Southern University of Science and Technology

神经计算与控制实验室
Neural Computing & Control Lab

Brain Intelligence and Artificial Intelligence

人脑智能与机器智能

Lecture 16 - EEG data analysis

Quanying Liu （刘泉影）

SUSTech, BME department

Email: liuqy@sustech.edu.cn

Lecture 16 – EEG data analysis

- Introduction to Electroencephalography (EEG)
- EEG preprocessing
  - Bad channel detection/repairmen
  - Filtering
  - Artifact removal
  - Re-referencing
- EEG sensor-level analysis
  - ERP
  - ERS/ERD
- EEG source reconstruction
  - Forward problem
  - Inverse problem
- EEG tutorial

History of EEG

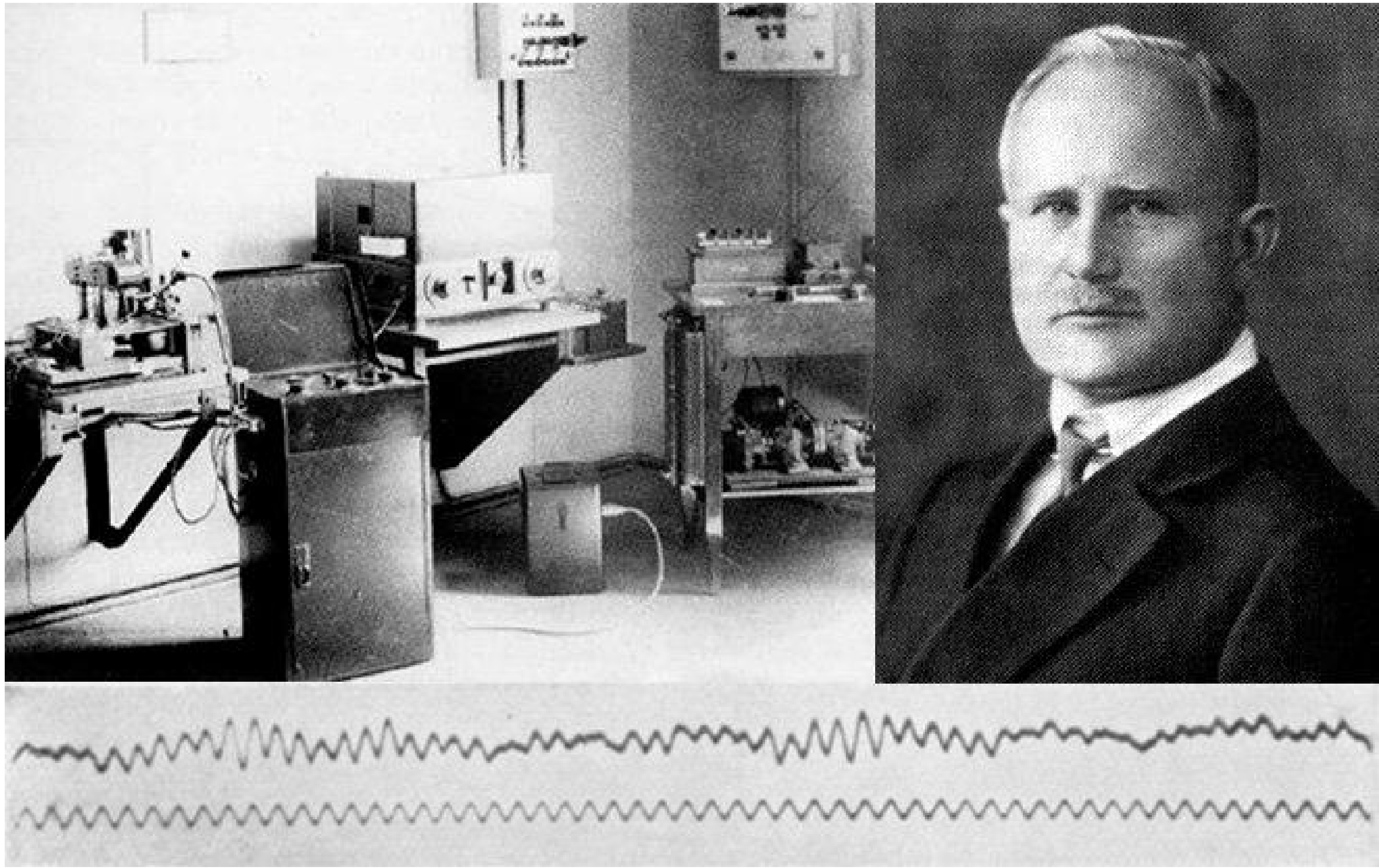
In 1875, **Richard Caton** observed the EEG from the exposed brains of rabbits and monkeys. But the meaning of this finding was ignored by people.

In 1912, Russian physiologist, **Vladimir Vladimirovich Pravdich-Neminsky** published the first animal EEG and the evoked potential of the mammalian (dog).

In 1914, **Napoleon Cybulski** and **Jelenska-Macieszyna** photographed EEG-recordings of experimentally induced seizures.

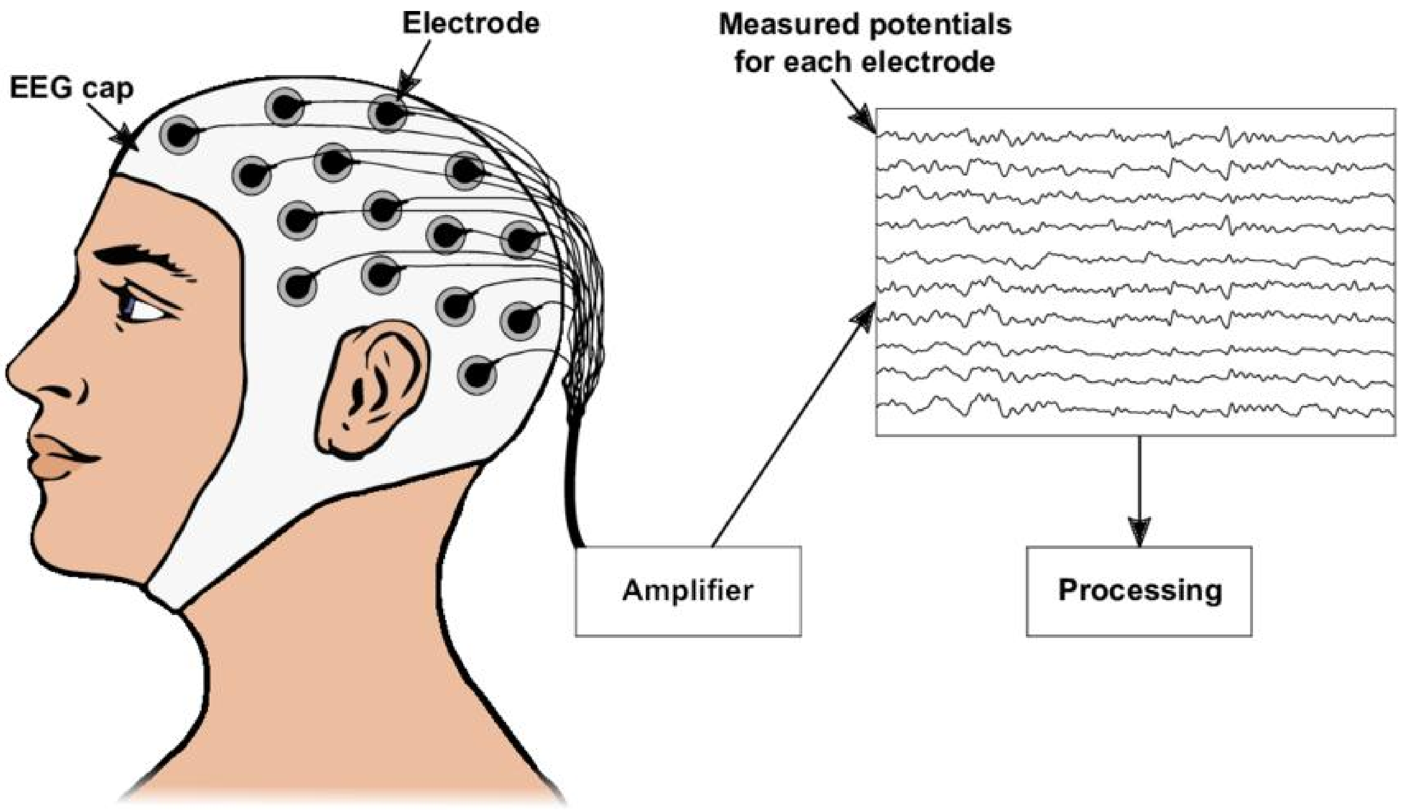
In 1924, **Hans Berger** used his ordinary radio equipment to amplify the brain's electrical activity measured on the scalp.

Hans Berger and his equipment



Introduction to EEG

Electroencephalography (**EEG**) is a method to record an electrogram of the electrical activity on the scalp that has been shown to represent the **macroscopic (宏观的)** activity of the post-synaptic activity.

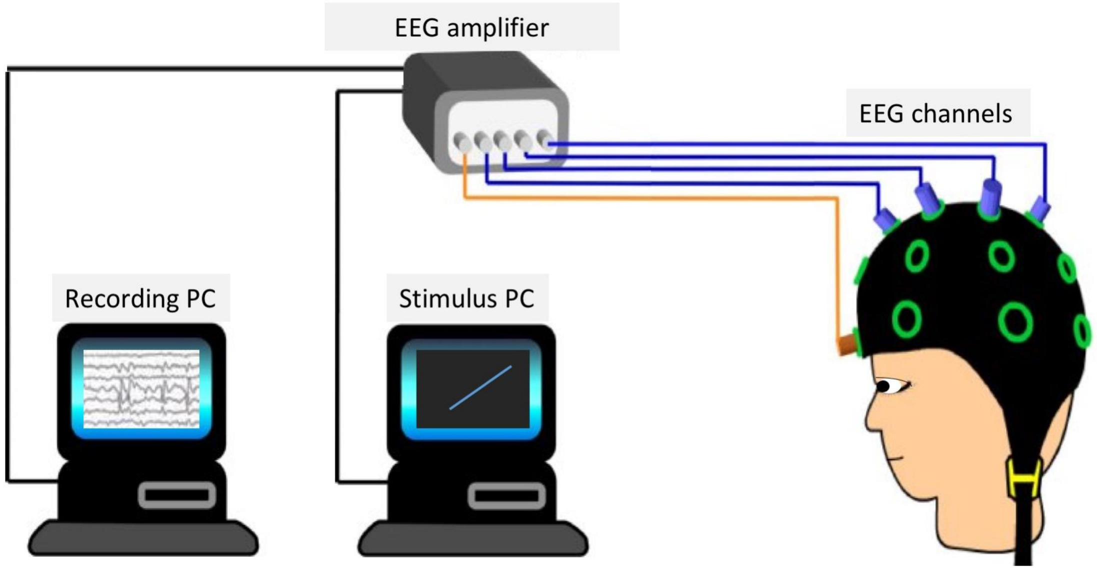


EEG measurements

Electroencephalography (EEG) is an electrophysiological process to record the electrical activity of the brain.

EEG measures changes in the electrical activity of the brain produced. Voltage changes come from **ionic current** within and between some brain cells (neurons).

An illustration of typical EEG equipment



Low-density EEG

Pros:
Cheap
Portable
Easy to setup

Cons:
Lost information

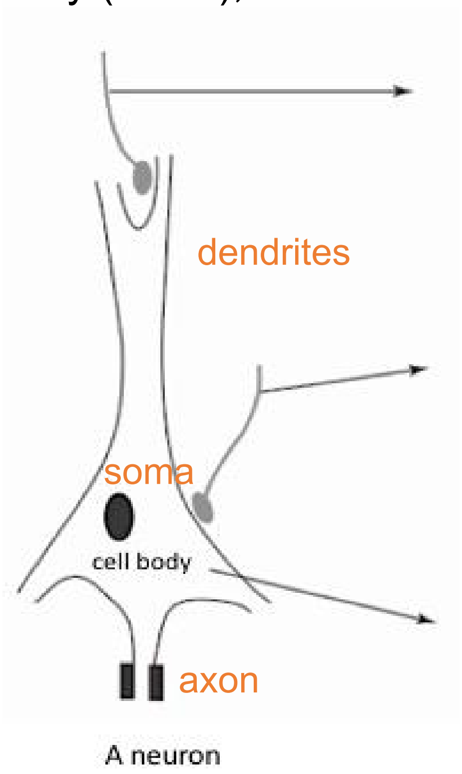
High-density EEG

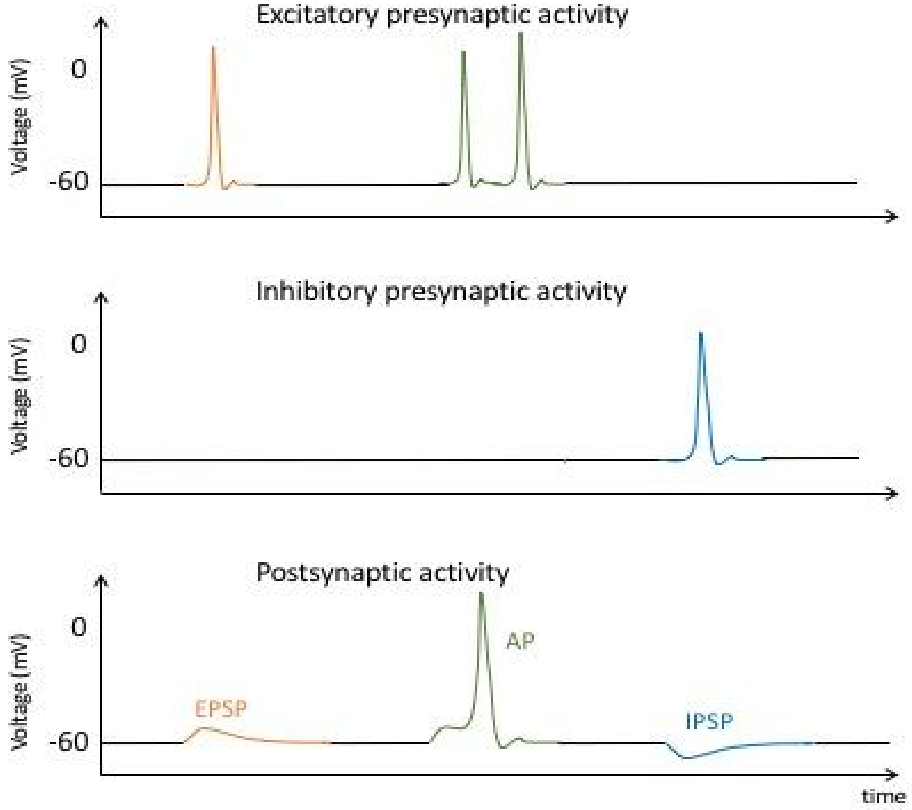
Pros:
Rich information

Cons:
Tedious to setup
Heavy to analyze data

EPSP and IPSP

A neuron consists of dendrites, cell body (soma), and axon.





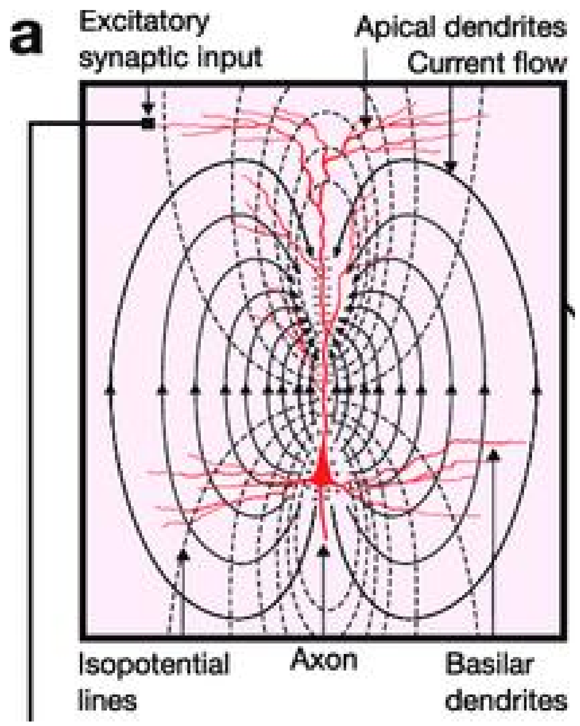
Activity measured at different locations of the neuron

If an action potential travels along the fiber, which ends in an **excitatory** synapse, an excitatory postsynaptic potential (**EPSP**) occurs in the following neuron.

If two or more action potentials travel along the same fiber over a short distance, there will be a summation of EPSPs producing an action potential (AP) on the postsynaptic neuron which may reach a certain threshold of membrane potential.

If the fiber ends in an **inhibitory** synapse, then hyperpolarization will occur, indicating an inhibitory postsynaptic potential (**IPSP**).

Neurophysiological basis of EEG

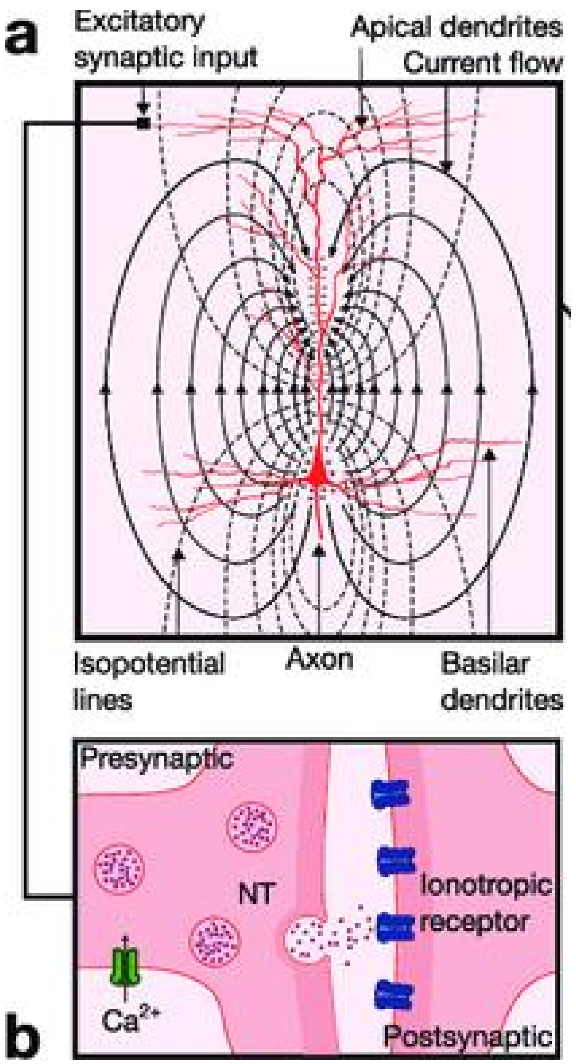


EEG signals reflect electrical brain activity that arises from the synchronous activation of groups of pyramidal neurons in the cerebral cortex.

Excitatory postsynaptic potentials (EPSPs) generate dipoles(偶极子) by creating separation of charge perpendicular(垂直) to the surface of the cortex.

Portillo-Lara, Roberto, et al. "Mind the gap: State-of-the-art technologies and applications for EEG-based brain–computer interfaces." *APL bioengineering* 5.3 (2021): 031507.

Neurophysiological basis of EEG

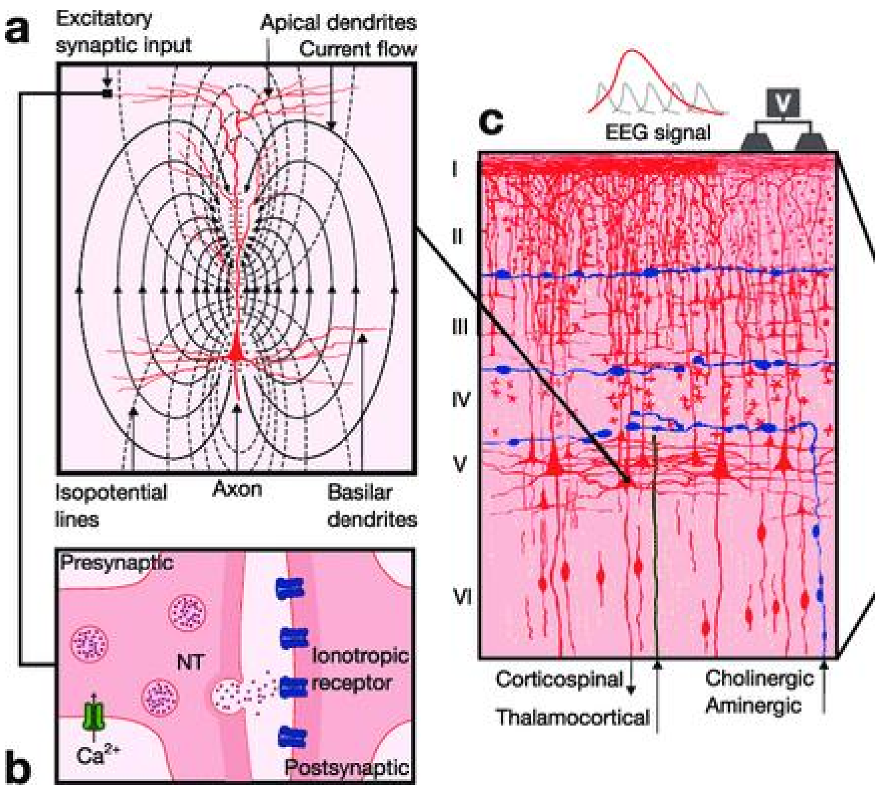


Communication between neurons is mediated at the synapse.

The arrival of an action potential at the presynaptic terminal leads to vesicular release of a neurotransmitter (神经递质) into the synaptic cleft, which then diffuses to reach membrane receptors on the postsynaptic terminal and trigger an EPSP.

Portillo-Lara, Roberto, et al. "Mind the gap: State-of-the-art technologies and applications for EEG-based brain–computer interfaces." *APL bioengineering* 5.3 (2021): 031507.

Neurophysiological basis of EEG



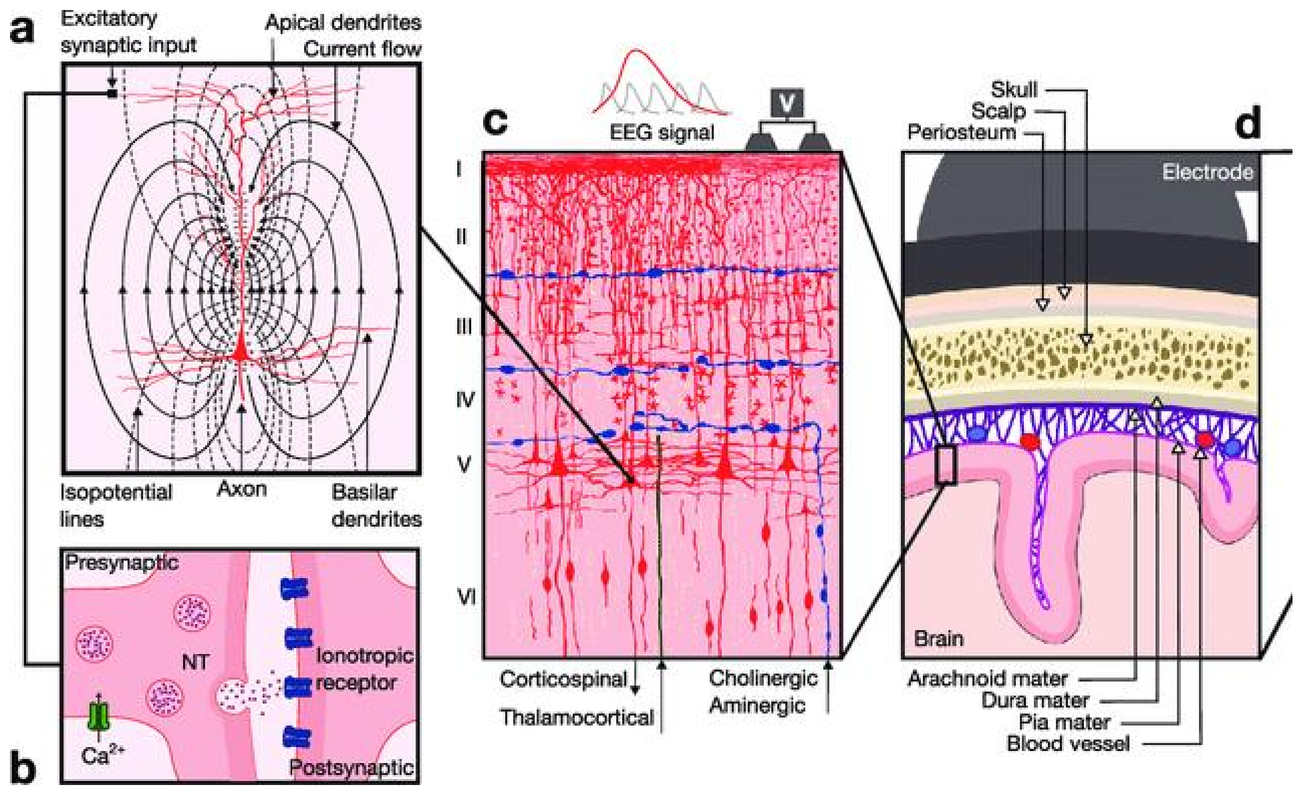
Portillo-Lara, Roberto, et al. "Mind the gap: State-of-the-art technologies and applications for EEG-based brain–computer interfaces." *APL bioengineering* 5.3 (2021): 031507.

The cerebral neocortex is organized in 6 layers (I-VI). The majority of EEG signals are generated by pyramidal neurons located primarily in layers III and V.

These neurons are spatially aligned perpendicular to the cortical surface, which yields a dipole layer orthogonal (正交) to the surface of the scalp.

EEG activity is measured as differences in voltages recorded at different locations on the scalp, which constitute the summation of postsynaptic potentials from thousands of neurons near each recording electrode.

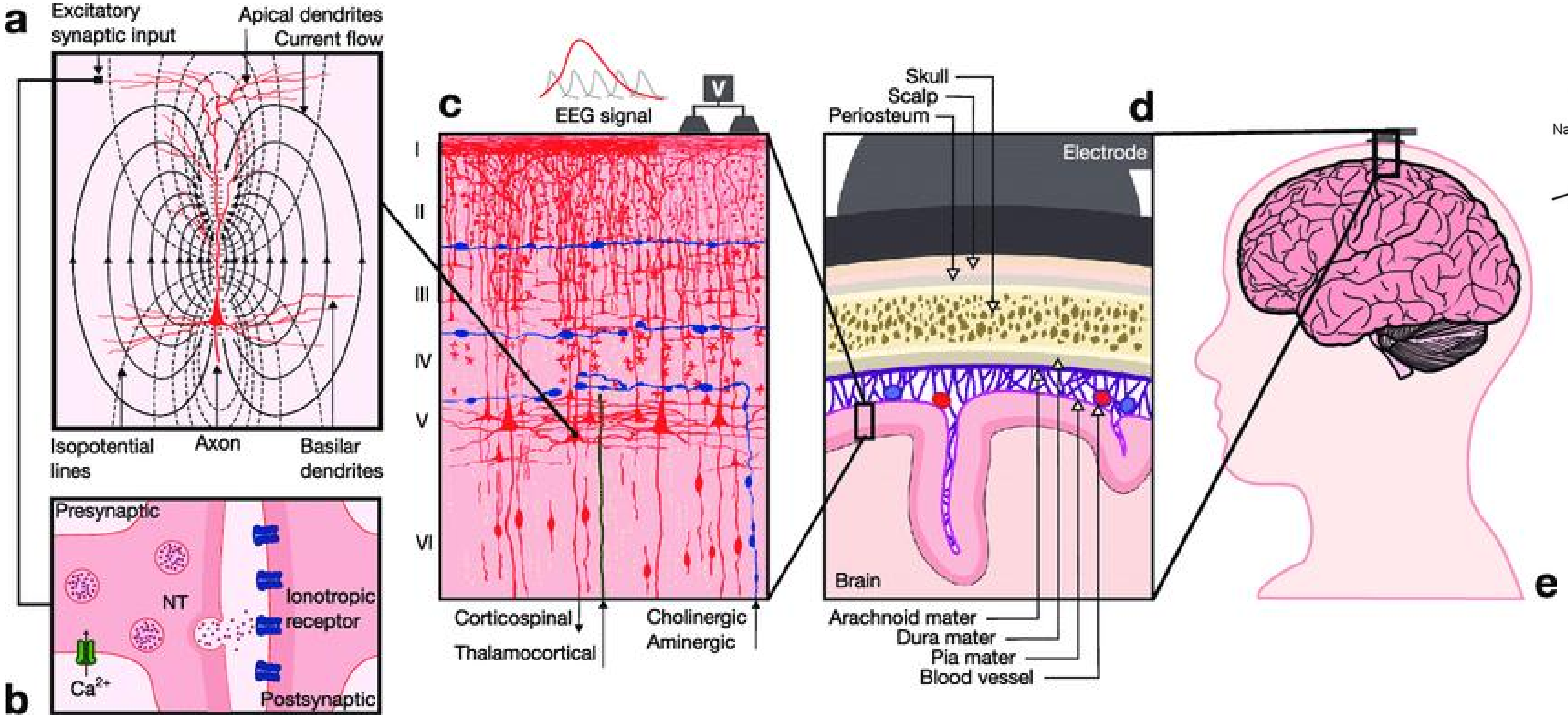
Neurophysiological basis of EEG



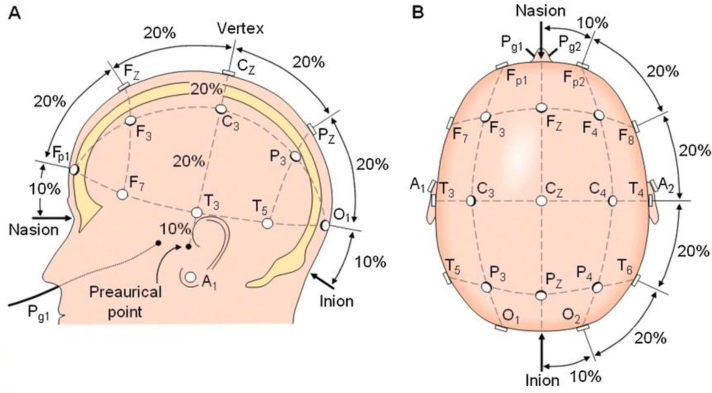
To reach scalp electrodes, EEG signals cross several layers of non-neural tissues with different conduction properties that **attenuate** the signal.

Portillo-Lara, Roberto, et al. "Mind the gap: State-of-the-art technologies and applications for EEG-based brain–computer interfaces." *APL bioengineering* 5.3 (2021): 031507.

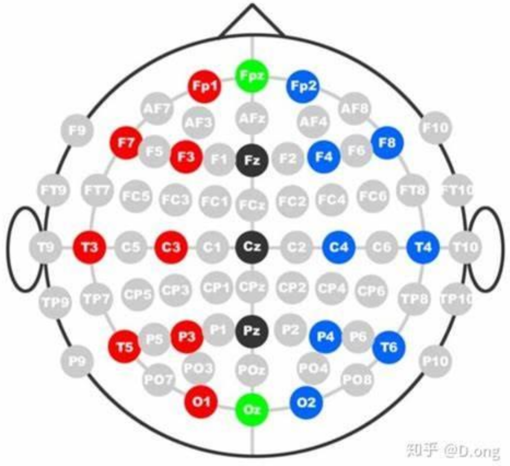
Neurophysiological basis of EEG



10-20 system



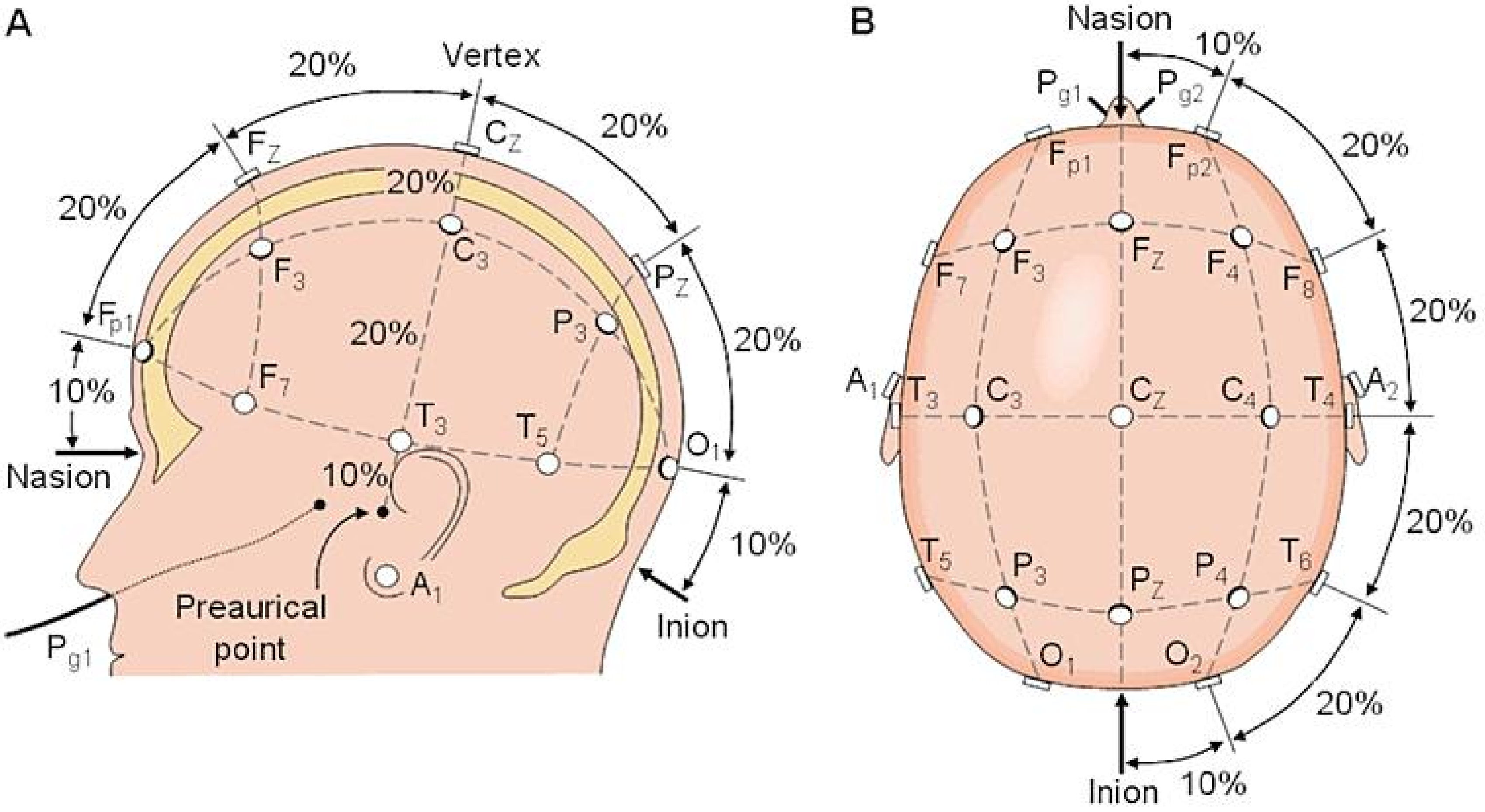
10-10 system



Electrodes are positioned on the scalp in defined configurations (e.g., 10-20 system, 10-10 system).

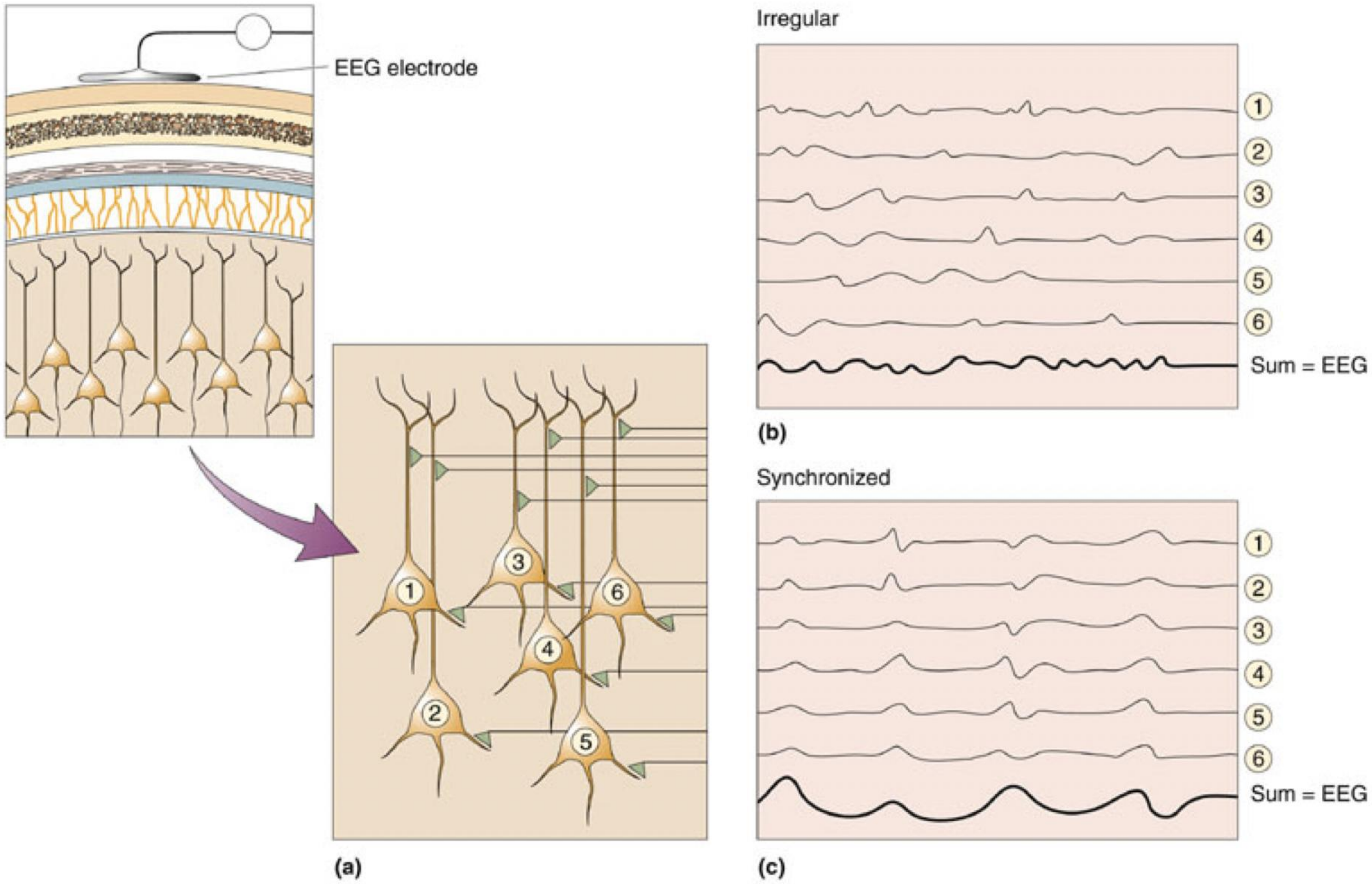
Portillo-Lara, Roberto, et al. "Mind the gap: State-of-the-art technologies and applications for EEG-based brain–computer interfaces." *APL bioengineering* 5.3 (2021): 031507.

EEG Montage



The 10-20 system with front-back (nasion to inion) 10% and 20% electrode distances.

Generation of EEG signals



The generation of EEG signals by **synchronous/asynchronous activity** in neurons.

(a) pyramidal cells under an EEG electrode, each neuron receives many synaptic inputs.

(b) If the inputs fire at **irregular** intervals, the pyramidal cell responses are not synchronized, and the summed activity detected by the electrode may have relatively small amplitude and high frequency.

(c) If the same number of inputs fire within a narrow time window so that the pyramidal cell responses are **synchronized**, the resulting EEG may have relatively high amplitude and low frequency.

EEG, compared to other neuroimaging modalities

EEG

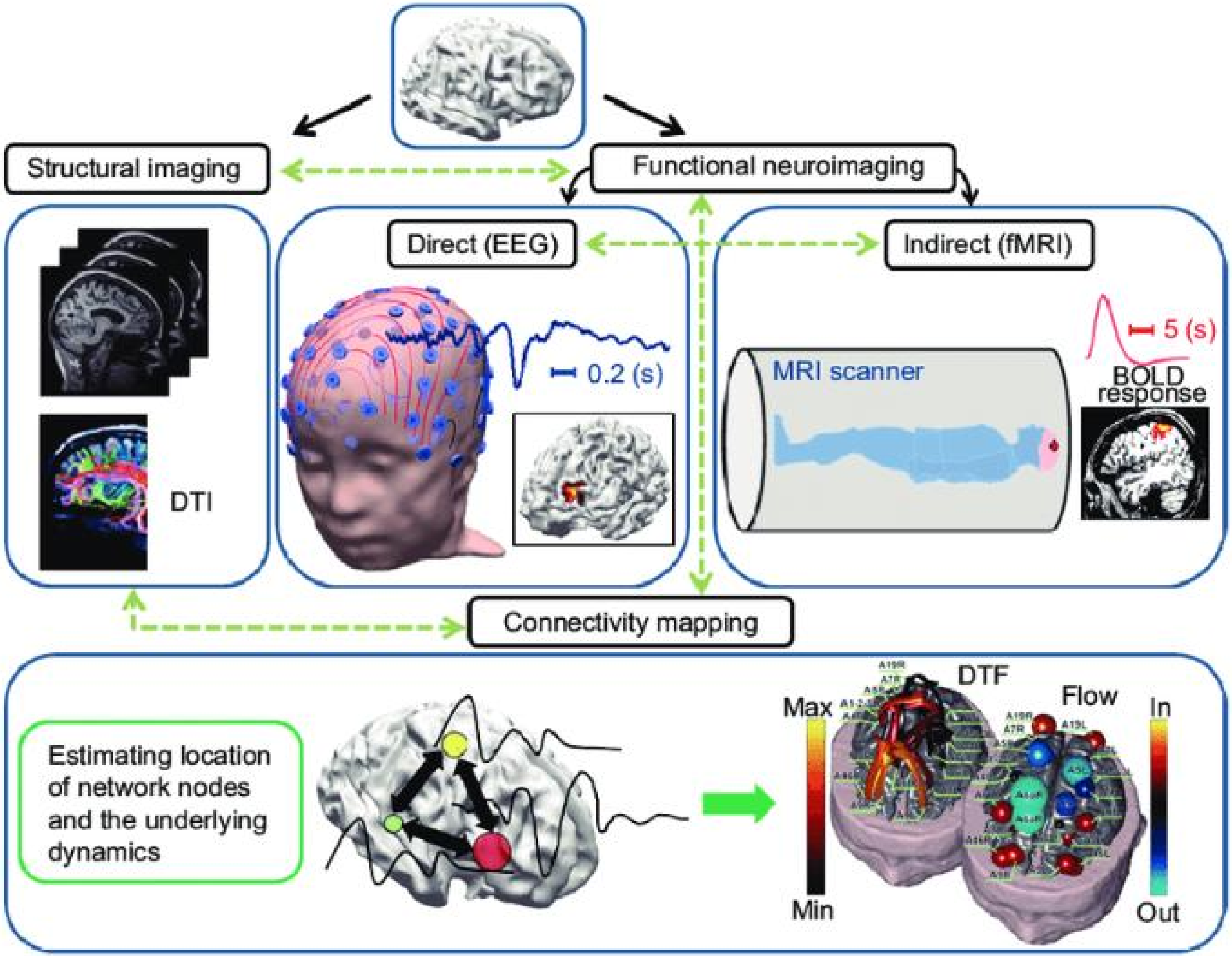
fMRI

PET

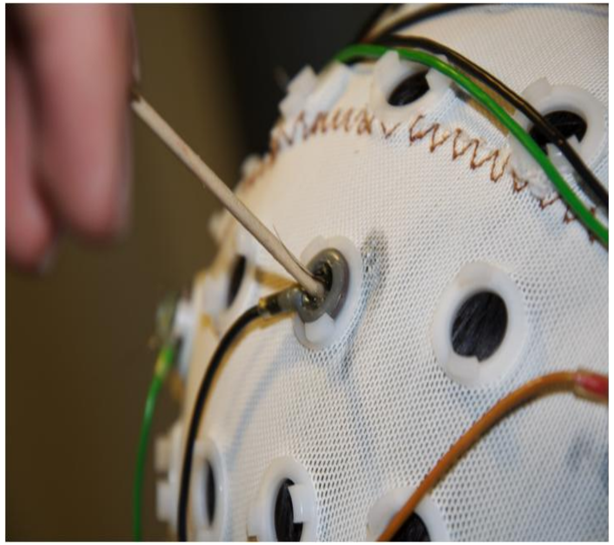
MEG

- In all modalities but EEG, the sensors are heavy.
- EEG is the only modality that does not require the head/body to be fixed.
- EEG might enable the monitoring of the brain functions of unconstrained participants performing normal tasks in the workplace and home.

Neuroimaging Modalities



EEG device



CGX Quick System at a glance:
Available with 8, 20 or 30 channels

News / Mapping of the Central Sulcus using g.Pangolin Ultra High-Density EEG/EMG/ECG System

MAPPING OF THE CENTRAL SULCUS USING G.PANGOLIN ULTRA HIGH-DENSITY EEG/EMG/ECG SYSTEM

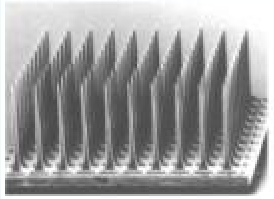
- Electrode caps
- EEG amplifier, ADC, transmitter
- EEG signal processing

Neural electrodes

神经电极的发展方向

柔性增强

柔性材料生物相容性高
可实现长期稳定记录

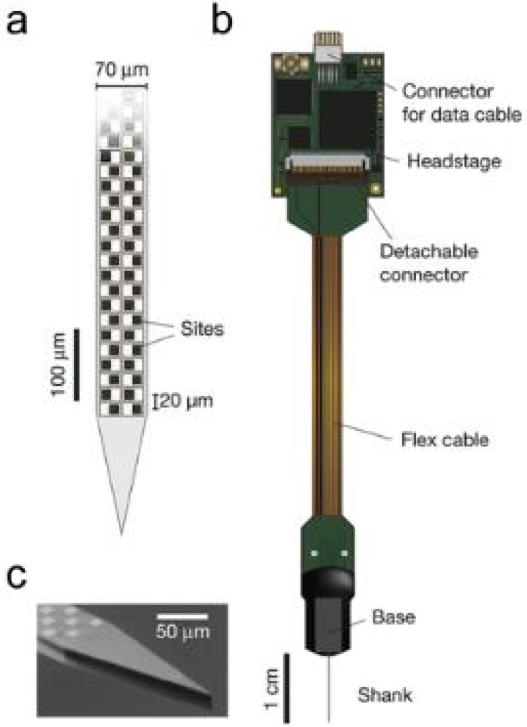


通道增多

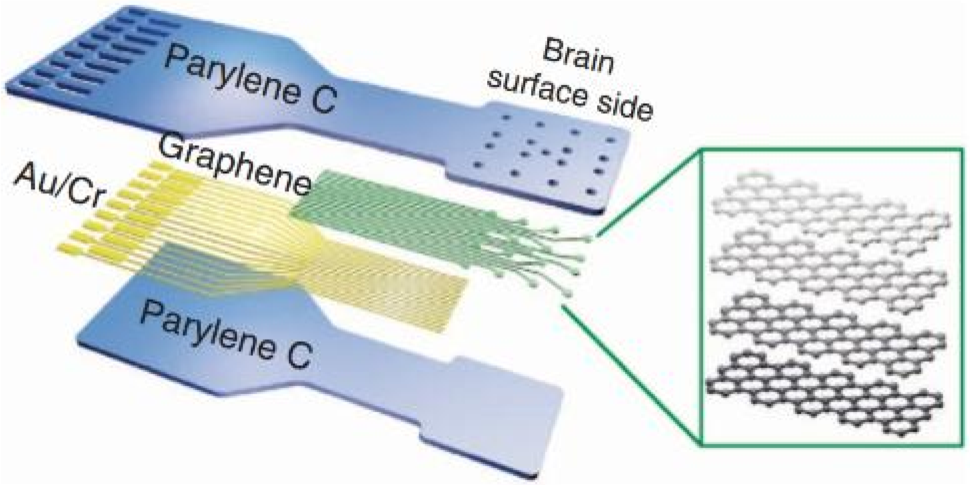
了解神经集群的活动
多通道测量必不可少

性能优化

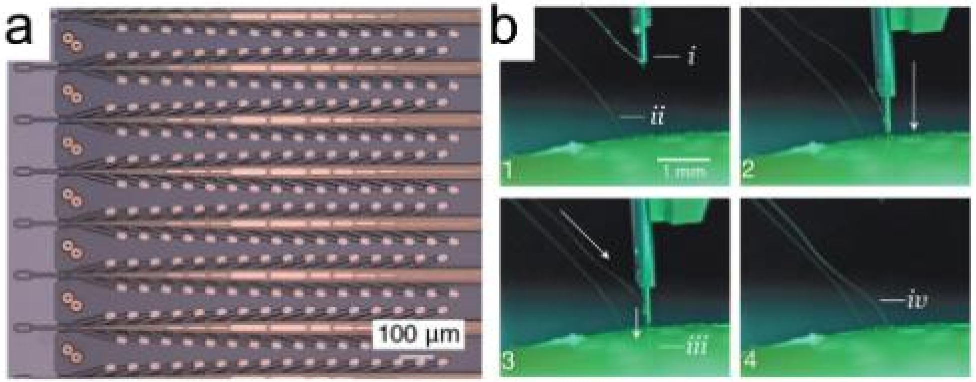
综合性能的提升使
神经电极更加强大



NeuroPixel
探针与前置芯片集成在一个硅片当中



CLEARs
基于 Parylene-C 和石墨烯的透明薄膜电极阵列

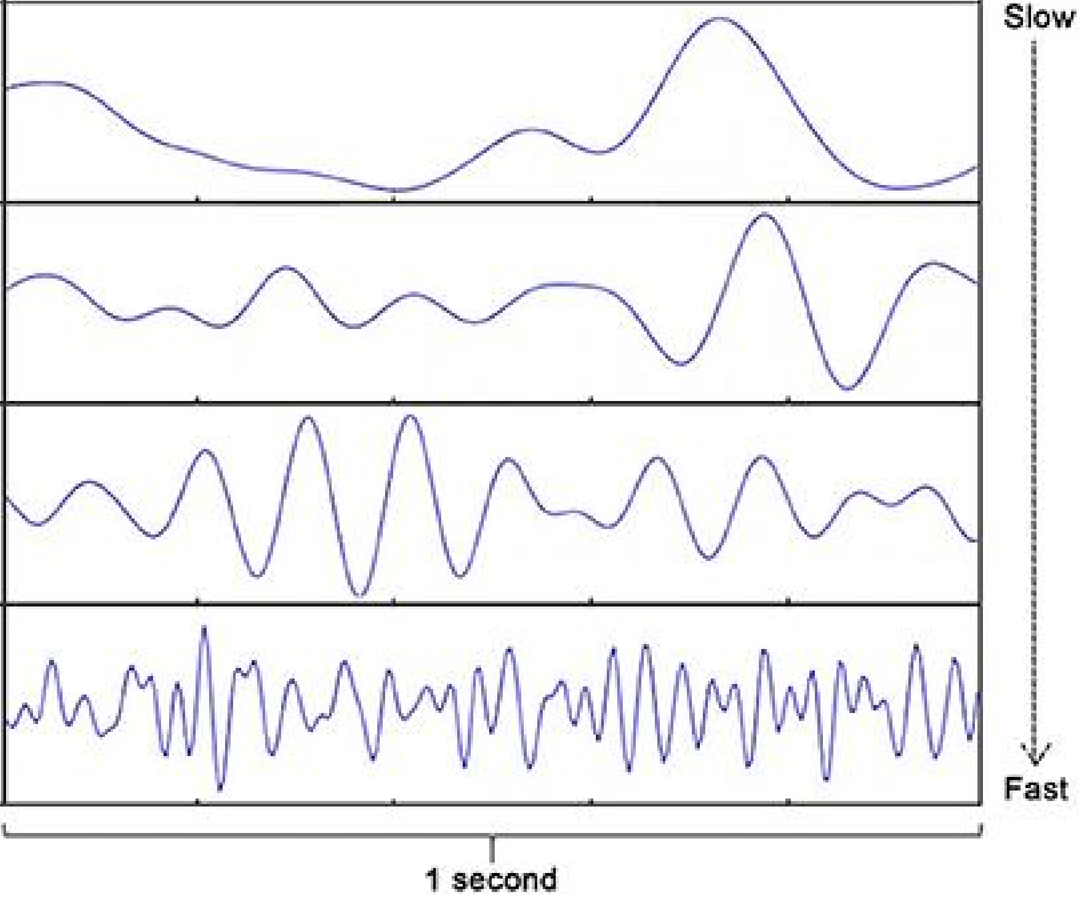


Neuralink
基于柔性微丝电极的千通道级记录系统

https://blog.jaspirit.cc/posts/abcc4c8b/

EEG Rhythms

Frequency band	Speed (Hz)	Mental state	Electroencephalography (EEG) recording
Delta	1-4	Deep sleep	
Theta	4-8	Drowsy	
Alpha	8-12	Relaxed	
Beta	12-30	Focused	



Neural Oscillation

Neural oscillations, or **brain waves**, are rhythmic or repetitive patterns of neural activity in the central nervous system.

- Pacemaker
- Central pattern generator
- Information processing
- Perception
- Motor coordination
- Memory
- Sleep and consciousness

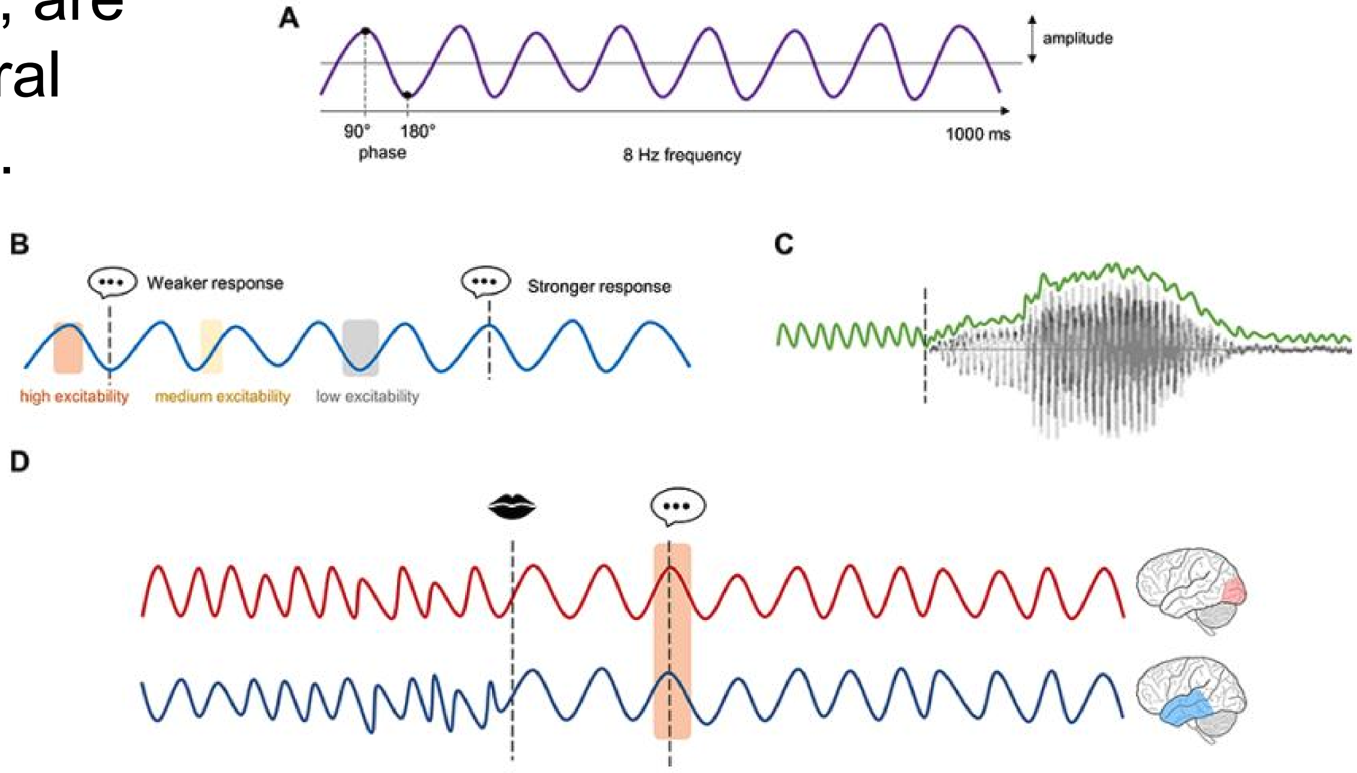
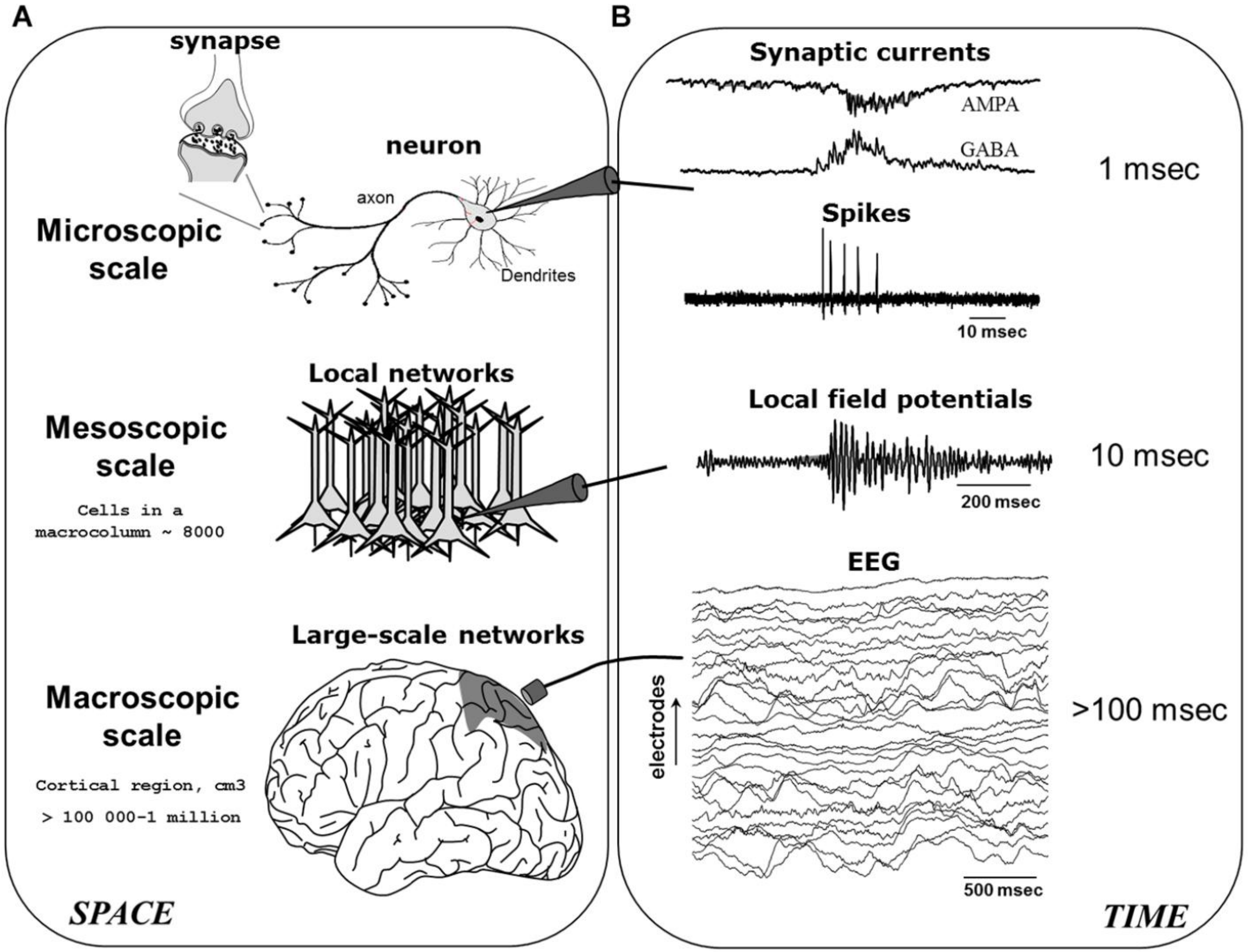


Figure 1. (A) Features of neural oscillations: phase, frequency, time, and amplitude. (B) States of excitability in an oscillatory cycle: Inputs that coincide with high excitability phases typically elicit stronger responses than inputs that are aligned with low excitability phases, suggesting that certain phases of an oscillatory cycle might be more optimal for neural processing. (C) Neural tracking of speech: the phasic relation of ongoing oscillatory activity and the speech signal. (D) Phase-reset by visual speech: processing of auditory speech is shifted to a high-excitability phase by visual information. Colors reflect brain regions where a certain oscillatory signal might occur (red: visual regions, blue: auditory regions).

Neural oscillations

The generation of electroencephalogram (EEG) network oscillations



Ros, Tomas, et al. "Tuning pathological brain oscillations with neurofeedback: a systems neuroscience framework." Frontiers in human neuroscience 8 (2014): 1008

Neural Oscillations

Main functional roles of neural oscillations

1) Coding specific information,
2) Setting and modulating brain attentional states,
3) Assuring the communication between neuronal populations such that specific dynamic workspaces may be created.

da Silva, Fernando Lopes. "EEG and MEG: relevance to neuroscience." *Neuron* 80.5 (2013): 1112-1128.

EEG preprocessing

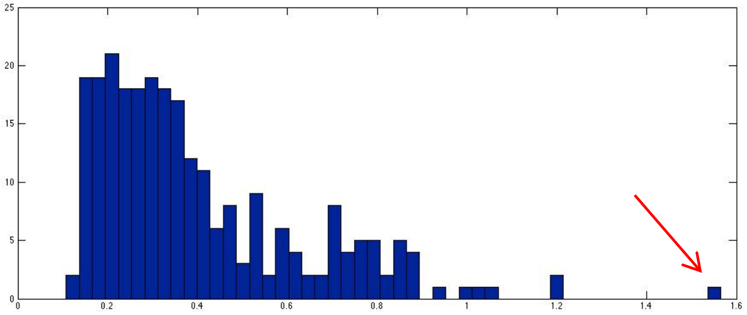
Bad channel repair → Filtering → Artifact removal → Re-referencing

EEG preprocessing – bad channel detection

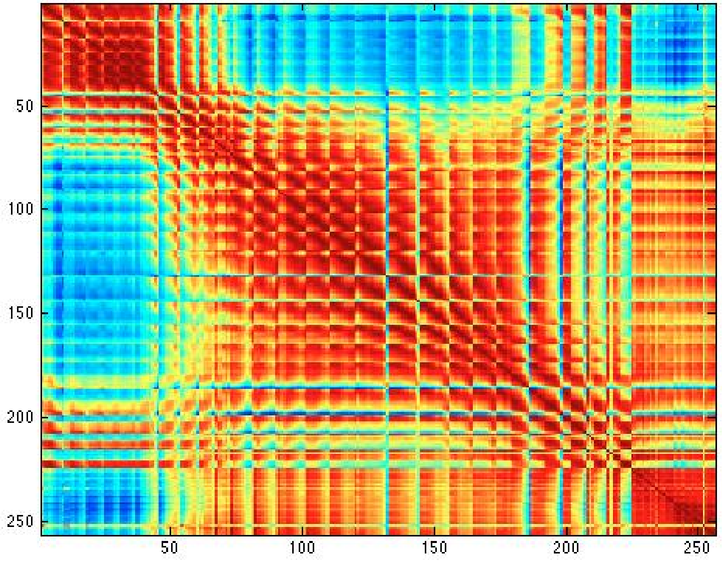
Bad channel repair → Filtering → Artifact removal → Re-referencing

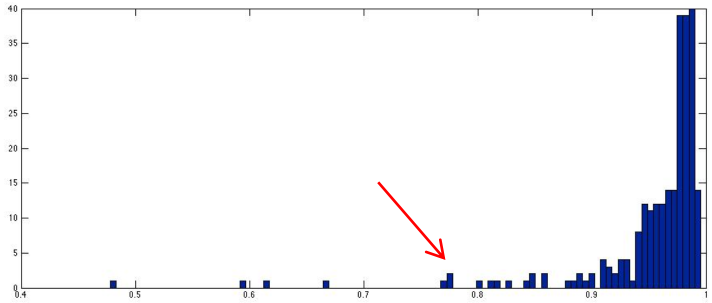
1. Bad channel detection
2. Channel interpolation

Covariance of signals in 200-250Hz



Correlation matrix between signals (0.5hz-99.5Hz)





Ref:

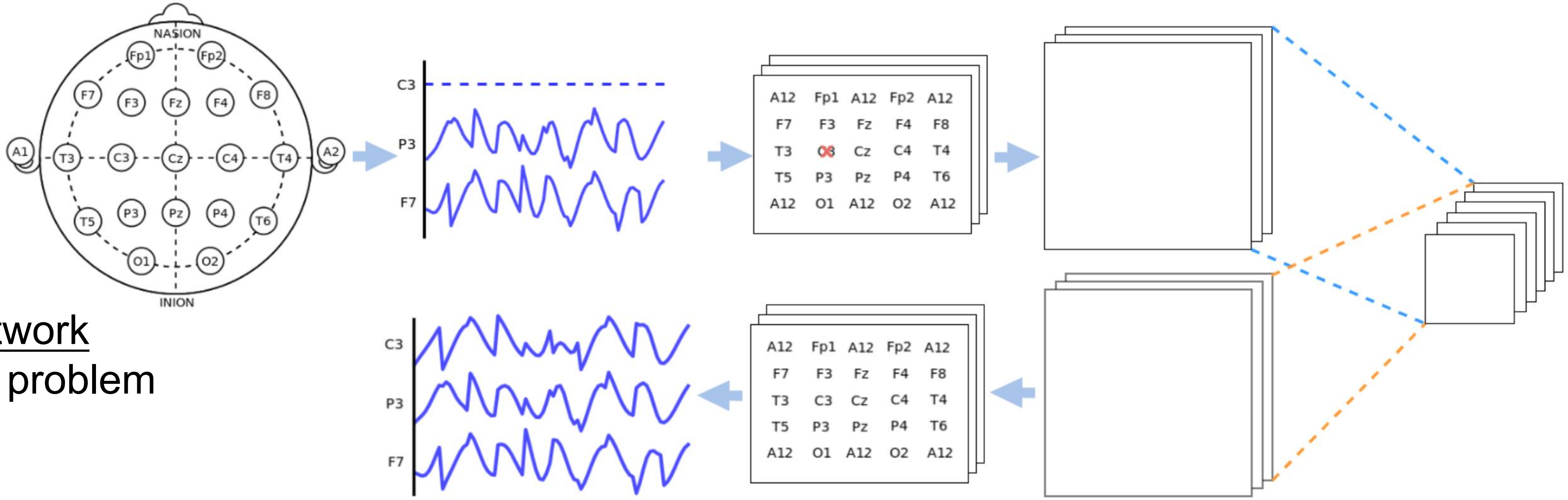
Oliveira et al (2017). A channel rejection method for attenuating motion-related artifacts in EEG recordings during walking
Tuyienge et al (2018). Automatic bad channel detection in intracranial electroencephalographic recordings using ensemble machine learning

EEG preprocessing – bad channel interpolation

Bad channel repair → Filtering → Artifact removal → Re-referencing

1. Bad channel detection
2. **Channel interpolation**

<u>Spherical splines</u>: The interpolant can be projected to the surface of the sphere to form a spherical triangulation of a polygonal domain of the spherical surface.



<u>Deep encoder-decoder network</u>
Similar to image inpainting problem in computer vision

Ref:

Perrin et al (1989). Spherical splines for scalp potential and current density mapping
Saba-Sadiya et al (2020) EEG Channel Interpolation Using Deep Encoder-decoder Networks

EEG preprocessing – filtering

Bad channel repair → **Filtering** → Artifact removal → Re-referencing

EEG preprocessing – filtering

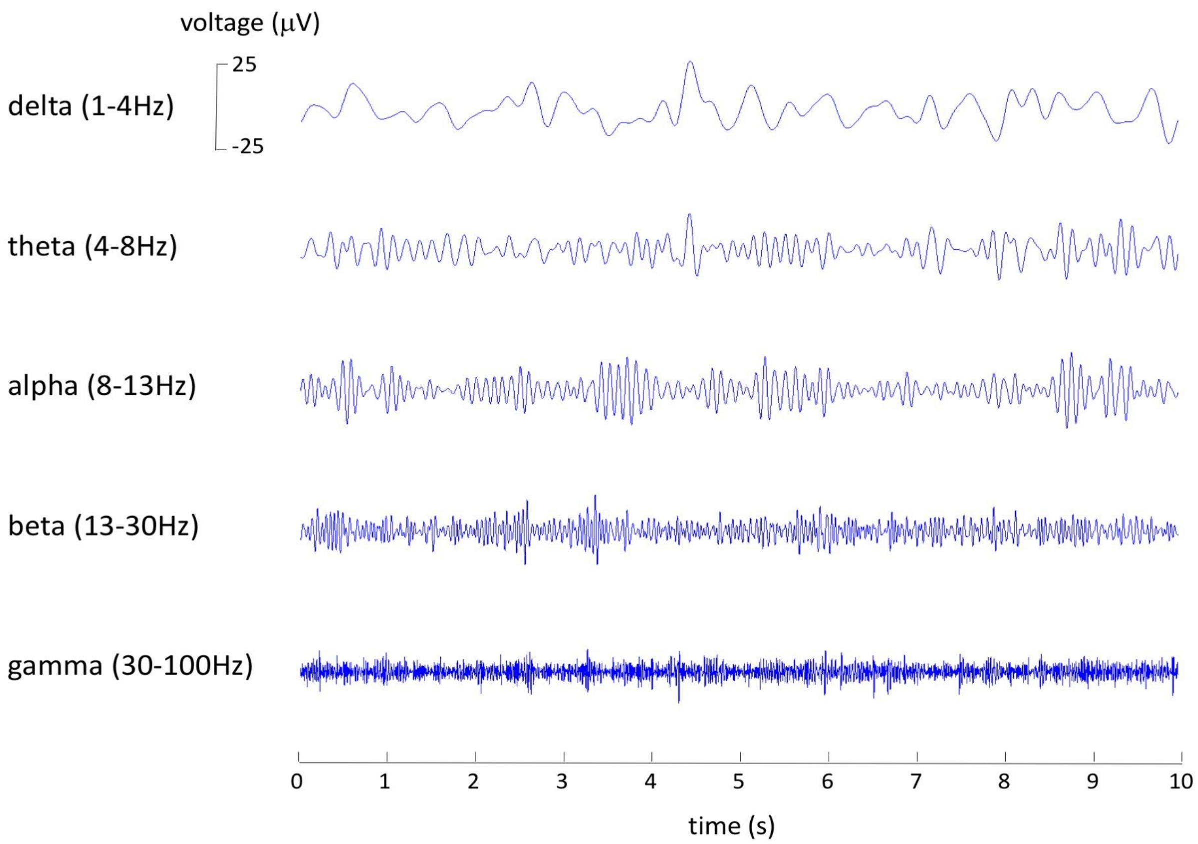
Digital filters are of **two** kinds:

- Finite impulse response (FIR) filters
- Infinite impulse response (IIR) filters

FIR filters have an impulse response of finite duration.
IIR filters do not become exactly zero after a certain point.
The most common IIR filters are: Butterworth filter, Chebyshev I or II type filter and Elliptic filter (Bhogeshwar et al 2014).

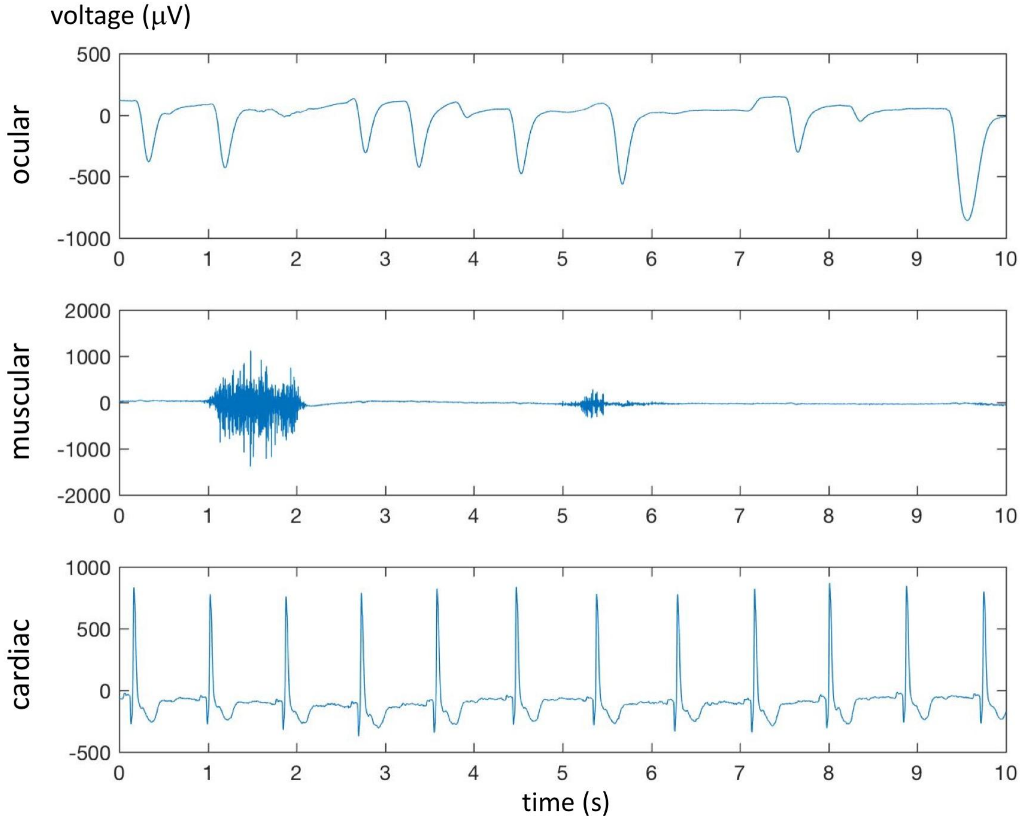
Filter parameters: cutoff frequency, filter order, roll-off, phase delay (zero-phase, linear-phase, non-linear phase).
Roll-off is the rate at which attenuation increases beyond the cut-off frequency.

EEG rhythms



The **phase** distortions and delays might be added to the signals, depending on the frequency response of the filter.

EEG preprocessing – artifact removal



The waveform of three types of non-neuronal signals mixed in raw EEG recordings:

1. Ocular artifacts
2. Muscular artifacts
3. Cardiac artifacts

Their frequencies overlap with the frequency of EEG signals.
Therefore, filtering cannot completely remove these artefacts.

Artifacts mixed in EEG signals

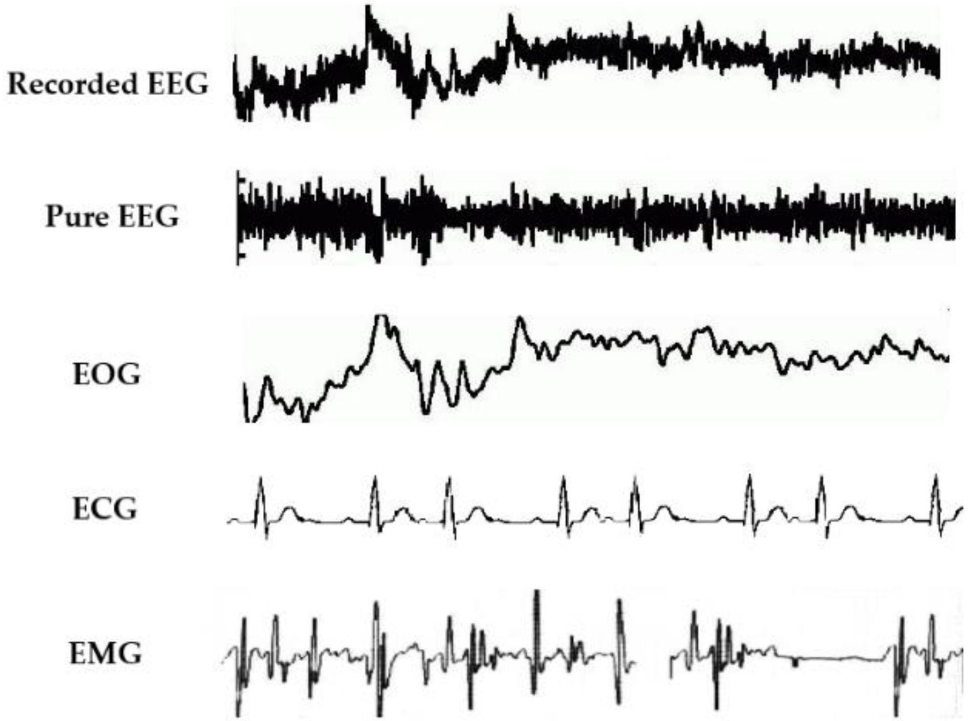
Artifacts are signals recorded by EEG but not generated by brain.

Physiological artifacts

- Ocular activity (EOG)
- Muscle activity (EMG)
- Cardiac activity (ECG)
- Perspiration
- Respiration

Non-physiological / Technical artifacts

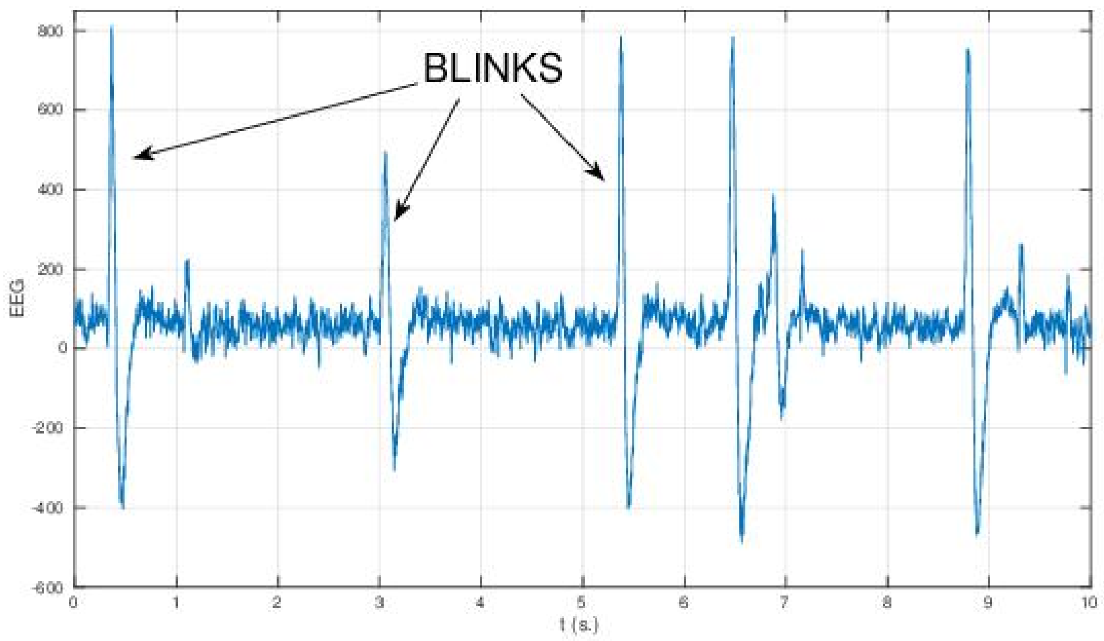
- Electrode pop
- Cable movement
- Incorrect reference placement
- AC electrical and electromagnetic interferences
- Body movements



EEG Artifacts

Ocular Artifacts

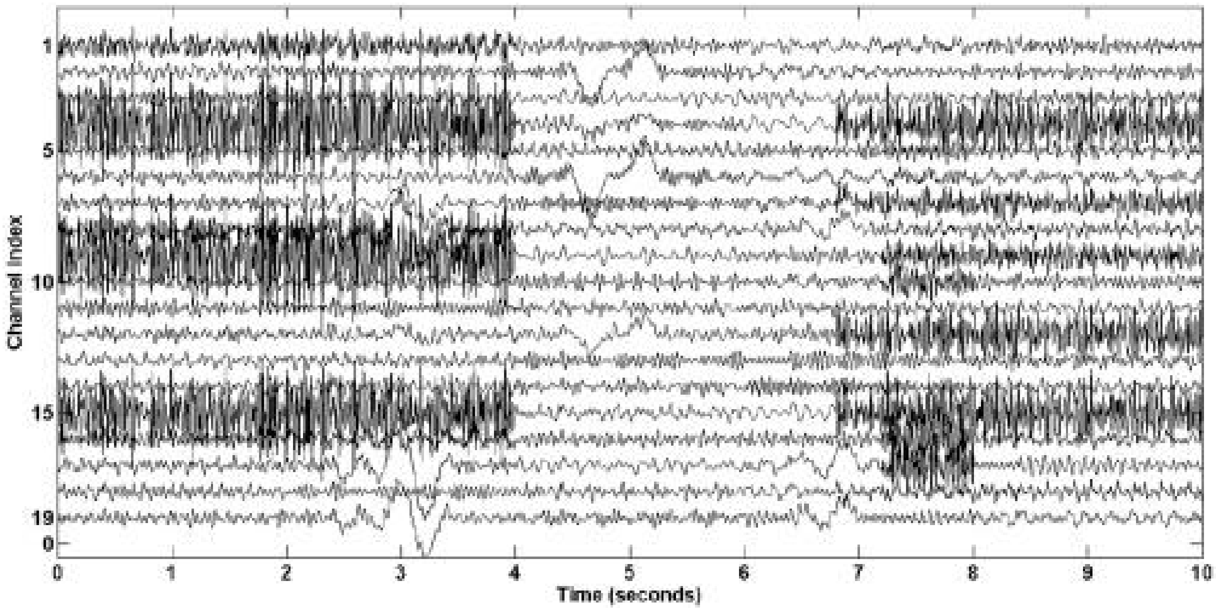
Ocular artifacts generate significant artifacts in the EEG recordings. The origin of ocular artifacts is eye movement and blinks which can propagate over the scalp and be recorded by EEG activity.



EEG Artifacts

Muscle Artifacts

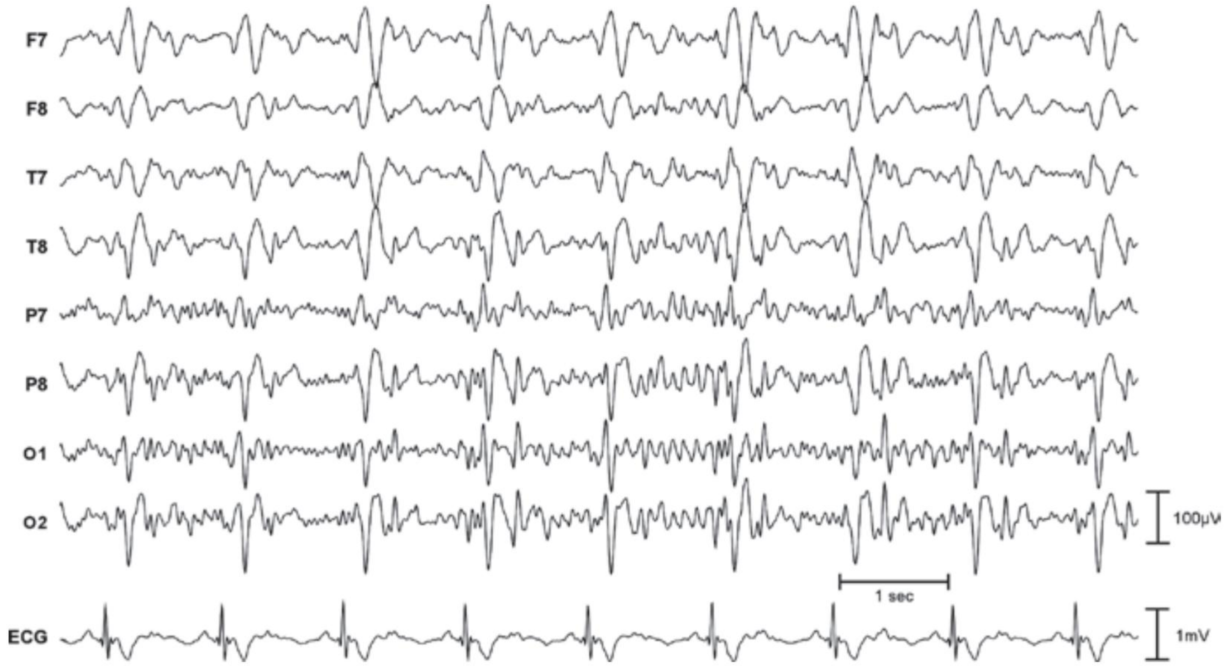
Contamination of EEG data by muscle activity is a well-recognized tough problem as it arises from different type of muscle groups. These artifacts can be caused by any muscle proximity to signal recording sites contraction and stretch, the subject talks, sniffs, swallows, etc.



EEG Artifacts

Cardiac artifacts

Cardiac artifacts can be introduced when the electrodes is placed on or near a blood vessel, in which the movement of expansion and contraction due to the heart.

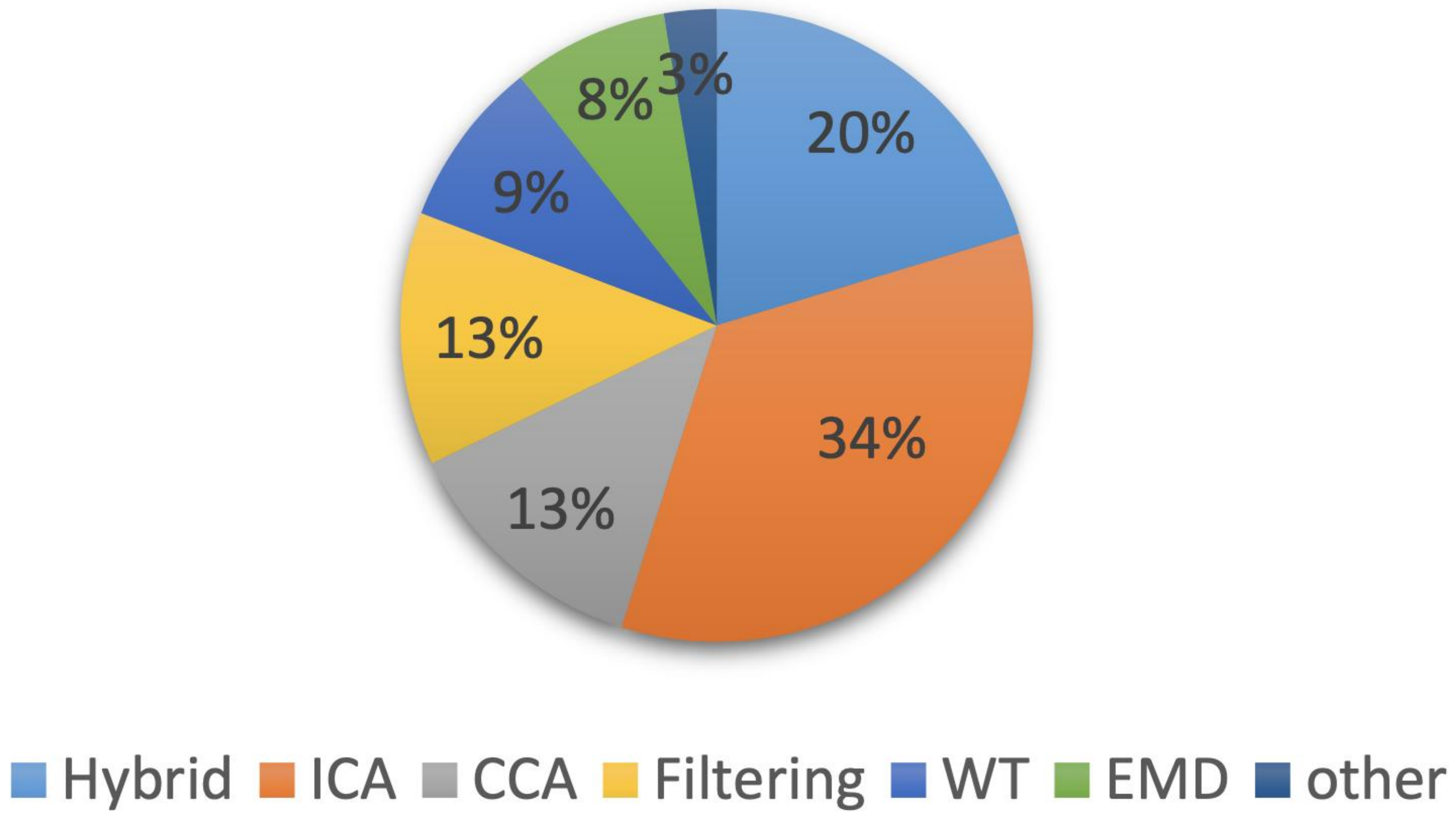


EEG Artifact Removal Method

Single Artifacts Removal Techniques

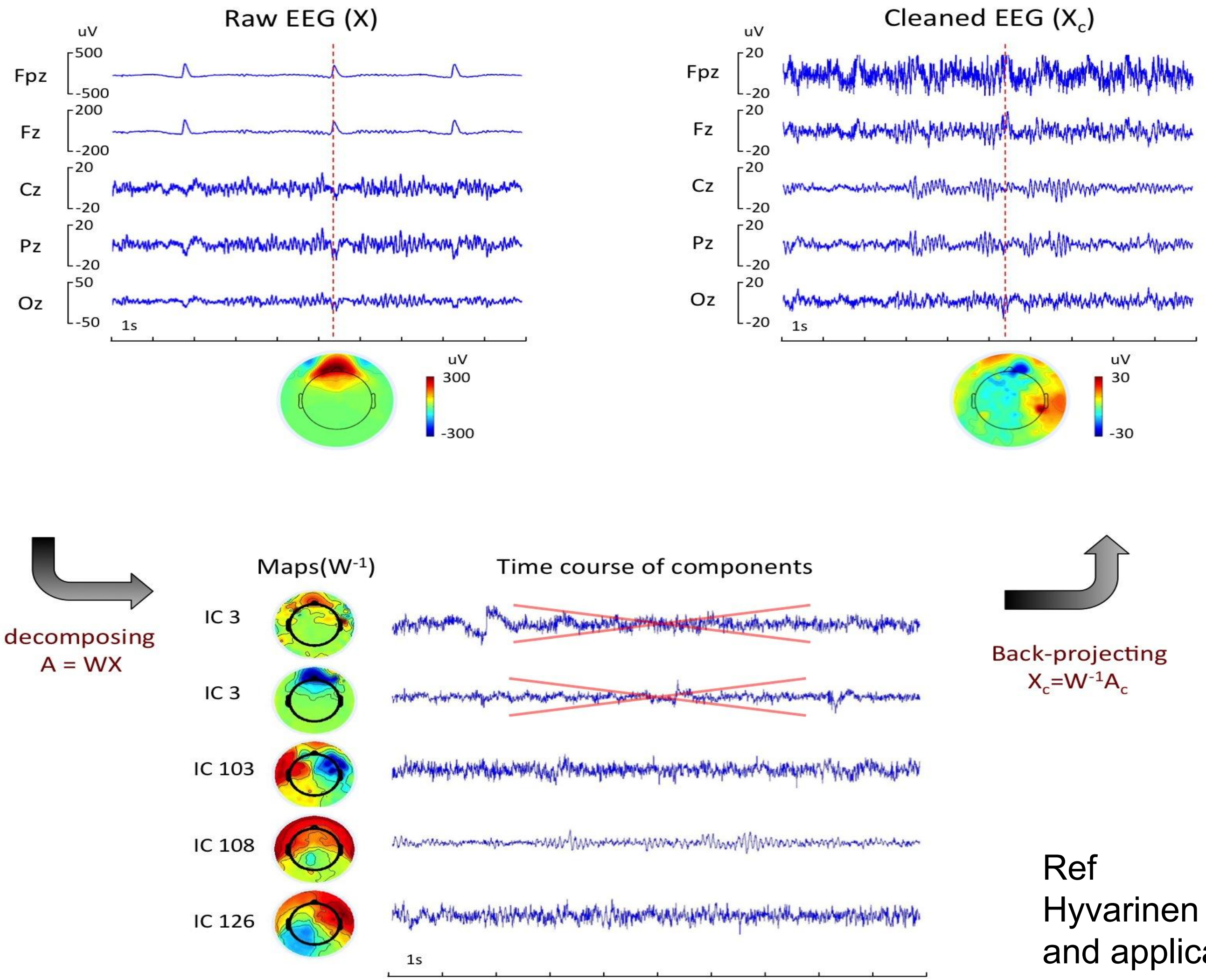
- Regression Methods
- Wavelet Transform
- Blind source separation method
  - Principal Component Analysis
  - Independent Component Analysis
  - Canonical Correlation Analysis
  - Source Imaging Based Method
  - Empirical Mode Decomposition

EEG Artifact Removal Method



(up to 2020)

ICA for EEG artifact removal



ICA is a computational method for separating a multivariate signal into *additive* subcomponents.

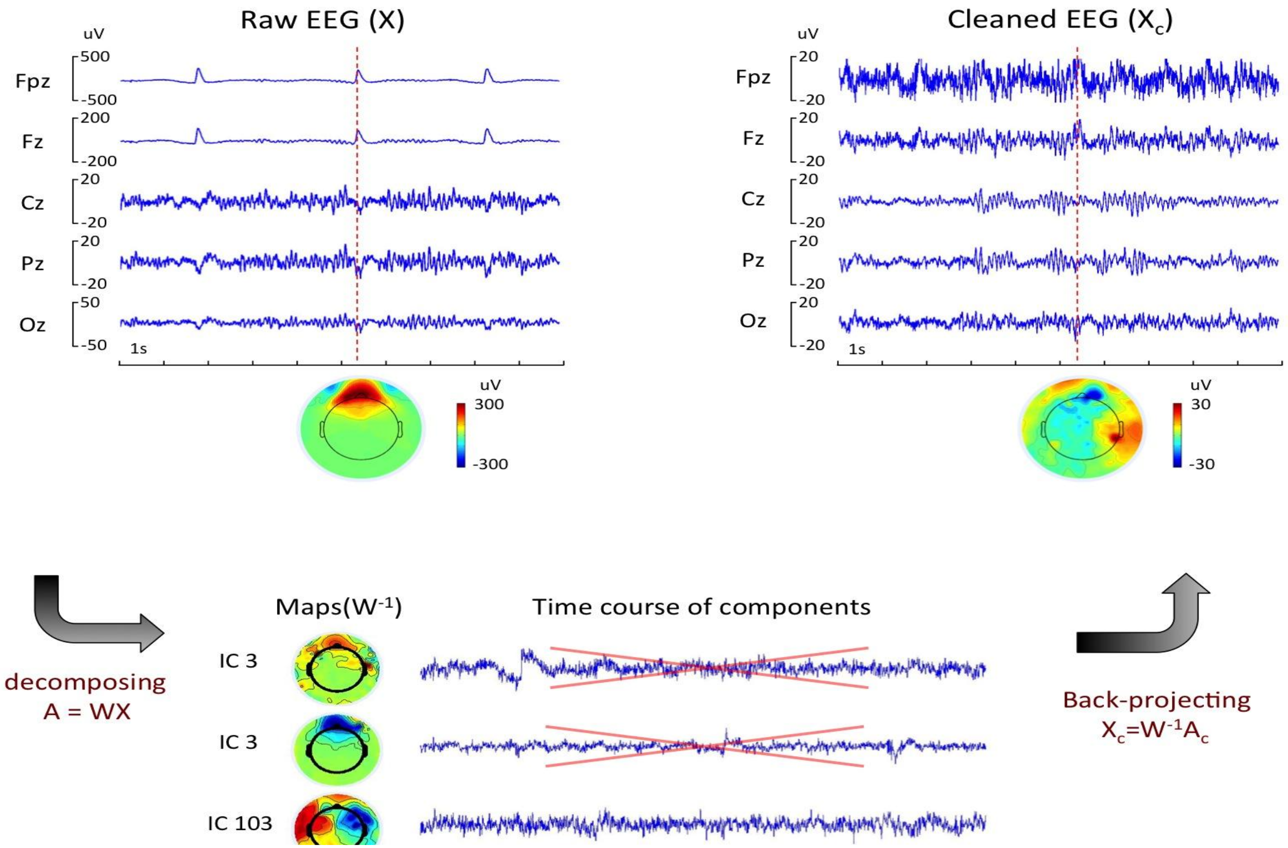
This can be done by **assuming** that the subcomponents are non-Gaussian signals and that they are statistically independent from each other (Hyvarinen & Oja 2000).

The core **mathematical concept** of ICA is to minimize the mutual information among the data projections or maximize their joint entropy.

Ref

Hyvarinen A, Oja E. (2000). Independent component analysis: algorithms and applications. *Neural networks*

ICA for EEG artifact removal



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The core **mathematical concept** of ICA is to minimize the mutual information among the data projections or maximize their joint entropy.

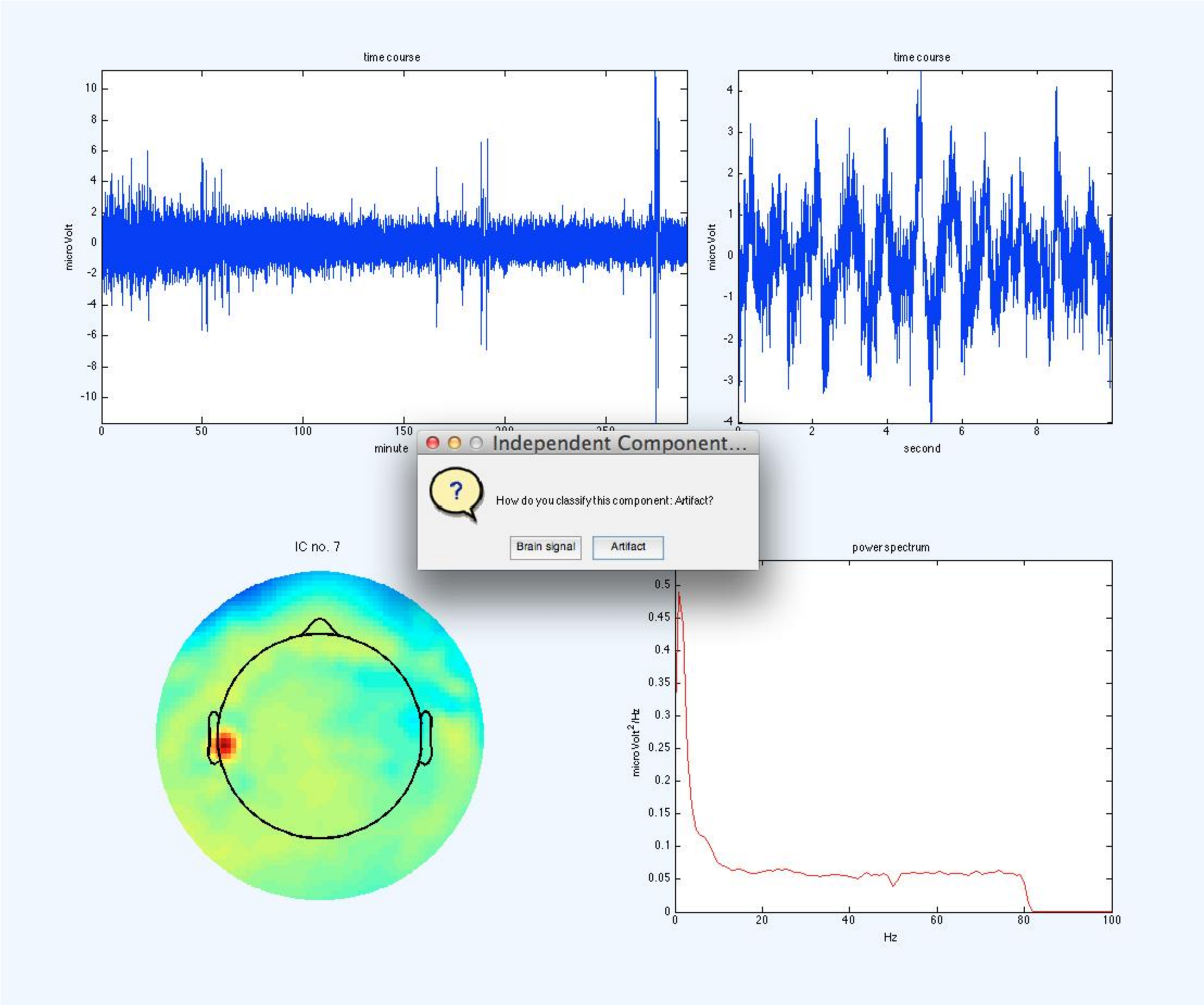
Question:
Which ICs shall be removed?

Question:
Which ICs shall be removed?

- Check IC time course
- Check IC spectrum
- Check IC topography （脑地形图）

- Machine learning to learn the latent features of artefactual ICs

Radüntz et al (2017). Automated EEG artifact elimination by applying machine learning algorithms to ICA-based features



ICA for EEG artifact removal

微信公众号推文 https://mp.weixin.qq.com/s/3XTYaWhbm6AsWrju8jiDvA

讲座总结 | 脑电信号降噪的若干新探索

Original NCC lab 神经计算与控制实验室 6/2

当下，脑电信号（EEG signal）在临床医学诊断、
了广泛的应用，但由于脑电信号十分微弱，很容易
迹等）的干扰，因而对其降噪就格外重要。受南
请，来自中国科学技术大学的陈勋教授于2020年5
动的例子从4个层次介绍了受肌电信号污染的脑电
析、联合盲源分离等）、动机、在该方向上的若干

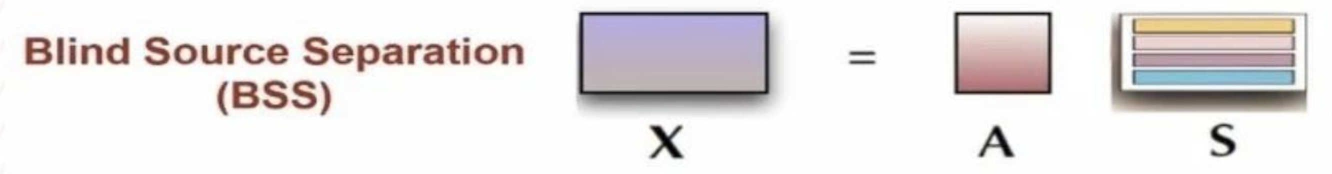


图2.盲源分离（Blind Source Separation, BSS）的公式表示

对于脑电信号和其中各种噪声分离的实现中使用盲源分离技术的思路由图3所示。

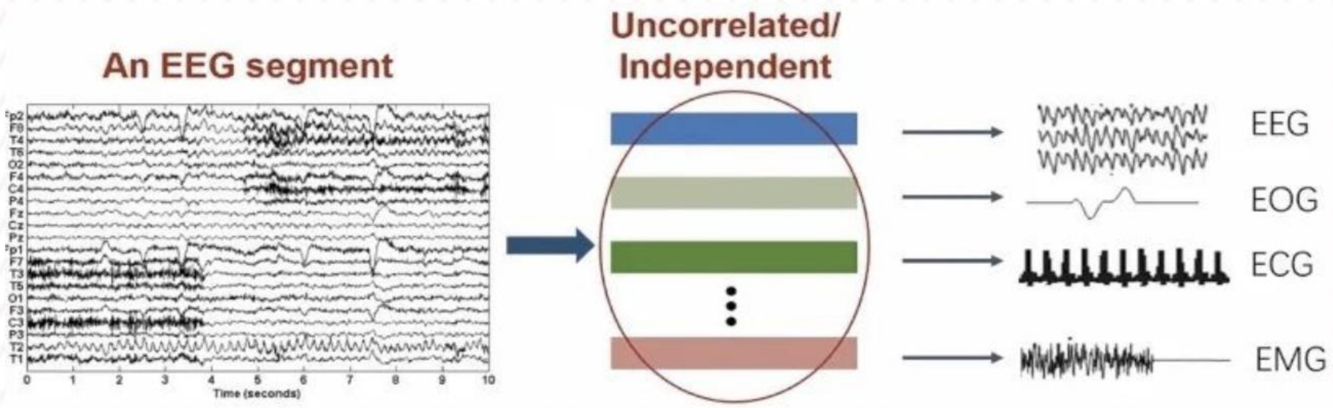


图3. 盲源分离技术在脑电及噪声信号分离中的应用思路

本文作者：NCC lab李哲汭，张皓铭

EEG Artifact Removal Method

Method	Additional Reference	Automatic	Online	Can Perform on Single Channel
Regression	Y	Y	N	N
Wavelet	N	Y	N	Y
ICA	N	N	Y	N
CCA	N	N	Y	N
Adaptive filter	Y	Y	Y	Y
Winner filter	N	Y	N	Y
Wavelet BSS	N	N	N	Y
EMD BSS	N	N	N	Y
BSS-SVM	N	Y	Y	N

EEG Artifact Removal Method

EEGdenoiseNet: benchmark dataset for EEG denosing

Table 1. Summary of the data collections used in our dataset.

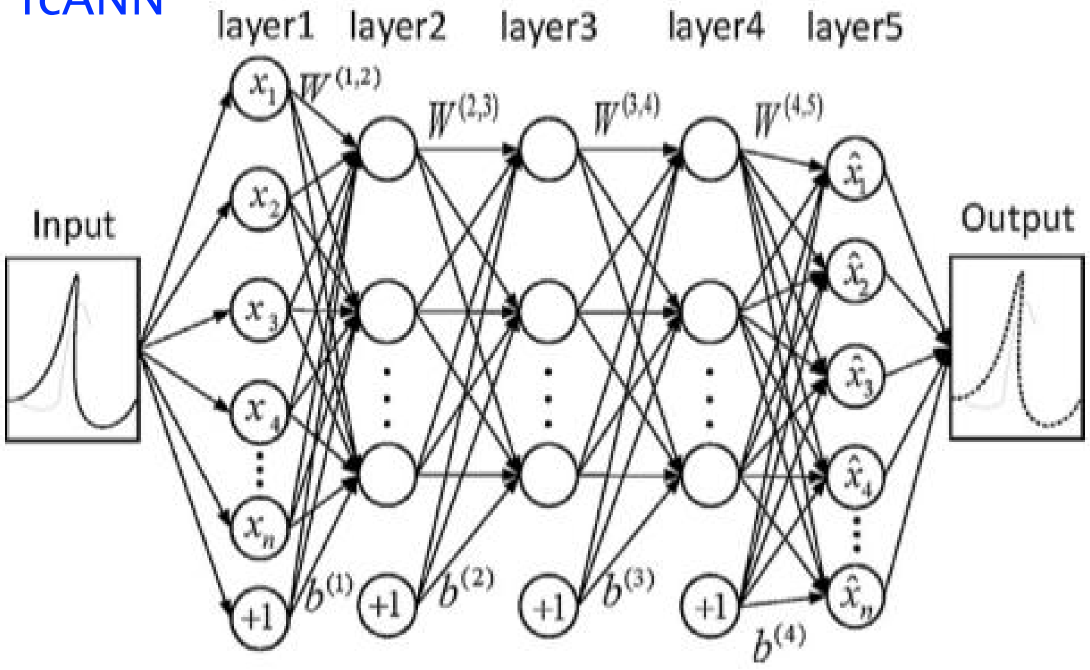
Dataset	Signal type	# of subjects	Mean age ± SD	Dataset website
Hohyun *et al* (2017) [53]	EEG	52	26 ± 3.86	http://gigadb.org/dataset/100295
Kangoga *et al* (2016) [54]	EOG	20	22.75 ± 1.45	http://u4ag2kanosr1.blogspot.jp/
Naeem *et al* [56]	EOG	8	23.8 ± 2.5	www.bbci.de/competition/iv/
Schlögl *et al* (2007) [57, 58]	EOG	10	Age between 17 and 31	www.bbci.de/competition/iv/
Rantanen *et al* (2015) [59]	EMG	15	40.7 ± 9.6	https://etsin.fairdata.fi/dataset/0f24bf09-c5d1-422e-8df5-eb44219f5dec

Zhang, Haoming, et al. "Eegdenoisenet: A benchmark dataset for deep learning solutions of eeg denoising." Journal of Neural Engineering 18.5 (2021): 056057.

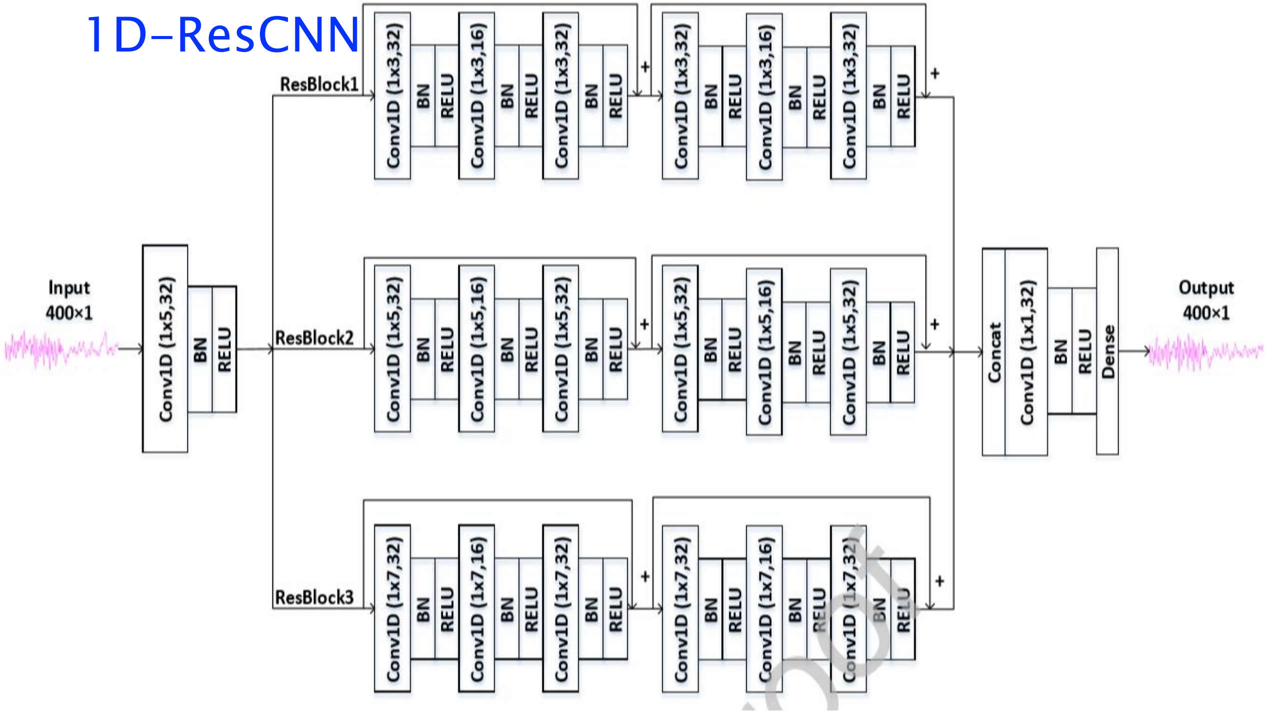
Remove artifacts from EEG signals

based on deep learning models

fcANN



1D-ResCNN

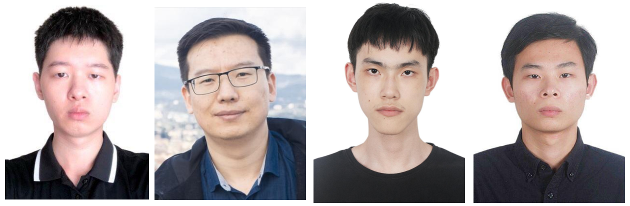


Yang et al., Biomed Singla Process (2018)

Sun et al., Neurocomputing (2020)

EEGdenoiseNet: A benchmark dataset for deep learning solutions of EEG denoising

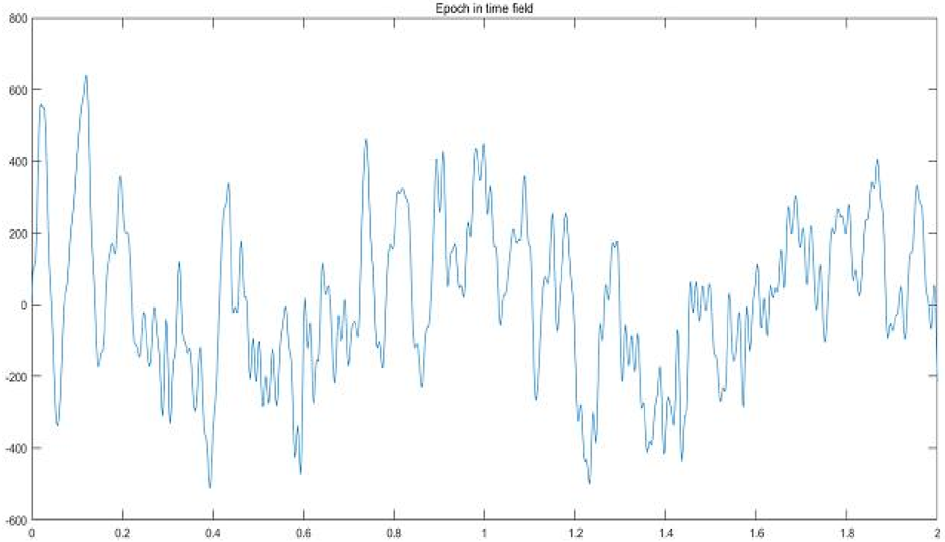
Haoming Zhang[1,†], Mingqi Zhao[1,2,†], Chen Wei[1],
Dante Mantini[2,3], Zherui Li[1], Quanying Liu[1,*]



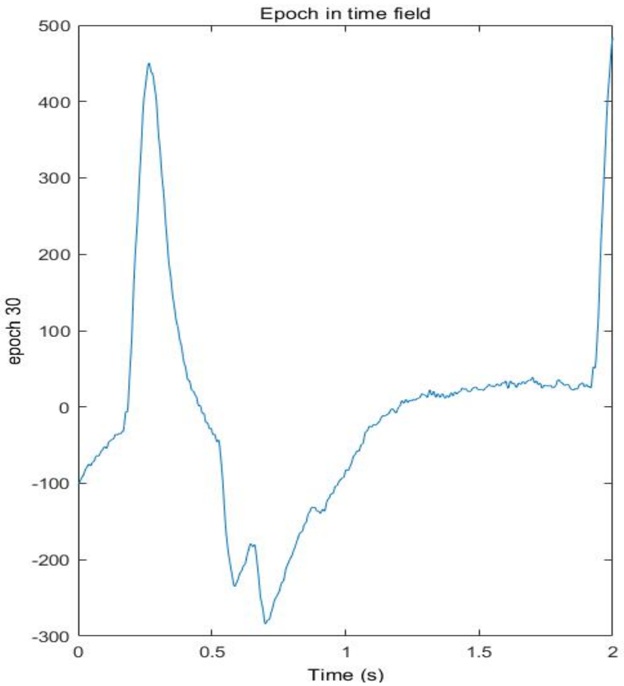
张皓铭 赵鸣奇 魏晨 李哲汭

Download at Github:
https://github.com/ncclabsustech/EEGdenoiseNet

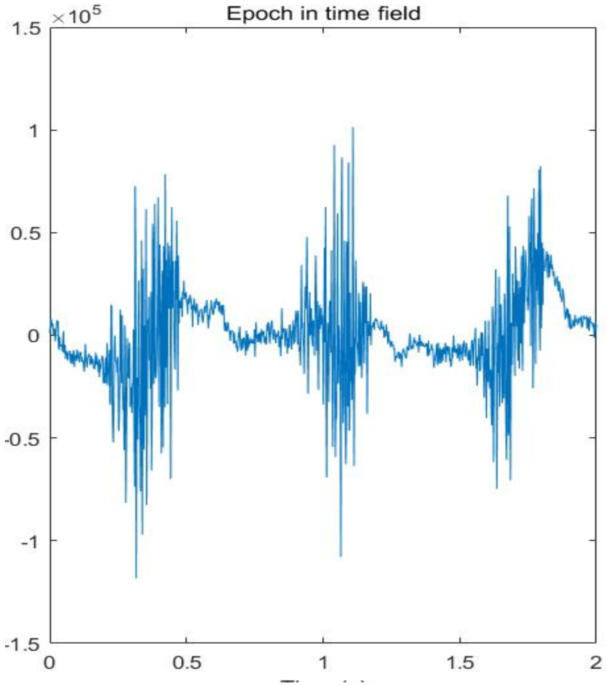
Clean EEG 4514 epochs



EOG 3400 epochs



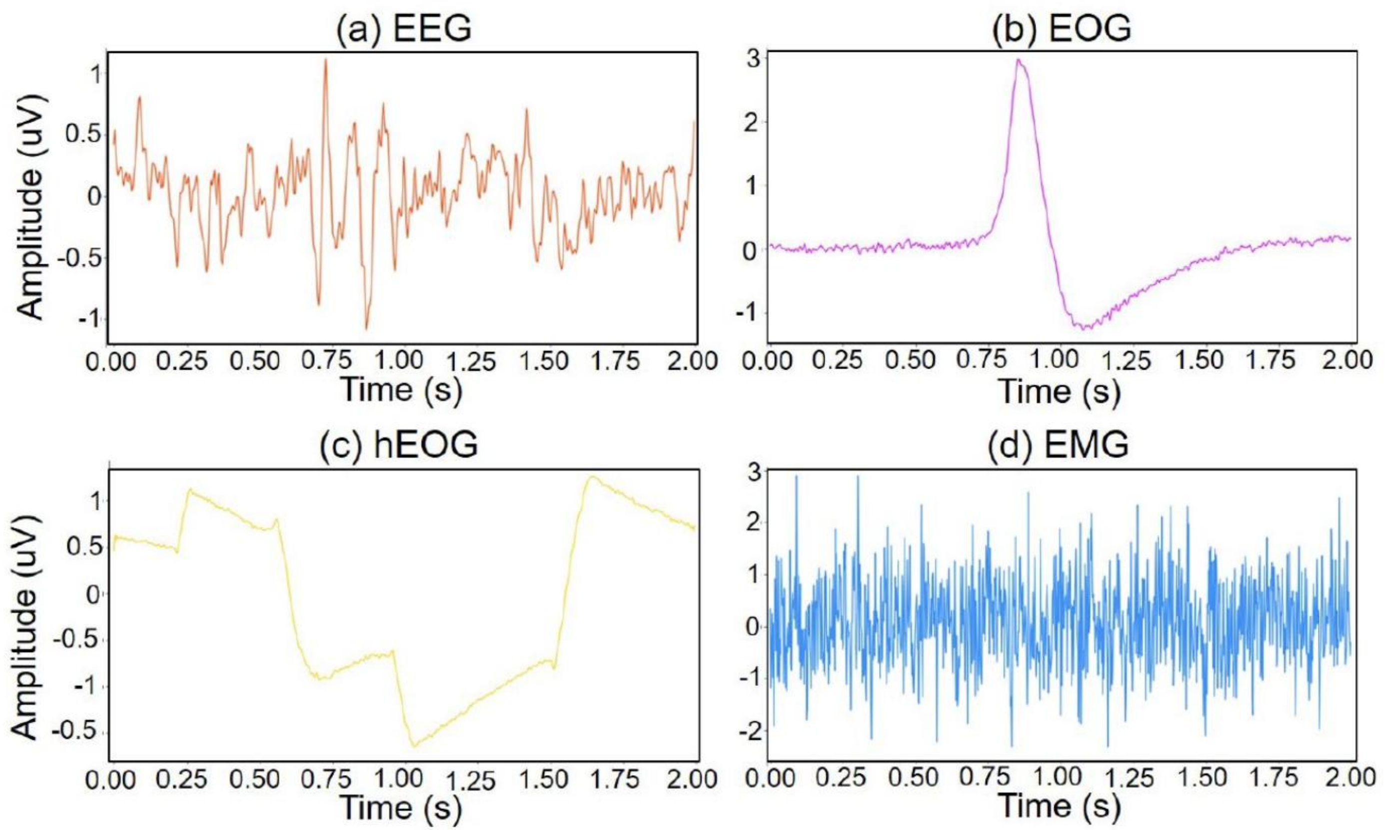
EMG 5598 epochs



Zhang, et al. "EEGdenoiseNET: A benchmark dataset for deep learning solutions of eeg denoising." J. Neural Eng. (2021).

EEG Artifact Removal Method

EEGdenoiseNet: benchmark dataset for EEG denosing



Zhang, Haoming, et al. "EEGdenoiseNET: A benchmark dataset for deep learning solutions of eeg denoising." Journal of Neural Engineering 18.5 (2021): 056057.

EEG Artifact Removal Method

Contaminated EEG Generation

The contaminated signals can be generated by linearly mixing the pure EEG segments with EOG or EMG artifact segments, according to equation:

$$y = x + \lambda \cdot n,$$

where y denotes the mixed one-dimensional signal of EEG and artifacts; x denotes the clean EEG signal as the ground truth; n denotes (ocular or myogenic) artifacts; λ is a hyperparameter to control the signal-to-noise ratio (SNR) in the contaminated EEG signal y.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EEGdenoiseNet: a benchmark dataset for deep learning solutions of EEG denoising

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Haoming Zhang, Mingqi Zhao, Chen Wei, Dante Mantini, Zherui Li, and Quanying Liu.

Miriam Maus
Publishing Director
IOP Publishing

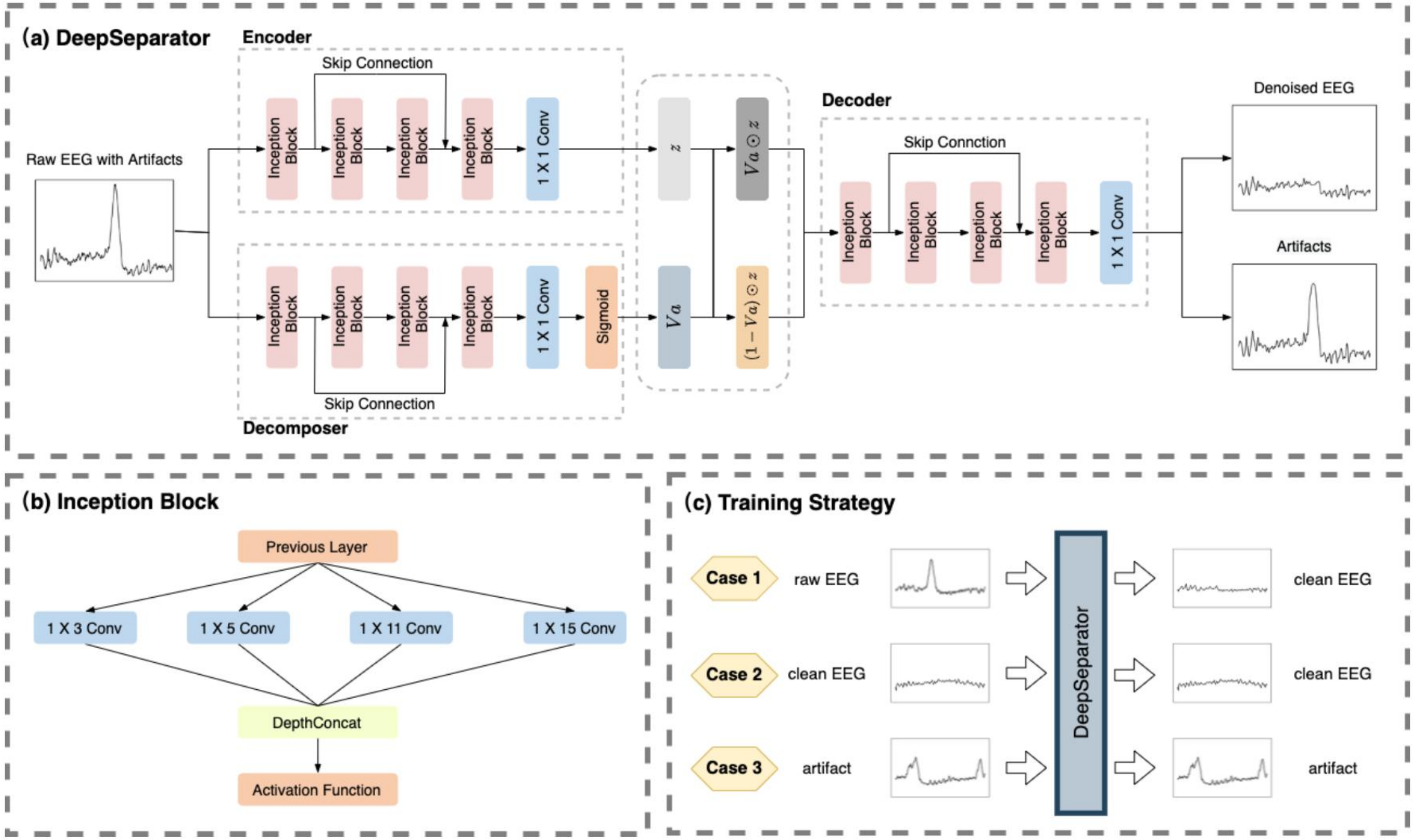
IOP Publishing

Download at Github:
https://github.com/ncclabsustech/EEGdenoiseNet

EEGdenoiseNET: A benchmark dataset for deep learning solutions of eeg denoising 155 2021
H Zhang, M Zhao, C Wei, D Mantini, Z Li, Q Liu
EI检索 SCI升级版 医学3区 SCI基础版 医学2区 IF 3.7 SWJTU A++
Journal of Neural Engineering 18 (5), 056057

EEG Artifact Removal Method

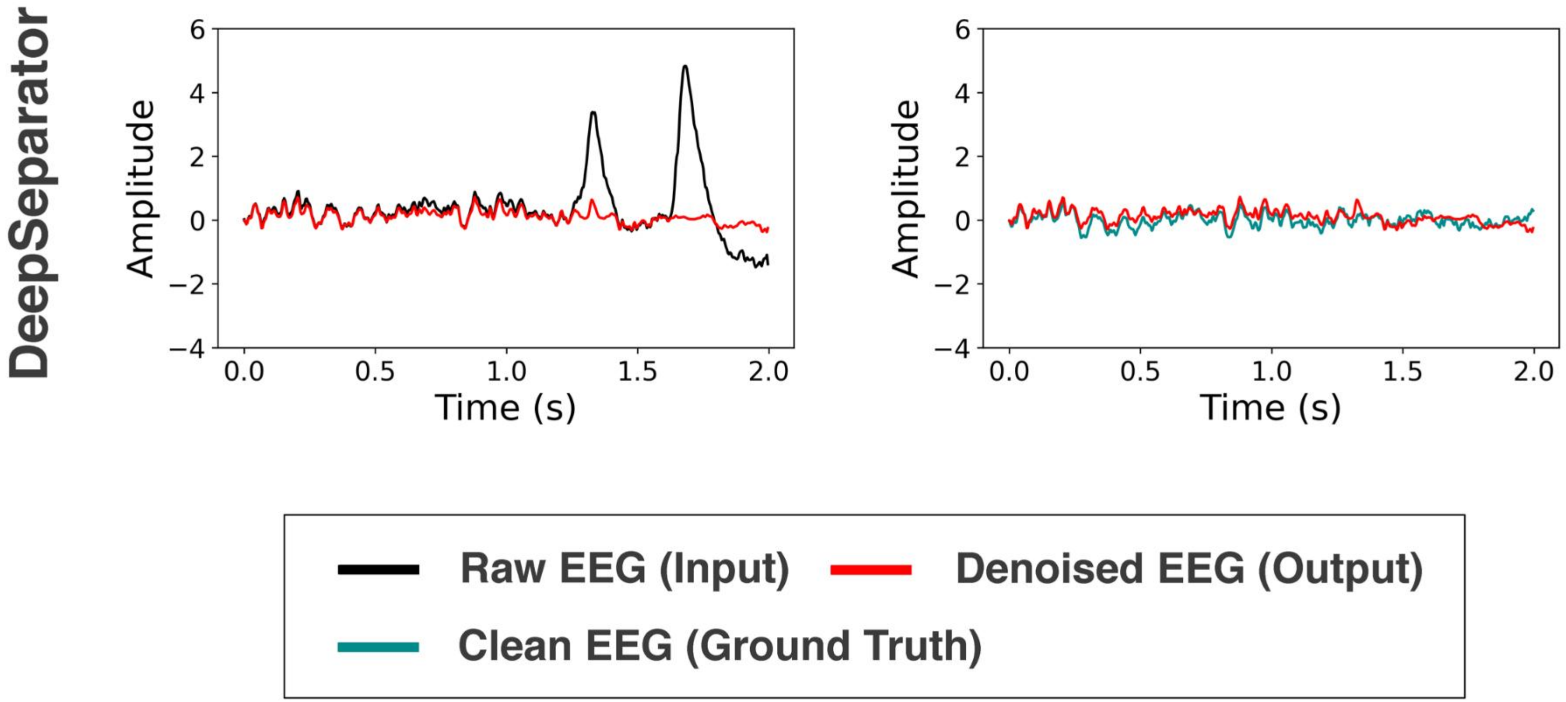
Deep learning for artifact removal



Yu, Junjie, et al. "Embedding decomposition for artifacts removal in EEG signals." *Journal of Neural Engineering* 19.2 (2022): 026052.

EEG Artifact Removal Method

Deep learning for artifact removal

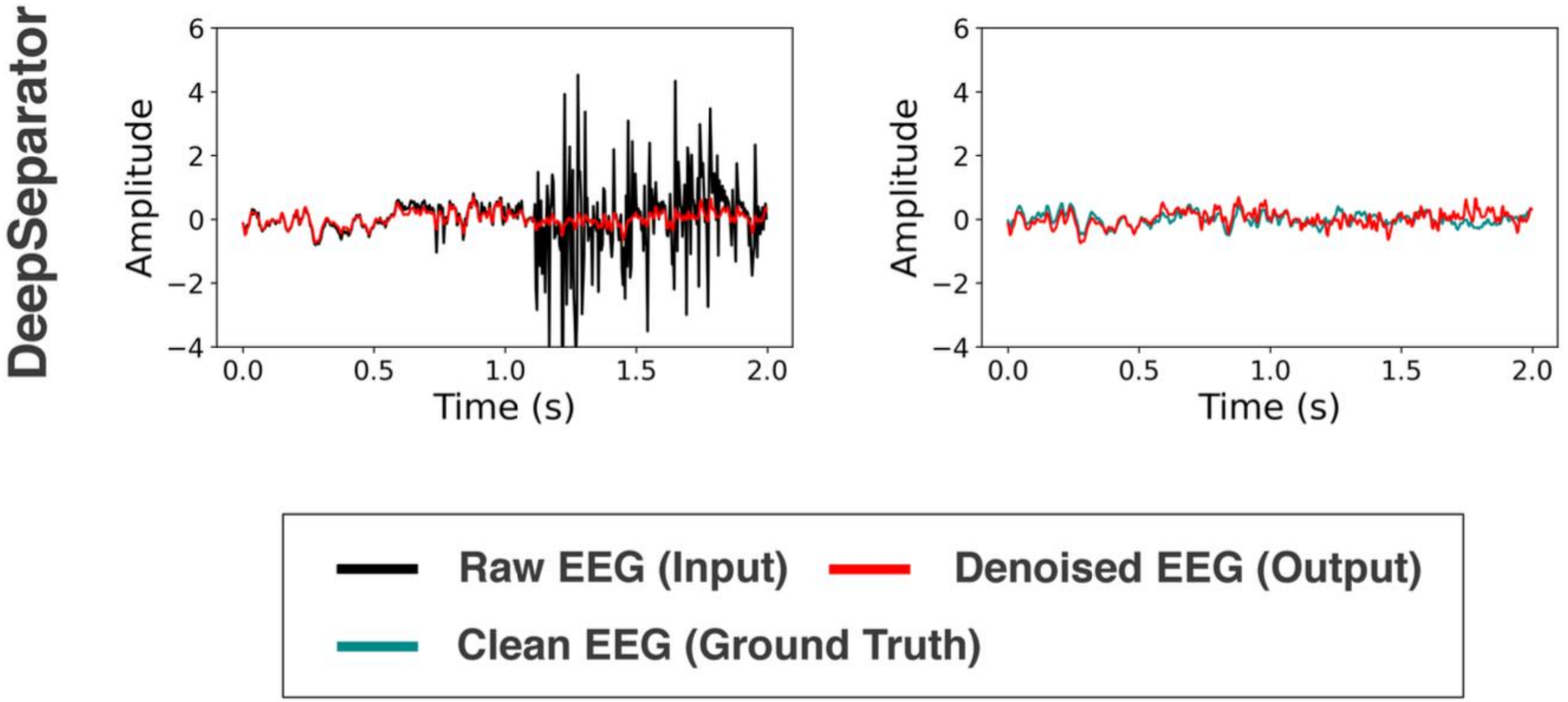


EOG Artifact Removal

Yu, Junjie, et al. "Embedding decomposition for artifacts removal in EEG signals." *Journal of Neural Engineering* 19.2 (2022): 026052.

EEG Artifact Removal Method

Deep learning for artifact removal

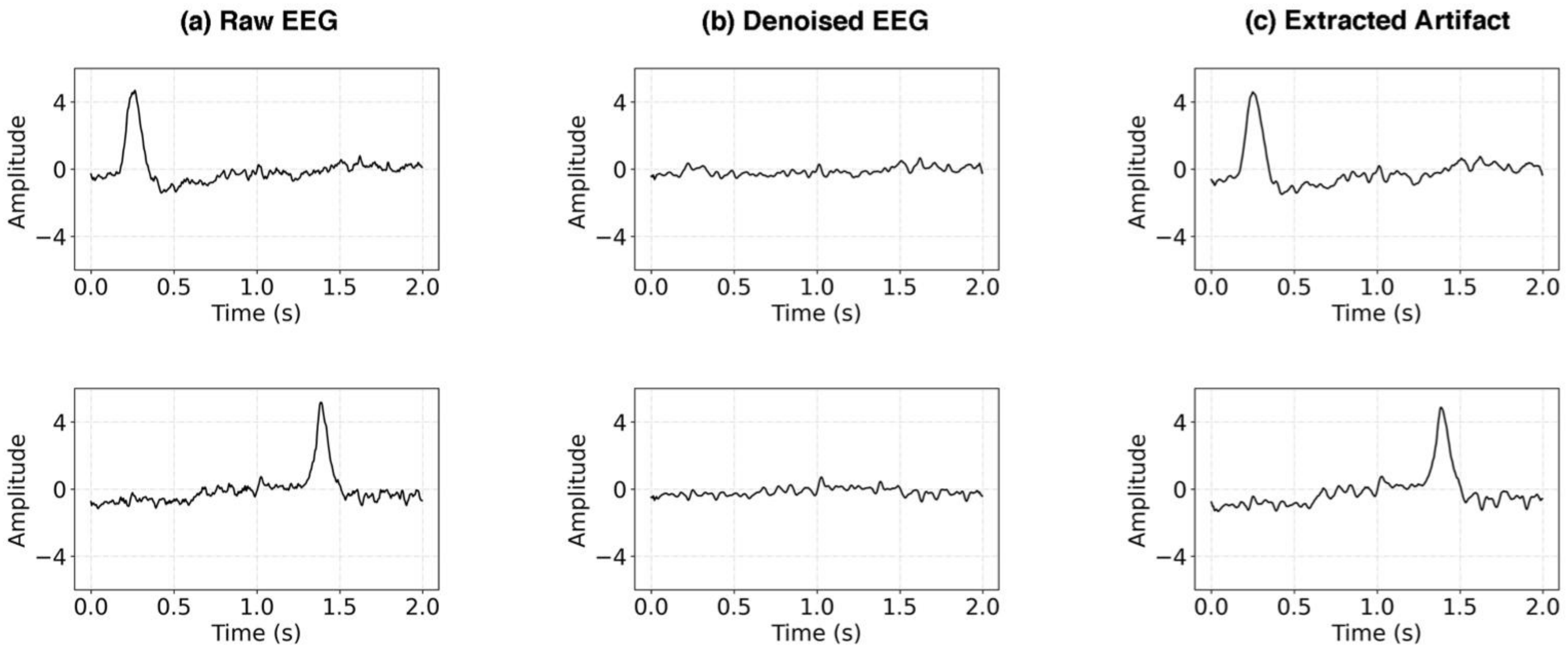


EMG Artifact Removal

Yu, Junjie, et al. "Embedding decomposition for artifacts removal in EEG signals." *Journal of Neural Engineering* 19.2 (2022): 026052.

EEG Artifact Removal Method

Deep learning for artifact removal



Extract signal and artifact simultaneously

Yu, Junjie, et al. "Embedding decomposition for artifacts removal in EEG signals." *Journal of Neural Engineering* 19.2 (2022): 026052.

Challenges of EEG Analysis

- Pervasive artifacts
- EEG recordings are mixtures of all brain activities arising from different networks
- Response variability
- Inverse problem
- others

EEG source-level analysis

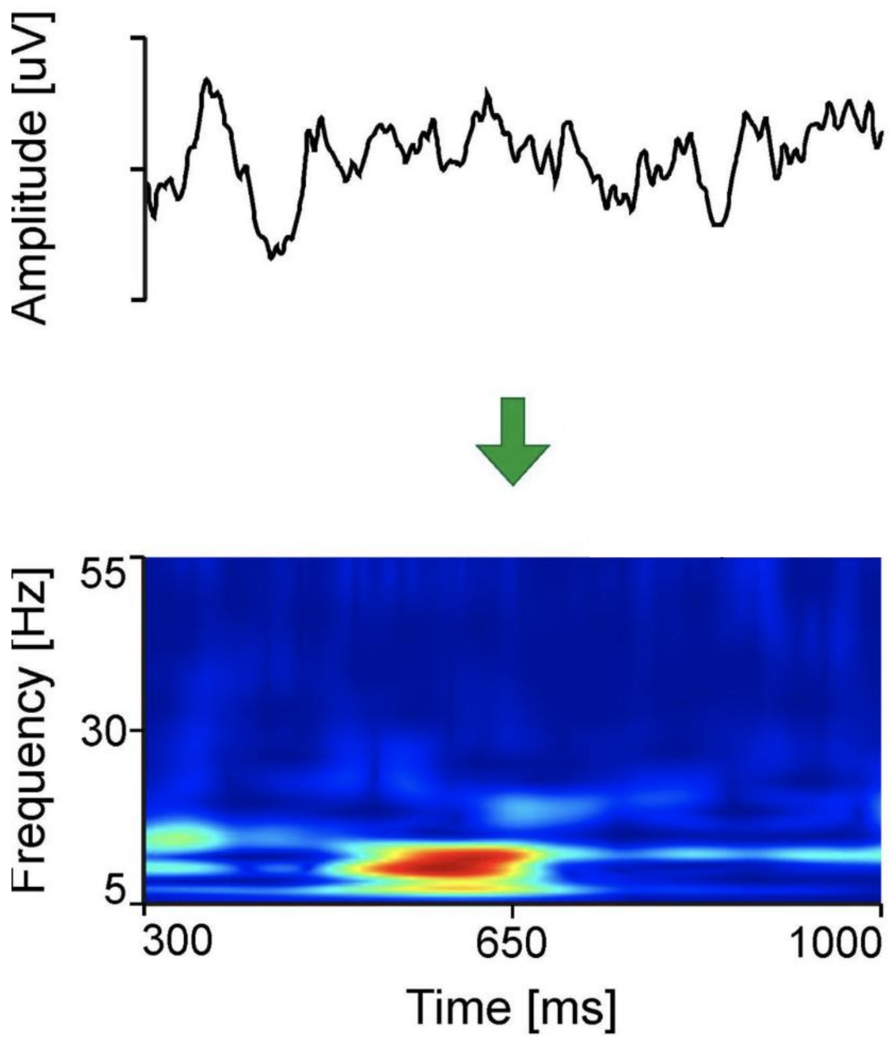
EEG at reat (resting-state EEG)

- Spectral analysis
- Time-frequency analysis
- Microstates
- Functional connectivity

EEG under specific task

- ERP analysis
- ERD/ERS analysis
- Topography analysis

EEG Time-Frequency Analysis



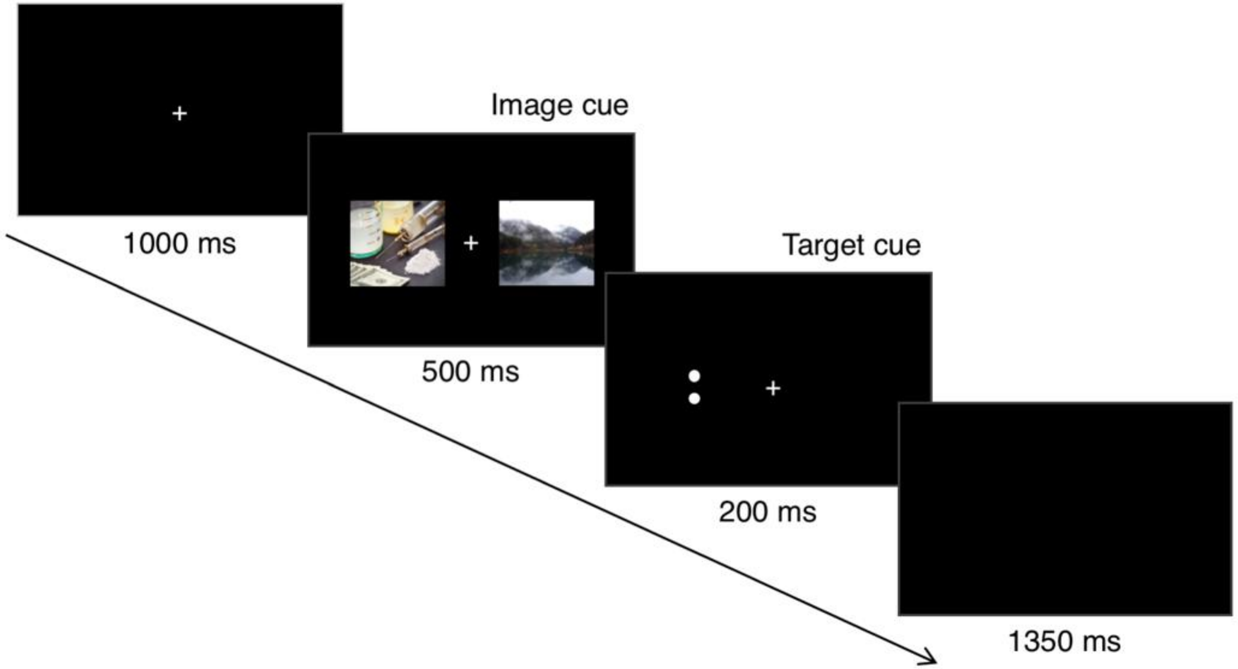
Time-frequency analyses of EEG provide additional information about neural synchrony not apparent in the ongoing EEG. They can tell us which frequencies have the most power at specific points in time and space and how their phase angles synchronize across time and space.

EEG sensor-level analysis

Resting EEG: Functional connectivity analysis; Resting-State Networks (RSNs)

Task EEG:

Event-related potential (ERP) analysis;



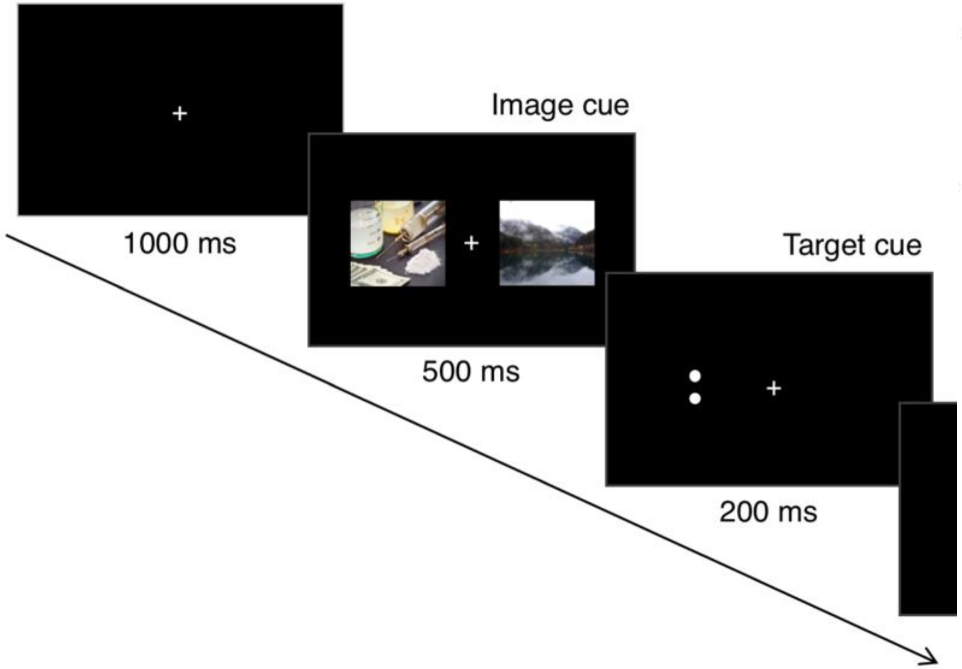
EEG under cognitive tasks

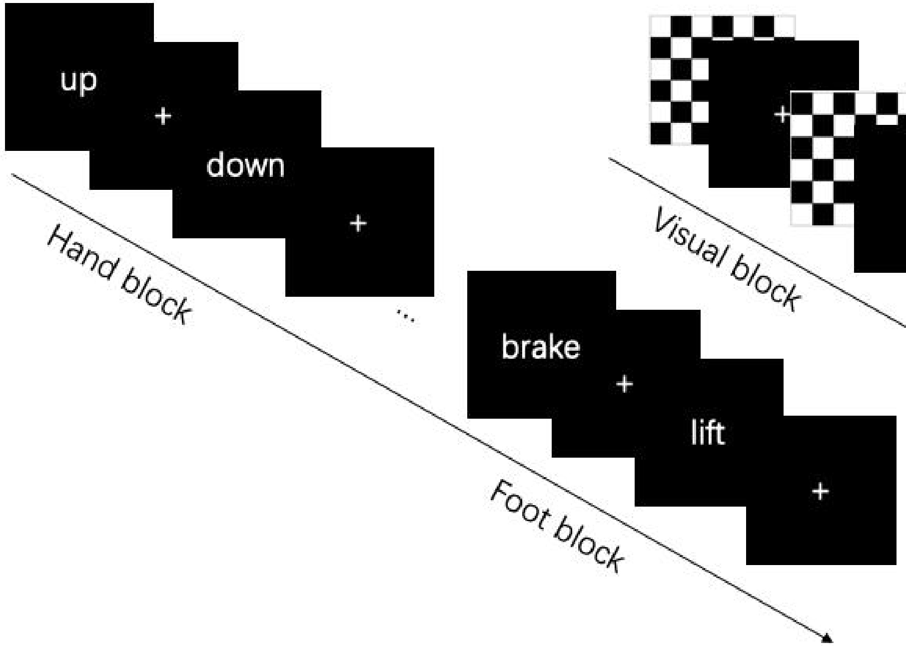
Resting EEG: Functional connectivity analysis; Resting-State Networks (RSNs)

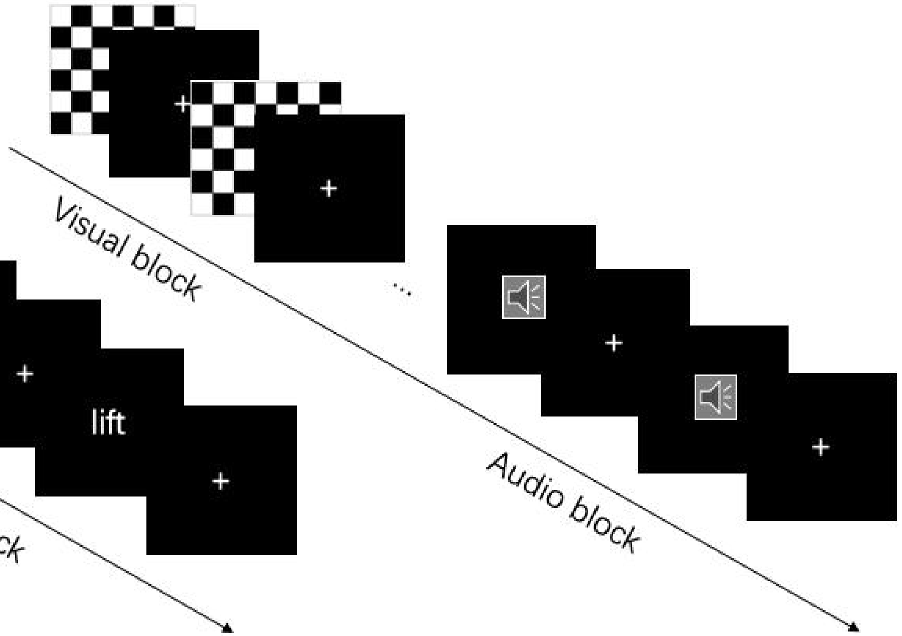
Task EEG:

Event-related potential (ERP) analysis;

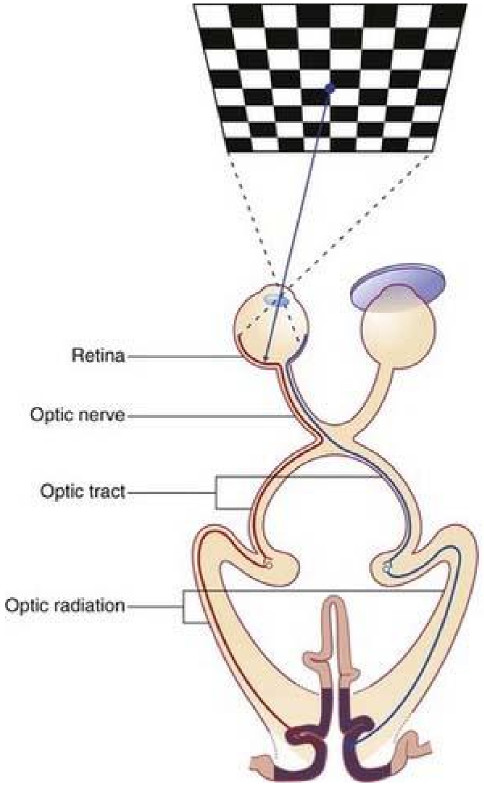
Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS)

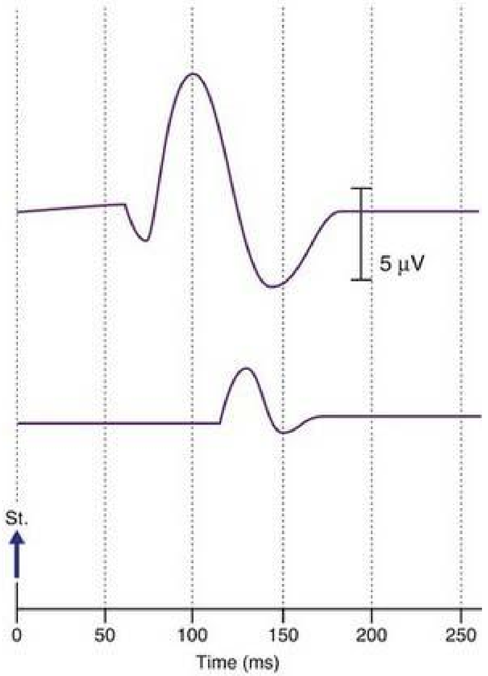






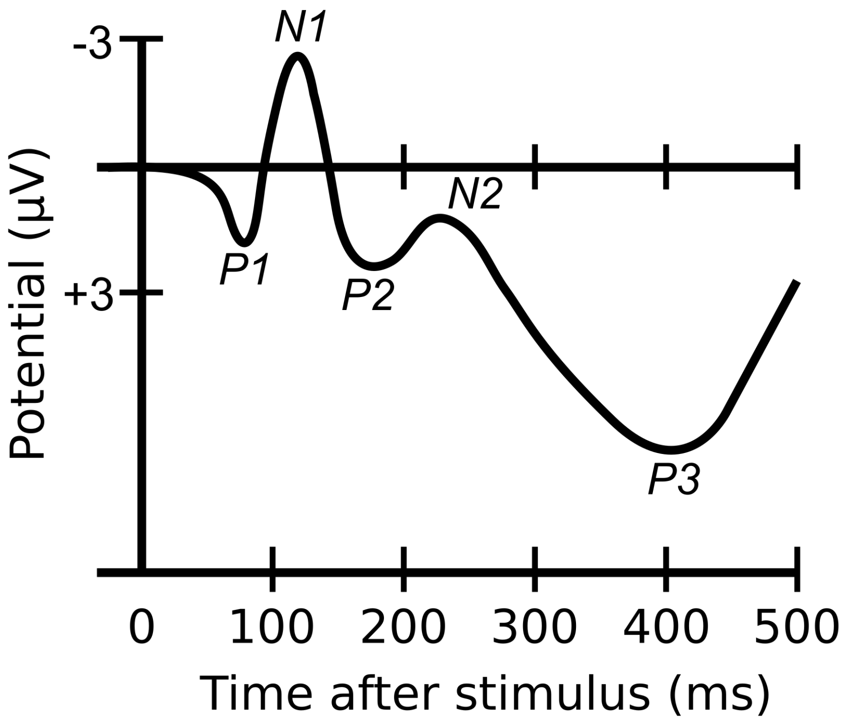
Event-related Potential (ERP) Analysis





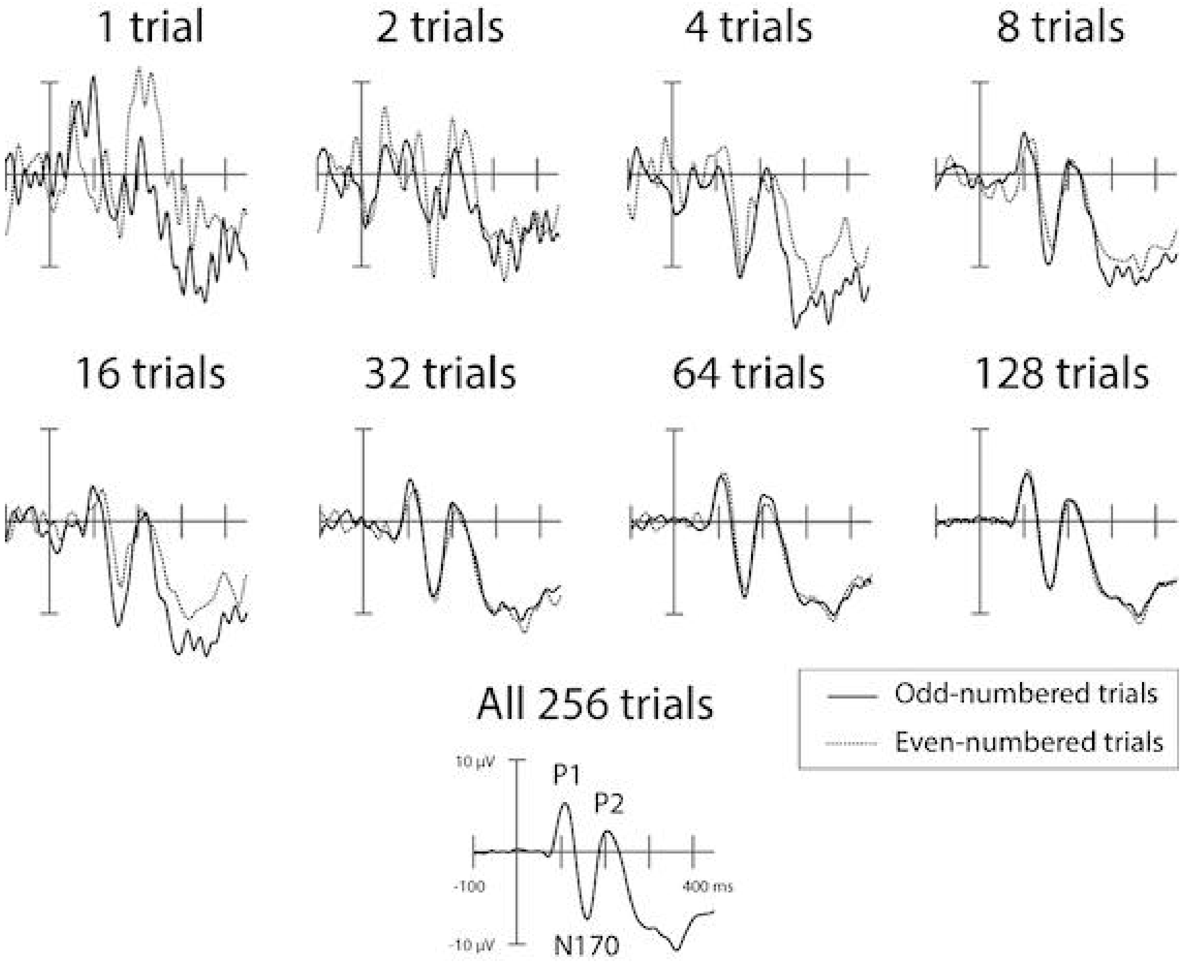
Evoked Potentials: An evoked potential or evoked response is an electrical potential in a specific pattern recorded from a specific part of the nervous system, especially the brain, of a human or other animals following presentation of a stimulus such as a light flash or a pure tone.

ERP Analysis



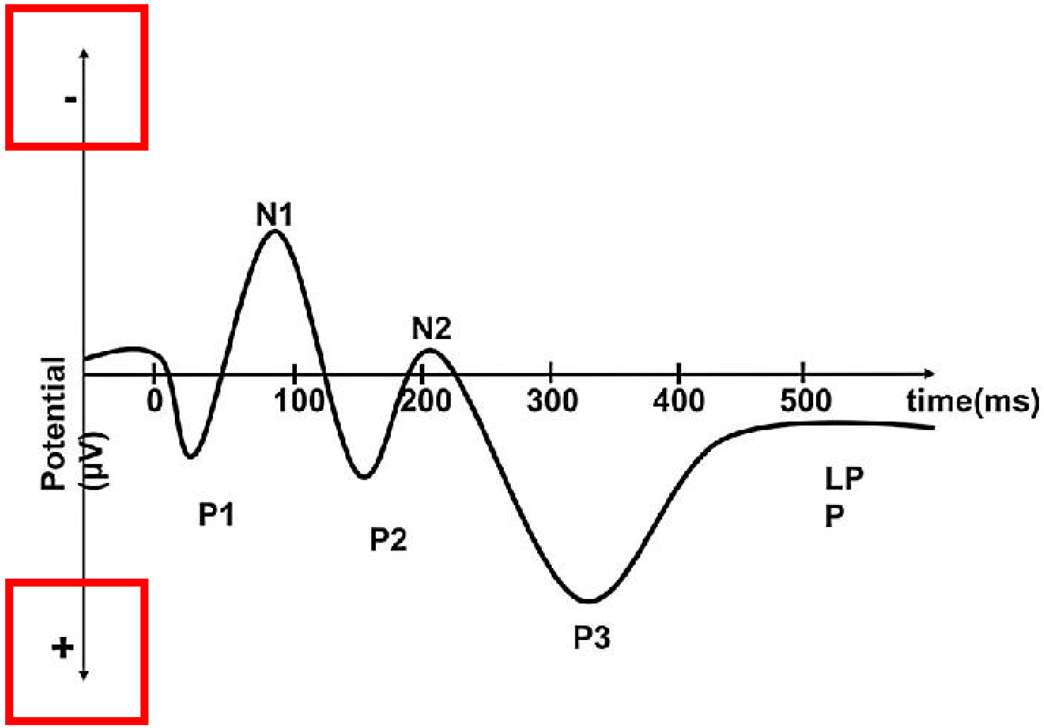
Event-related potential (ERP) : the measured brain response that is the direct result of a specific sensory, cognitive, or motor event. More formally, it is any stereotyped electrophysiological response to a stimulus.

ERP Analysis



The traditional method of estimating an ERP is to take the average of signal epochs time locked to a set of similar experimental events. This averaging method is useful as long as the experimental procedure can sufficiently isolate the brain or non-brain process of interest.

ERP Analysis



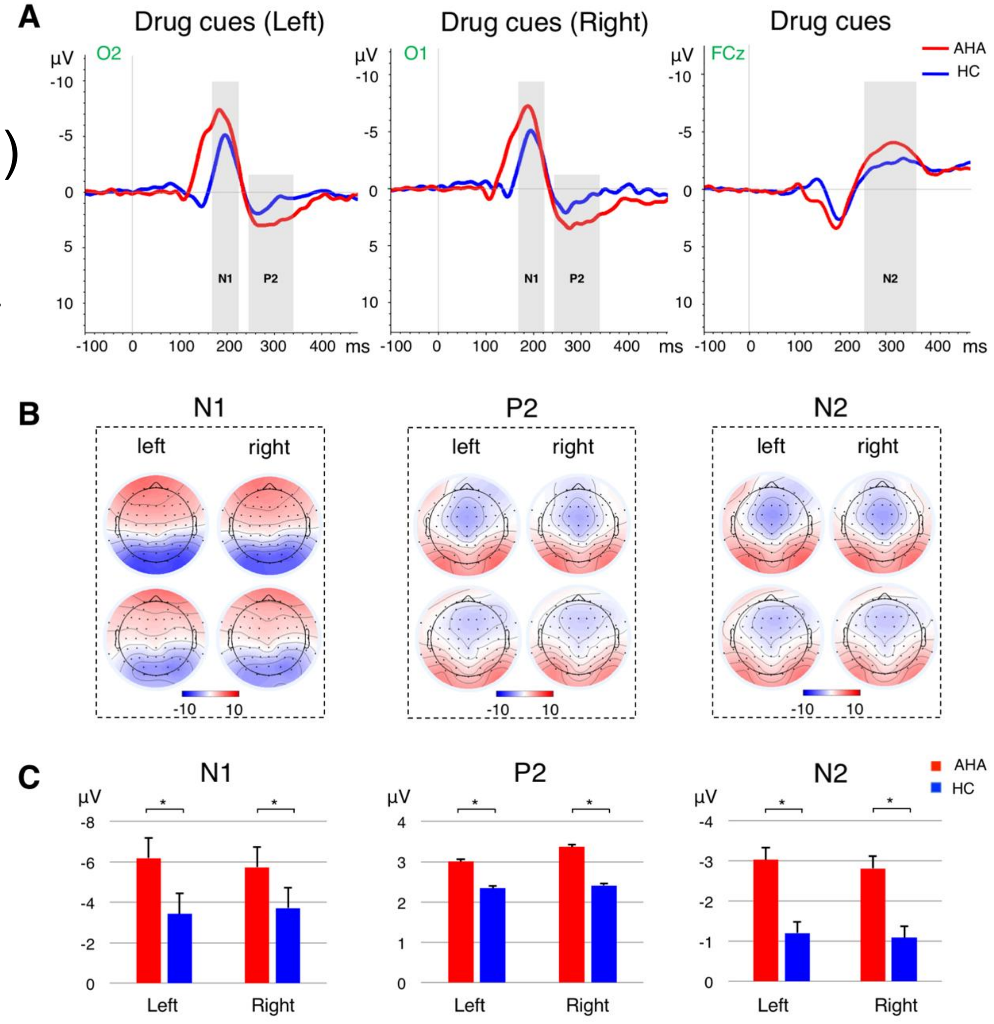
- Positive ⟹ ‘P’
- Negative ⟹ ‘N’
- 1st, 2nd, 3rd ⟹ ‘P1’, ‘P2’, ‘P3’
- Precise latency: ‘P300’
  - Latency of peak or of onset
- 1 name can refer to same component
  - e.g. P3 = P300
- Note that the ERP is plotted with negative voltages upward, a common, but not universal, practice in ERP research

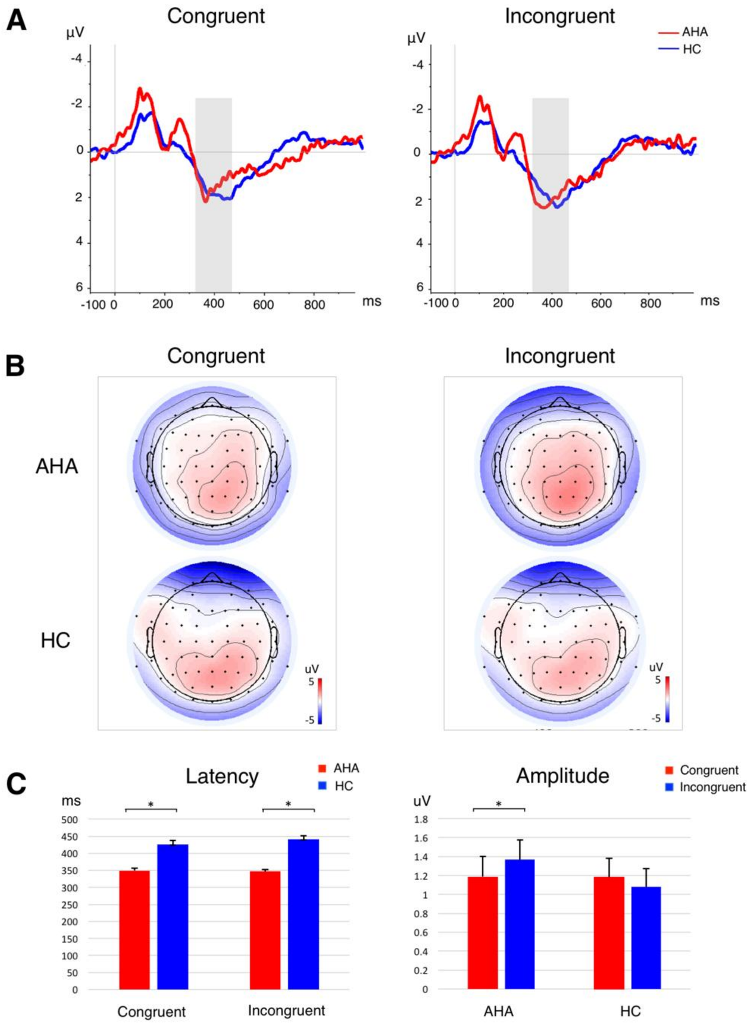
ERP analysis

Procedure to get ERP:
- Filter
- Epoch (-100ms to 1000ms)
- Bad trial removal
- Average across <u>conditions</u>

ERP components
- N1 (negative: ~100ms)
- P2
- N2
- P3 or P300

Different ERP components are associated with different cognitive processes.
- Latency
- Amplitude





Zhao et al. (2018), Neural correlates of drug-related attentional bias in heroin dependence

ERP analysis

Procedure to get ERP:

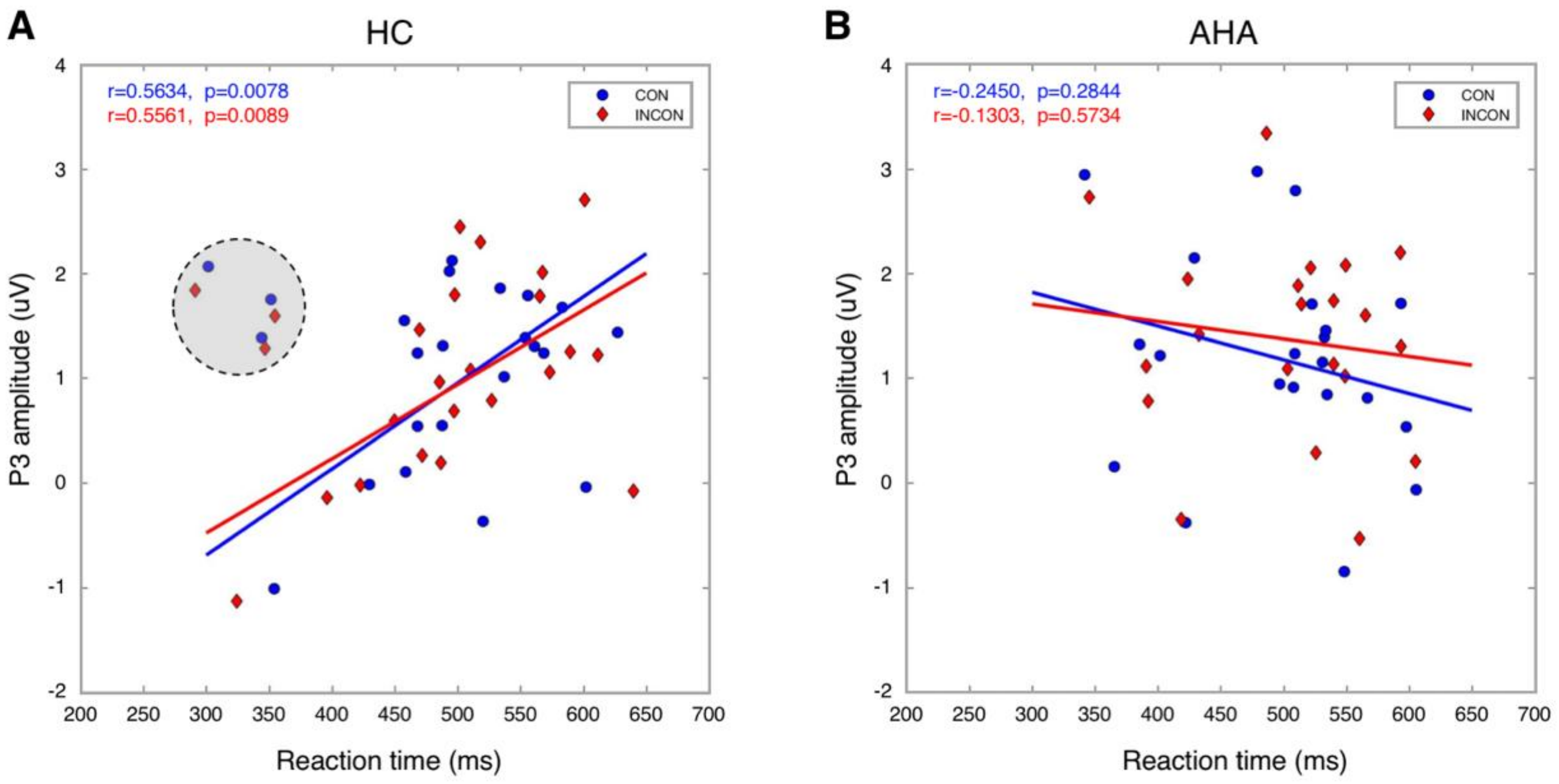
- Filter
- Epoch (-100ms to 1000ms)
- Bad trial removal
- Average across conditions

ERP components

- N1 (negative: ~100ms)
- P2
- N2
- P3 or P300

Different ERP components are associated with different cognitive processes.

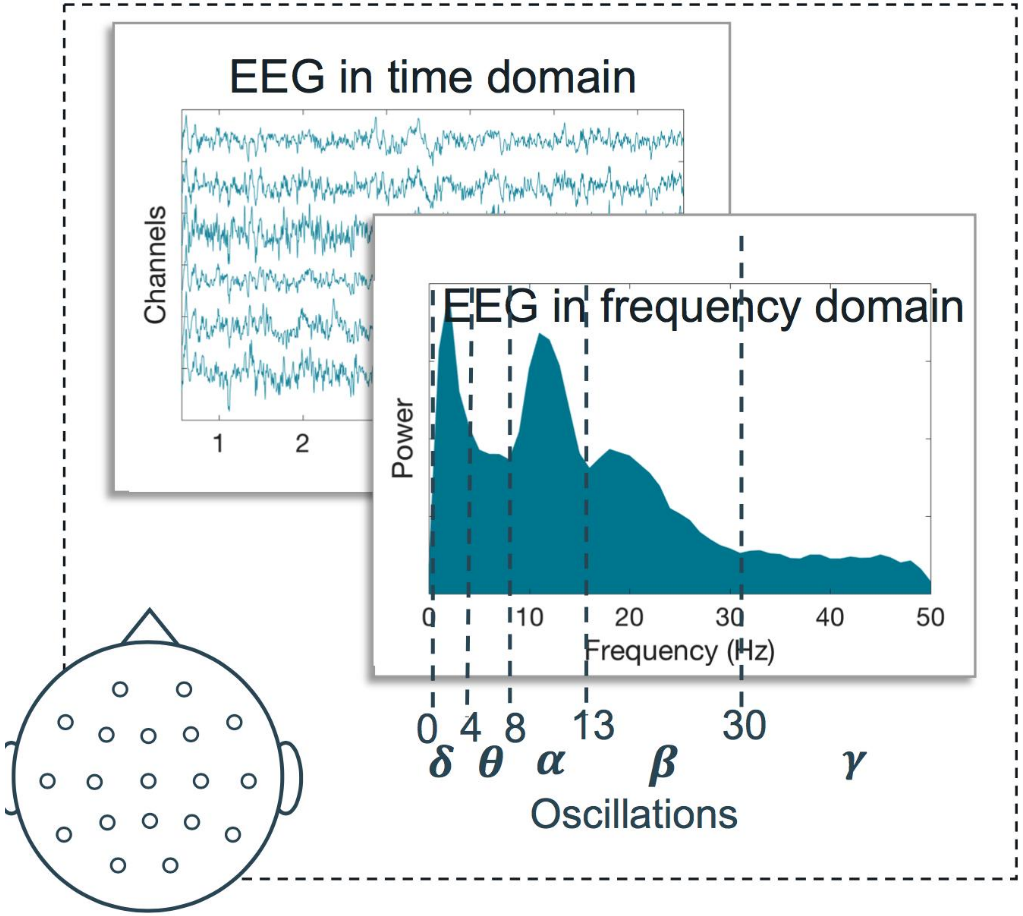
- Latency
- Amplitude



Zhao et al. (2018), Neural correlates of drug-related attentional bias in heroin dependence

ERD/ERS analysis

Multi-dimensionality: • **space** • **time** • **frequency** • **feature**



Some movement-related features

- Event-related desynchronization/synchronization (ERS/ERD)[3]

$$ERD/ERS(f,t) = \frac{P(f,t) - P_B(f)}{P_B(f)} \times 100\%$$

- Cortico-kinematic coherence (CKC)[4]

$$CKC(f) = \frac{|PEEG_{KIN}(f)|^2}{P_{EEG}(f)P_{KIN}(f)}$$

- Cortico-muscular coherence (CMC)[4]

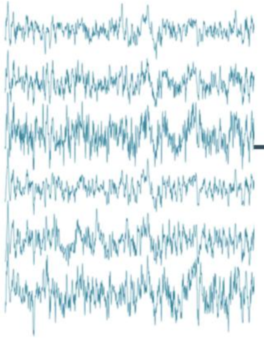
$$CMC(f) = \frac{|PEEG_{EMG}(f)|^2}{P_{EEG}(f)P_{EMG}(f)}$$

Other dimensions? Condition, trial ...

[3] Pfurtscheller, G., et al (1999)
[4] Bourguignon, M., et al (2019)

ERD/ERS analysis

An example of ERD/ERS

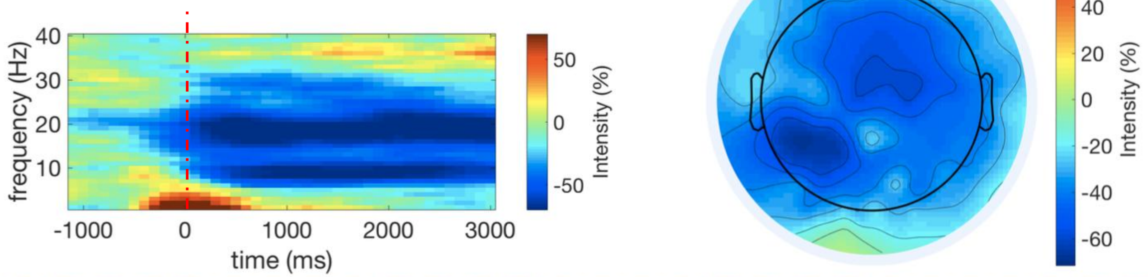


Time-frequency decomposition

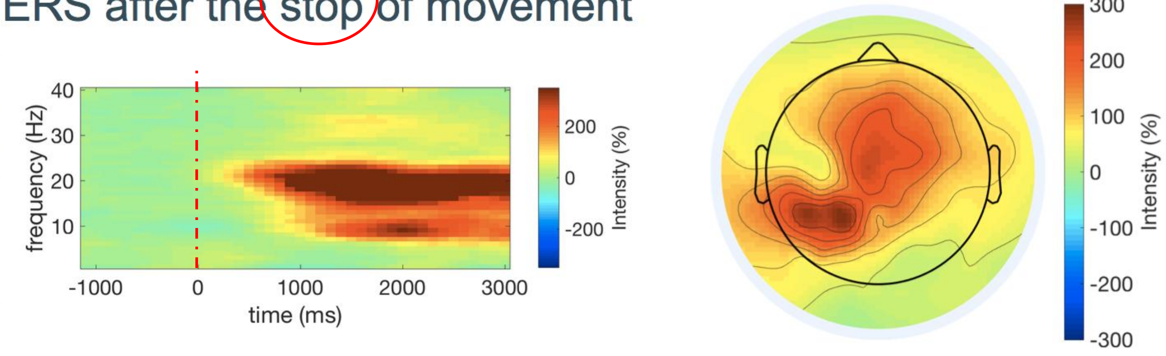
$p_i(f, t)$

$$ERD/ERSi(f,t) = \frac{P_i(f,t) - P_{Bi}(f)}{P_{Bi}(f)} \times 100\%$$

ERD after the start of movement

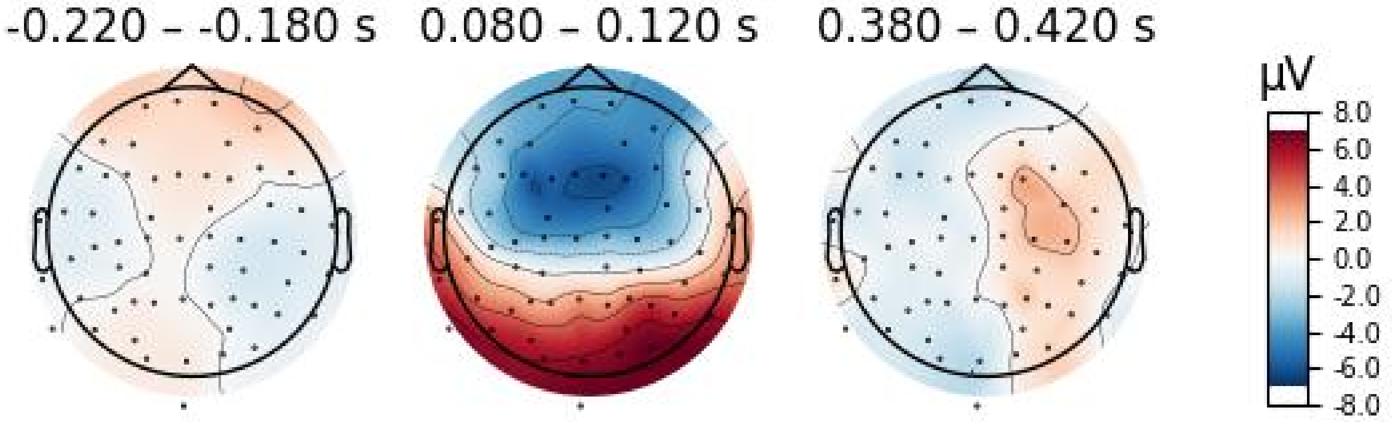


ERS after the stop of movement



EEG Topography Analysis

EEG topography is a neuroimaging technique in which a large number of EEG electrodes are placed onto the head, following a geometrical array of even-spaced points.

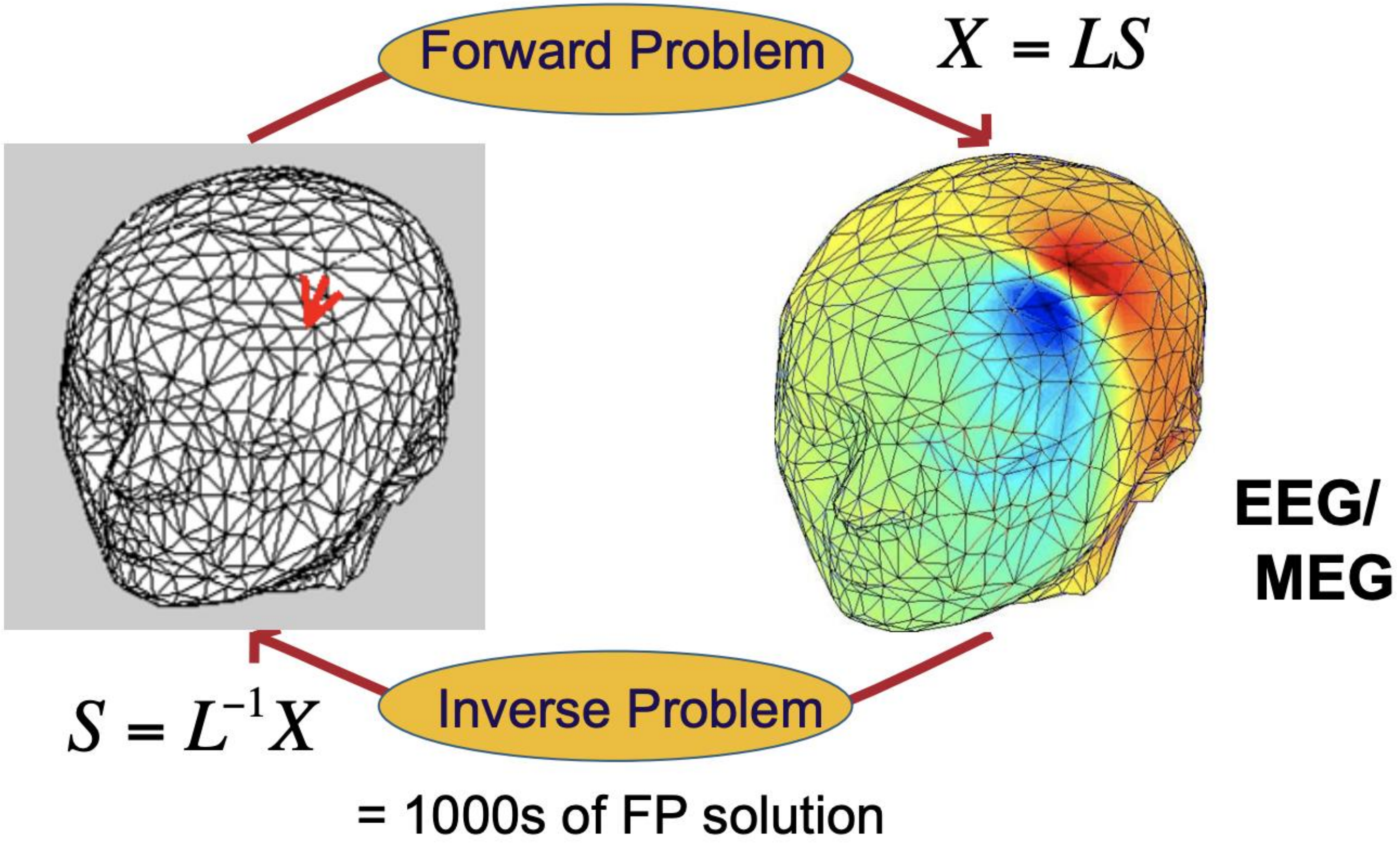


How do we know what is happening **inside** the brain through observations from **outside** of the brain?

EEG source-level analysis

- Forward problem (head model)
- Inverse problem (source reconstruction)

EEG Source Analysis



Forward Solution and Inverse Problem

Head model: bridging sensor/source levels

Source level

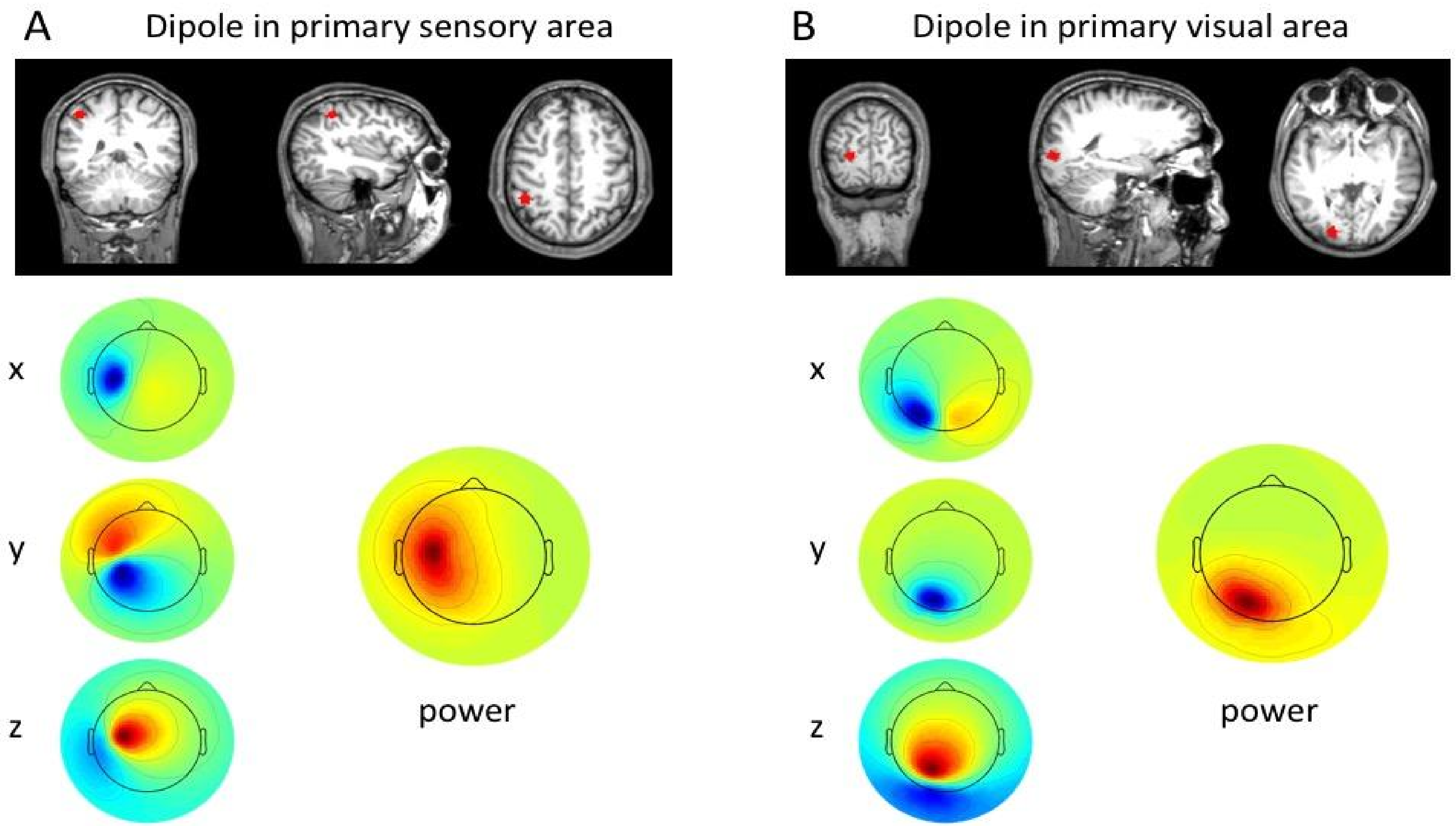
S

Forward problem

Inverse problem

Sensor level

X



Forward Problem → Inverse Problem

$X = LS$ $S = L^{-1}X$

Observations

Sensor Signal (X)

[M * T] dimension

&

Head model

Leadfield Matrix (L)

[M * 3N] dimension

→

Estimated source distribution

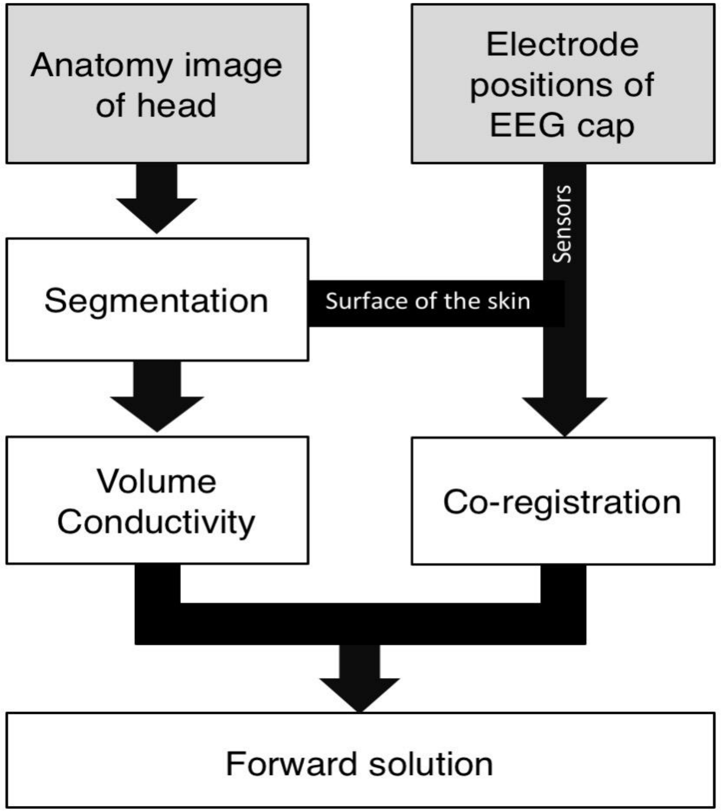
Source Signal (S)

[3N * T] dimension

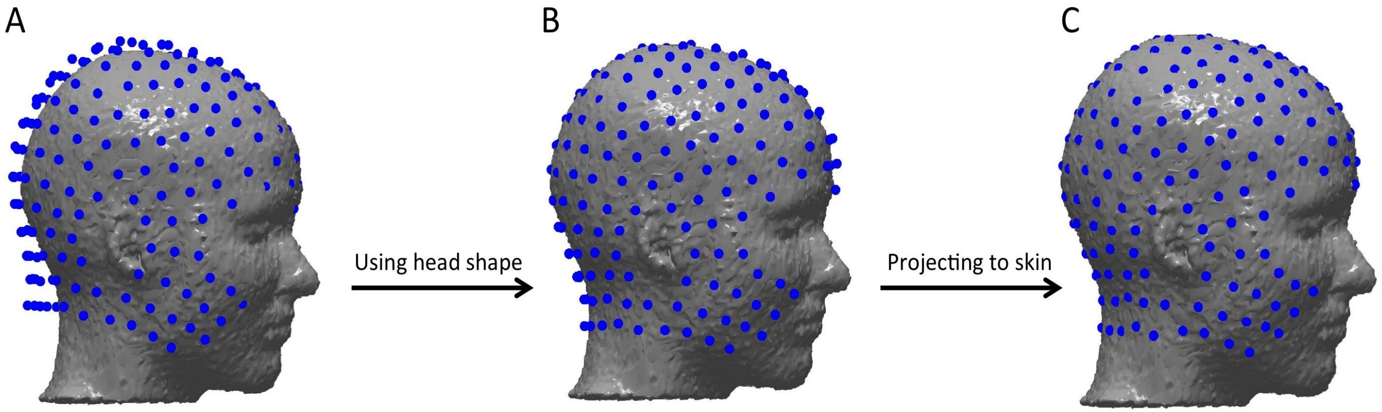
1, Solve forward problem, to obtain the leadfield matrix L.

The solution of <u>the forward problem</u> is the leadfield matrix L.

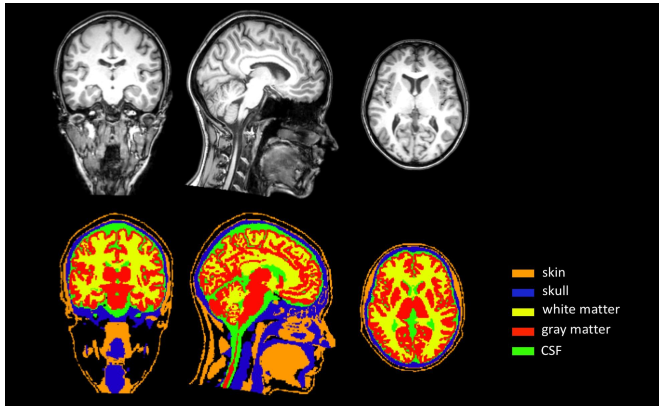
Pipeline for the solution of forward problem

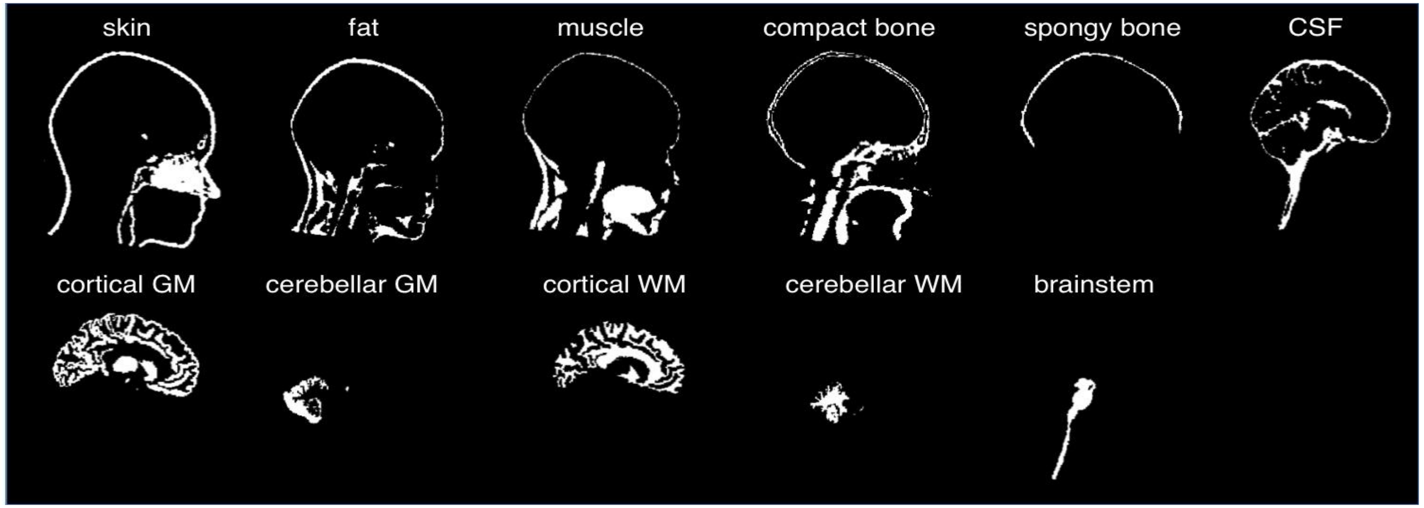


EEG Electrodes co-registration： 电极配准到头皮



Segmentation
图像分割





Head volume conductivity

<u>A realistic head model</u> requires the definition of multiple tissues of the head, each characterized by a specific conductivity value.

However, the conductivity value is usually measured **in vitro** (体外的).

How to estimate the head conductivity **in vivo** (在活体的) is still a technical issue!

Conductivity values of different tissues

Tissue name	Conductivity (S/m)
Skin	0.4348
compact bone	0.0063
spongy bone	0.0400
CSF	1.5385
cortical gray matter	0.3333
cerebellar gray matter	0.2564
cortical white matter	0.1429
cerebellar white matter	0.1099
brainstem	0.1538
eyes	0.5000
muscle	0.1000
fat	0.0400

During the last two decades, researchers have tried to solve **Poisson's equation** in a realistically shaped head model obtained from <u>3D medical images</u>, which requires **numerical methods**.

Warning: math heavy!!!

- **J(x, y, z):** current density with the unit *A/m2*
- **Im**: the current source density with the unit *A/m3*
- **sigma**: position dependent conductivity tensor with units *A/(Vm)* = *S/m*
- **E**: the electric field with the unit *V/m*
- **V**: the scalar potential field with unit volt

Poisson's equation $\nabla \cdot \mathbf{J} = I_m.$

Ohm's law $\mathbf{J} = \sigma \mathbf{E},$

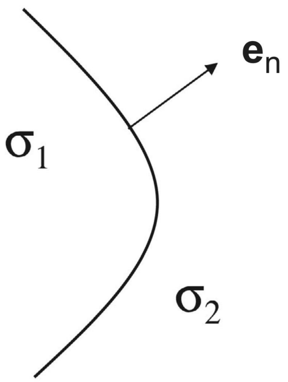
$\mathbf{E} = -\nabla V.$

$$\sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_{22} & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_{33} \end{bmatrix}$$

$$\nabla \cdot (\sigma \nabla (V)) = -I_m$$

$$\boxed{\nabla \cdot (\sigma \nabla (V)) = -I\delta(\mathbf{r} - \mathbf{r}_2) + I\delta(\mathbf{r} - \mathbf{r}_1)}$$

$$\sigma_{11}\frac{\partial^2 V}{\partial x^2} + \sigma_{22}\frac{\partial^2 V}{\partial y^2} + \sigma_{33}\frac{\partial^2 V}{\partial z^2} + 2\left(\sigma_{12}\frac{\partial^2 V}{\partial x \partial y} + \sigma_{13}\frac{\partial^2 V}{\partial x \partial z} + \sigma_{23}\frac{\partial^2 V}{\partial y \partial z}\right)$$
$$+\left(\frac{\partial \sigma_{11}}{\partial x} + \frac{\partial \sigma_{12}}{\partial y} + \frac{\partial \sigma_{13}}{\partial z}\right)\frac{\partial V}{\partial x} + \left(\frac{\partial \sigma_{12}}{\partial x} + \frac{\partial \sigma_{22}}{\partial y} + \frac{\partial \sigma_{23}}{\partial z}\right)\frac{\partial V}{\partial y} + \left(\frac{\partial \sigma_{13}}{\partial x} + \frac{\partial \sigma_{23}}{\partial y} + \frac{\partial \sigma_{33}}{\partial z}\right)\frac{\partial V}{\partial z} =$$
$$-I\delta(x - x_2)\delta(y - y_2)\delta(z - z_2) + I\delta(x - x_1)\delta(y - y_1)\delta(z - z_1).$$



Boundary condition at two compartments

$$\mathbf{J}_1 \cdot \mathbf{e}_n = \mathbf{J}_2 \cdot \mathbf{e}_n,$$
$$(\sigma_1 \nabla V_1) \cdot \mathbf{e}_n = (\sigma_2 \nabla V_2) \cdot \mathbf{e}_n,$$

Boundary condition at the surface

$$\mathbf{J}_1 \cdot \mathbf{e}_n = 0,$$
$$(\sigma_1 \cdot \nabla V_1) \cdot \mathbf{e}_n = 0.$$

Hallez et al (2007) Review on solving the forward problem in EEG source analysis

Methods to solve forward problem,

- Boundary element method (BEM)
- Finite element method (FEM)
- Finite difference method (FDM)

Leadfield Matrix (L)

[M * 3N] dimension

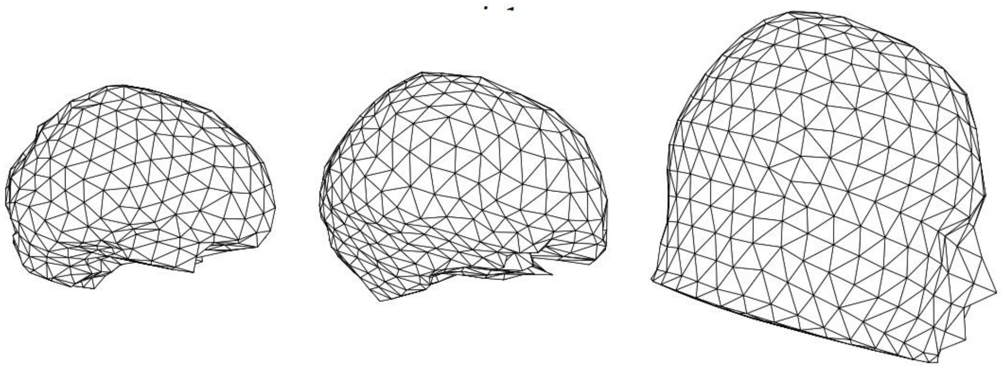


Figure 9
Example mesh of the human head used in BEM. Triangulated surfaces of the brain, skull and scalp compartment used in BEM. The surfaces indicate the different interfaces of the human head: air-scalp, scalp-skull and skull-brain.

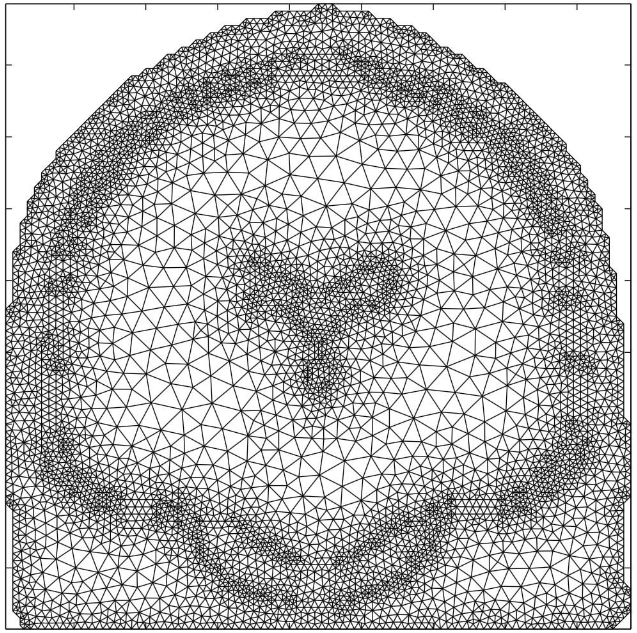


Figure 10
Example mesh in 2D used in FEM. A digitization of the 2D coronal slice of the head. The 2D elements are the triangles.

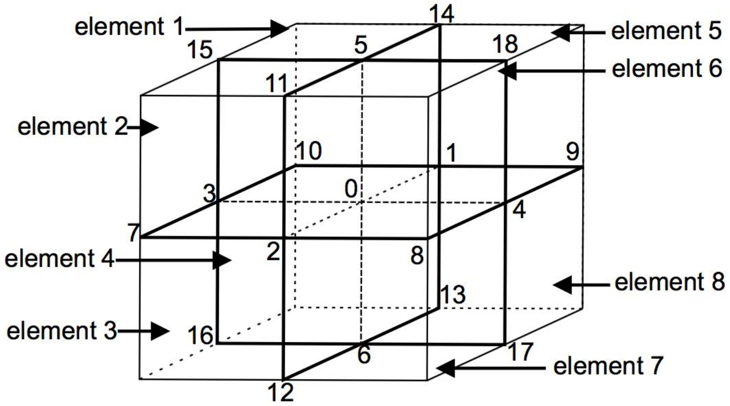


Figure 12
The computation stencil used in FDM if anistropic conductivities are incorporated. The potential at node 0 can be written as a linear combination of 18 neighbouring nodes in the FDM scheme. For each node we obtain an equation, which can be put into a linear system $Ax = b$.

Hallez et al (2007) Review on solving the forward problem in EEG source analysis

Forward Problem → Inverse Problem

$X = LS$ $\qquad$ $S = L^{-1}X$

Observations

Sensor Signal (X)

[M * T] dimension

&

Head model

Leadfield Matrix (L)

[M * 3N] dimension

→

Estimated source distribution

Source Signal (S)

[3N * T] dimension

2. Estimate source distribution
N>>M, Source localization is ill-posed.

The inverse problem refers to finding S given the known X.

objective function: $\underset{S}{\operatorname{argmin}} \|X - LS\|^2$

Some regularizations from prior knowledge on sources: sparsity, connectivity

$$\varphi = Kj + n_0 \tag{1}$$

Objective function: with additional regularization terms

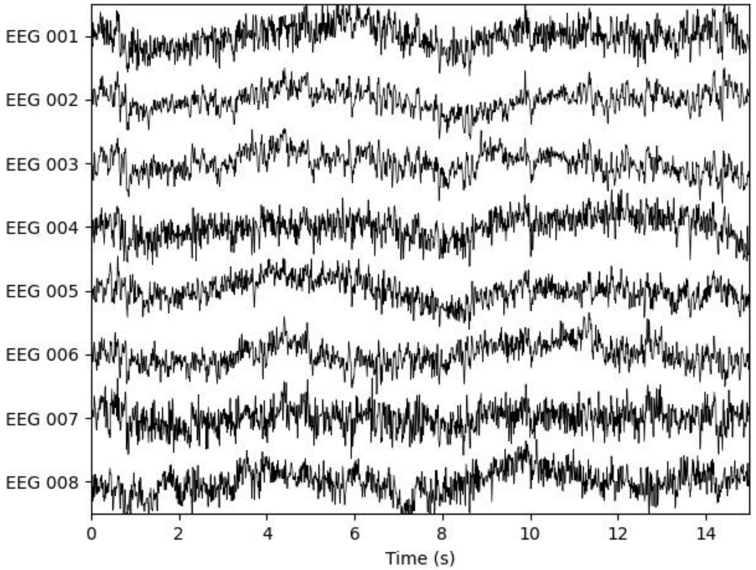
$$\begin{aligned} j^{est} &= \operatorname{argmin}_j \|Vj\|_1 + \alpha \|j\|_1 \\ \text{subject to} &\quad (\varphi - \mathrm{Kj})^T \Sigma^{-1} (\varphi - \mathrm{Kj}) \leq \beta \end{aligned} \tag{2}$$

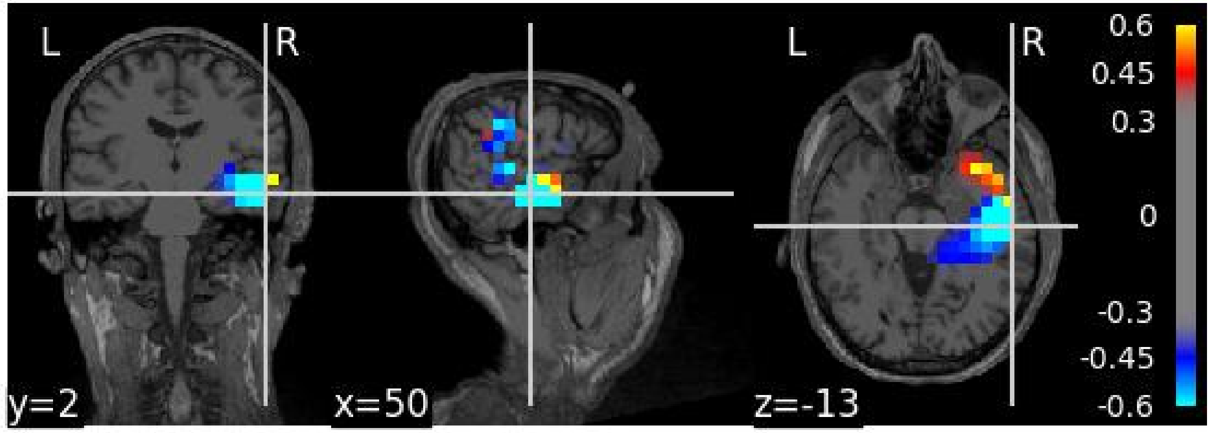
Iteratively reweighted edge sparsity minimization (IRES)

$$V = \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{T1} & \cdots & v_{Tn} \end{pmatrix}$$
$$\begin{cases} v_{ij} = 1 \ \textit{and} \ v_{ik} = -1 & \text{if dipole } j \text{ and } k \text{ are neighbors over edge } i \\ v_{ij} = 0 & \text{otherwise} \end{cases} \tag{4}$$

Abbas Sohrabpour et al (2020) Nature communications

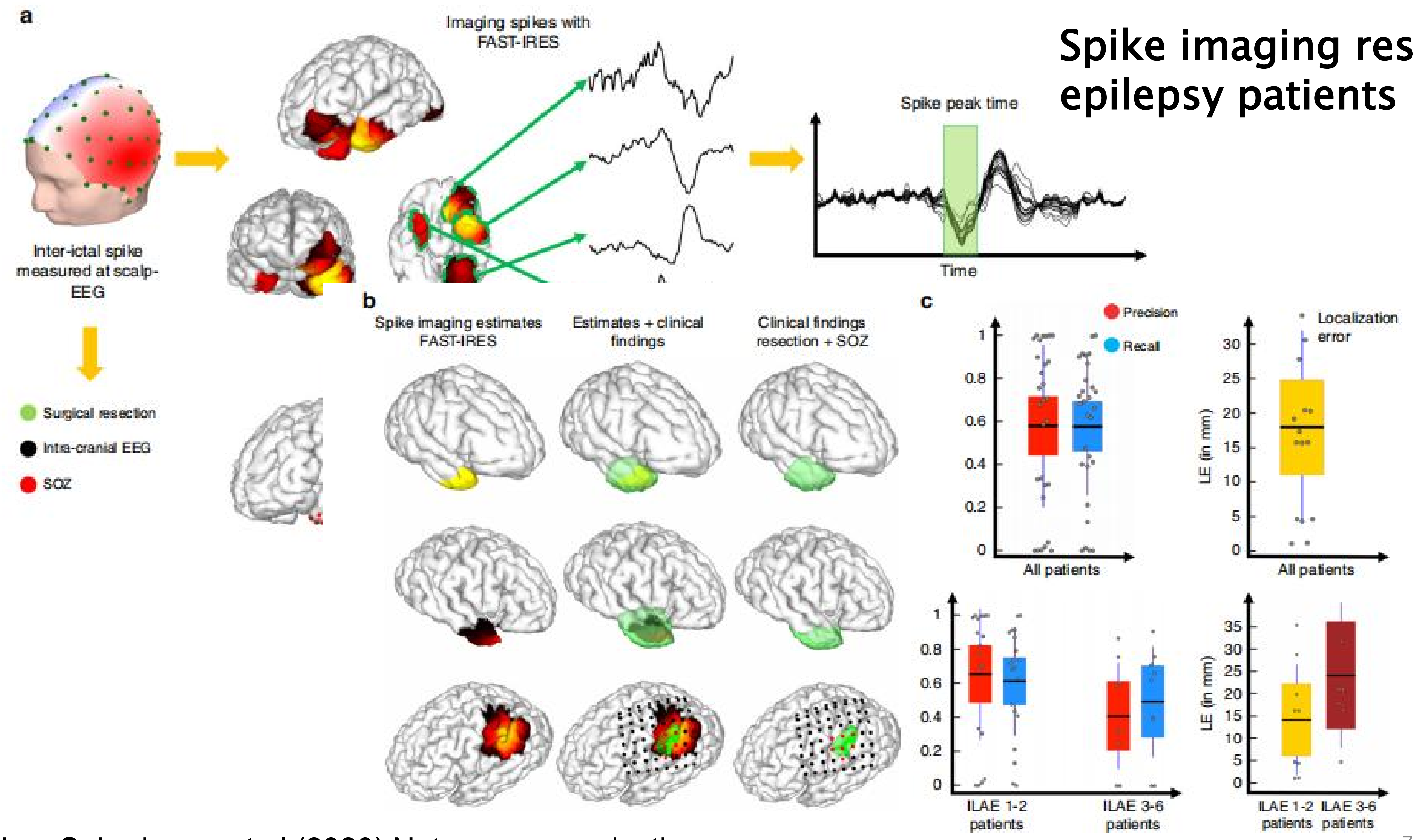
EEG Source Analysis



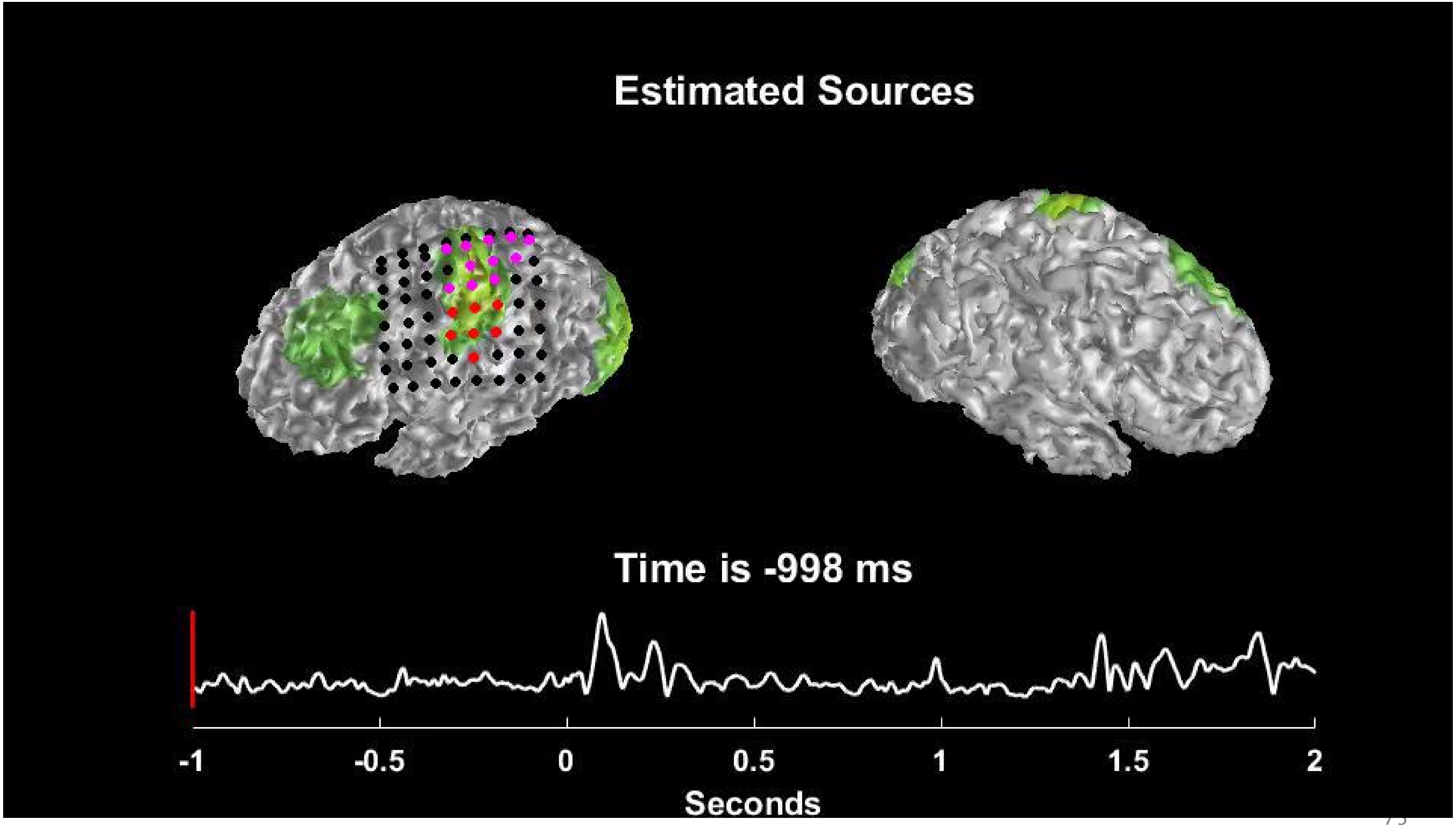


MNE, wMNE
Beamforming
LORETA, sLORETA, eLORETA
...

Spike imaging results on epilepsy patients



Abbas Sohrabpour et al (2020) Nature communications

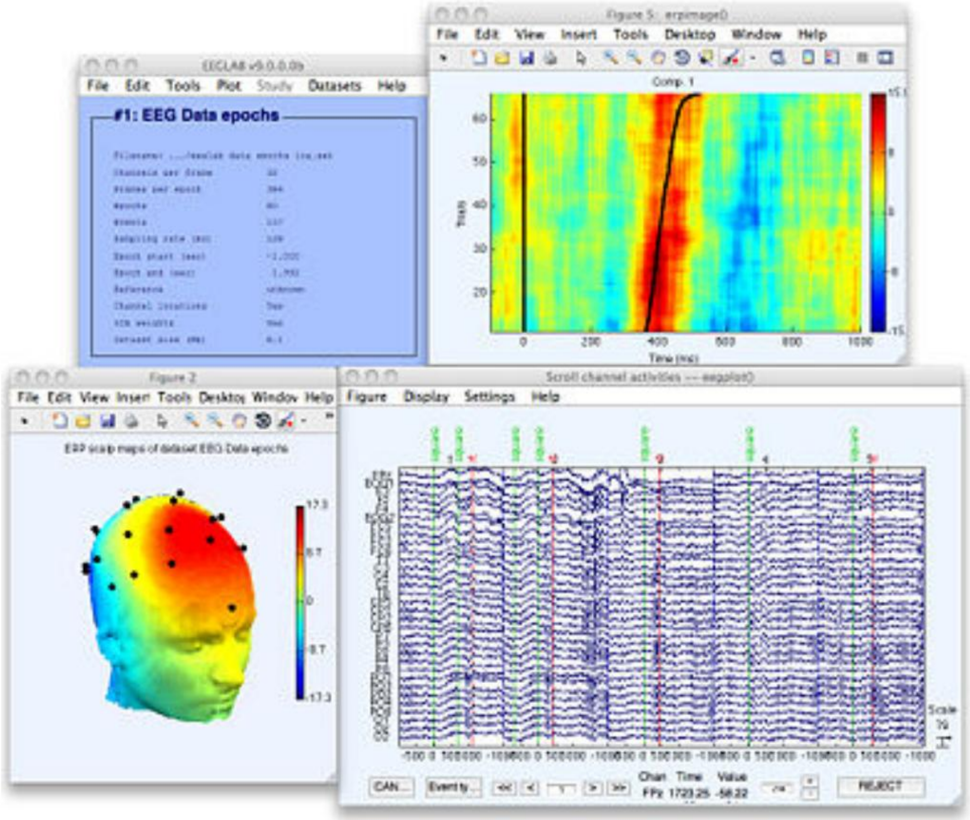

Estimated Sources
Time is -998 ms
-1
-0.5
0
0.5
1
1.5
2
Seconds

Toolbox for EEG analysis

EEGlab (mathlab)

Official webpage https://sccn.ucsd.edu/eeglab/index.php

Tutorial https://www.bilibili.com/video/BV1mJ411s7vH



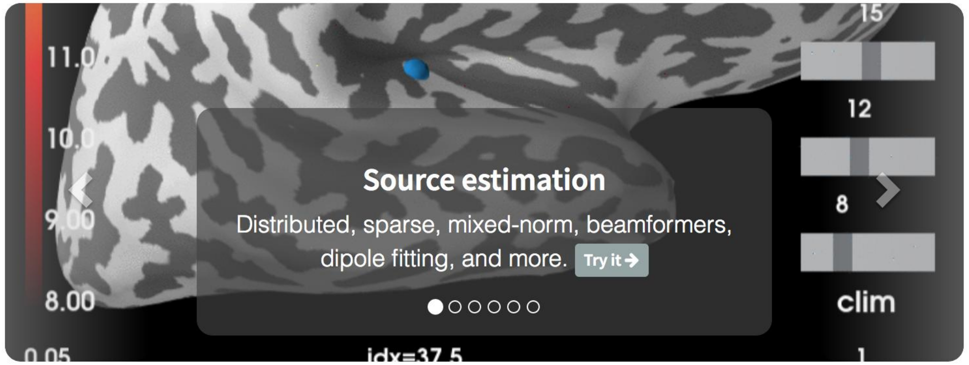
MNE-python

Official webpage https://mne.tools/stable/index.html

Tutorial https://www.bilibili.com/video/BV1YK411T7H

MEG + EEG ANALYSIS & VISUALIZATION

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



EEG Analysis Tool: MNE

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

EEG Analysis Tool: MNE

What can MNE do?

Source Estimation
Distributed, sparse, mixed-norm, beamformers, dipole fitting, and more.

Machine Learning
Advanced decoding models including time generalization.

Encoding Models
Receptive field estimation with optional smoothness priors.

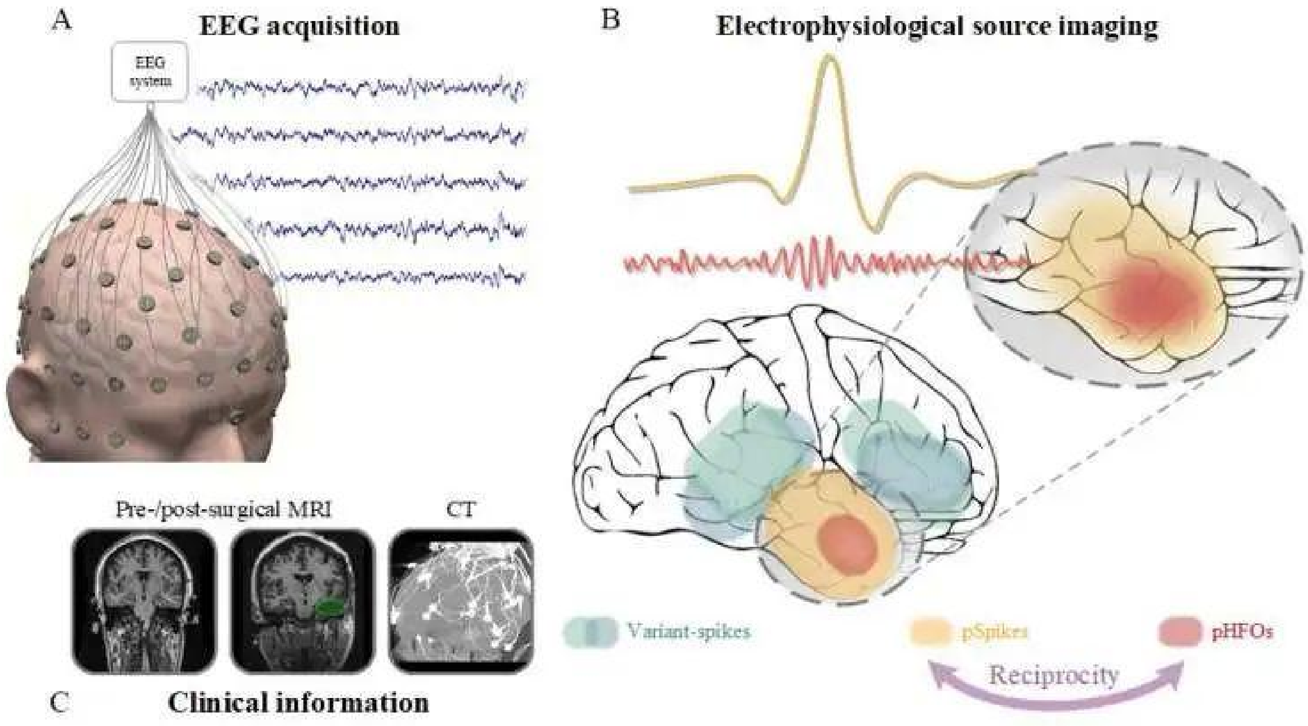
Statistics
Parametric and non-parametric, permutation tests and clustering.

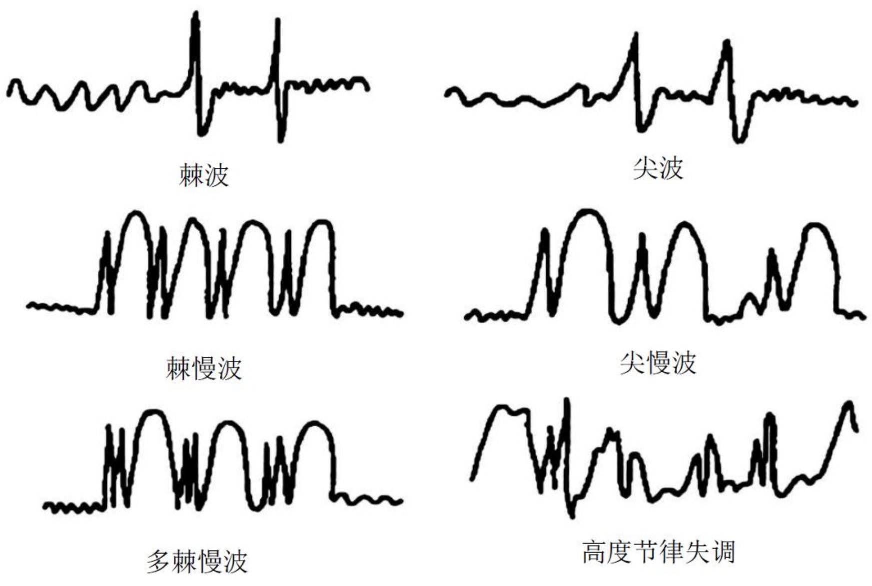
Connectivity
All-to-all spectral and effective connectivity measures.

Data Visualization
Explore your data from multiple perspectives.

EEG Applications

In disease diagnosis (e.g., epilepsy, depression, ADHD…)





Summary of Lecture 16 – EEG data analysis

- Introduction to Electroencephalography (EEG)
- EEG preprocessing
  - Bad channel detection/repairmen
  - Filtering
  - Artifact removal
  - Re-referencing
- EEG sensor-level analysis
  - ERP
  - ERS/ERD
- EEG source reconstruction
  - Forward problem
  - Inverse problem
- EEG tutorial