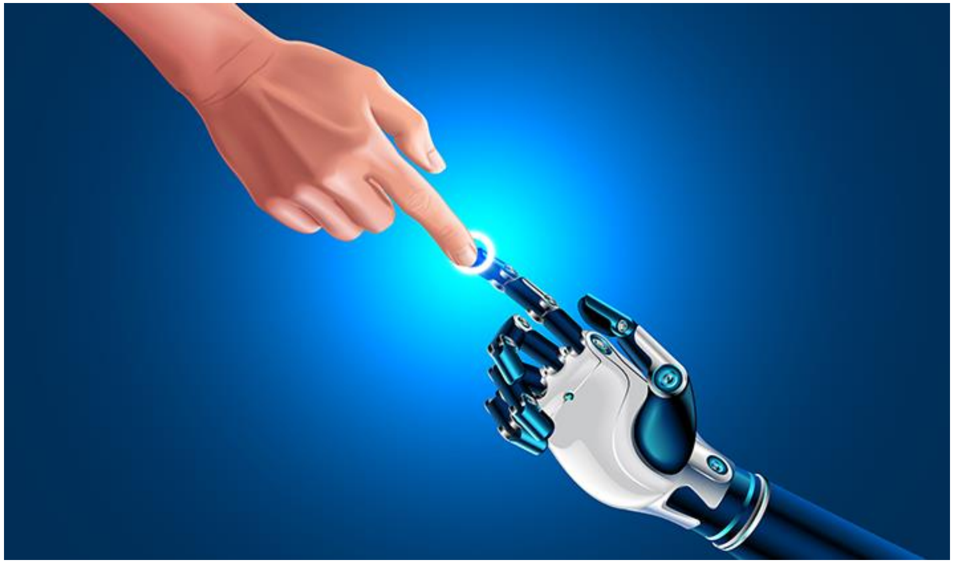
Communication

Can we **train** people to trust their gut feeling (work with cBCIs)?



AI-Human Teaming

Collaborating between Human and Machine



s.bhattacharyya@ulster.ac.uk