Introduction to EEG signal processing

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Content of the lecture

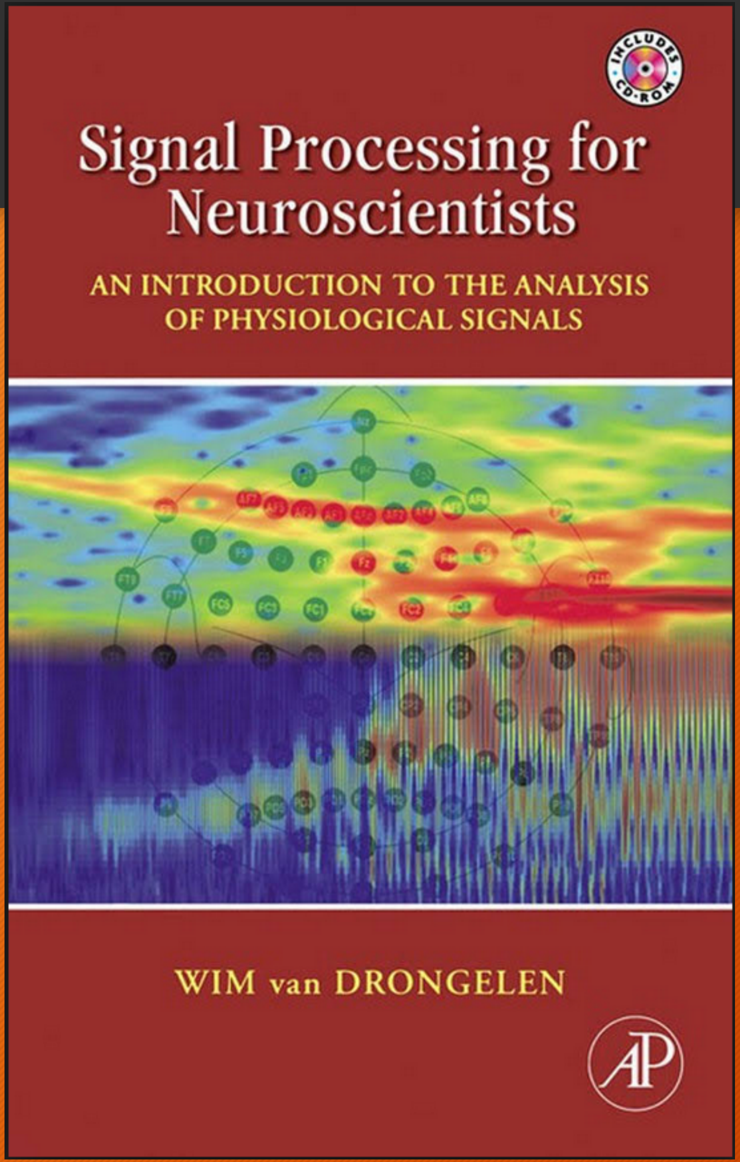
- Giving examples and illustrating the utility of the different methods

1. Spectral distributions
2. (TMS) evoked potential analysis
    1. Muscle artifact removal
3. Source localization
4. Brain computer interface

- Signal processing methods for continuous signal and evoked potentials (EP)
- EP’s are time locked brain responses that are very weak (1 mikroVolts) compared to the background EEG activity (~tens of mikroVolts)
- You have to average up to 20 to 1000 EP’s to get a visible signal

Basic components of biosignal processing

- Averaging
- Fourier analysis
- Filtering


INCLUDES CD-ROM
Signal Processing for Neuroscientists
AN INTRODUCTION TO THE ANALYSIS OF PHYSIOLOGICAL SIGNALS
WIM van DRONGELEN
AP

Contents

Example #1 Spectral distributions

- Aim: visually inspecting large amounts of EEG data at a single glance in order to detect relevant changes (long time periods)

Or

Creating a finger print of the brain dynamics (short and/or time-locked dynamics)

- Goal: Time-frequency plot of the power of EEG

Spectral analysis

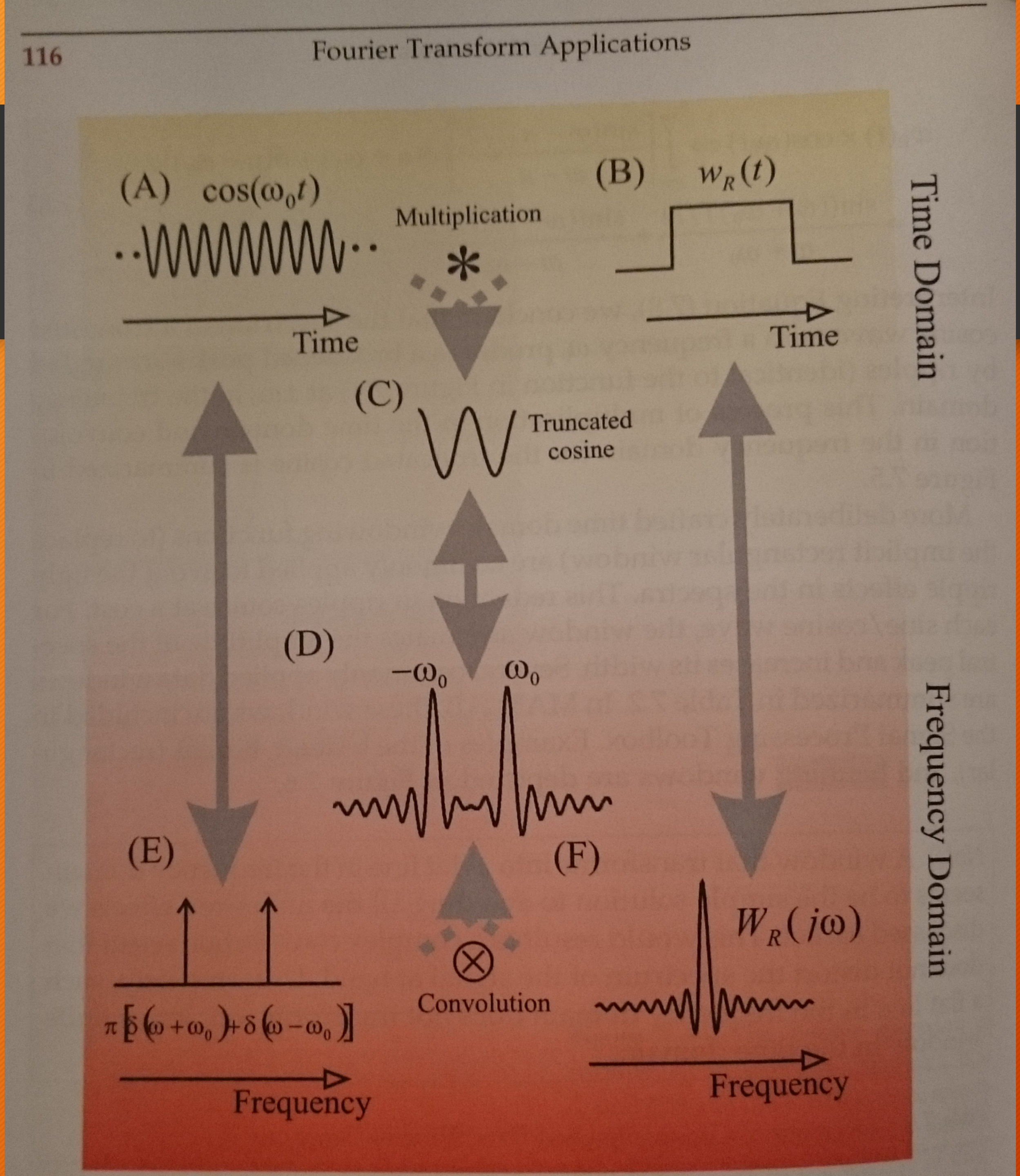
- Fourier theorem: any signal can be expressed as an infinite sum of sine and cosine components
- Theoretically straightforward but biosignals have characterisrics that complicate the analysis
- Namely, they are not stationary and contain periodic and non-periodic components
- Solution is to analyse small periods of EEG and make an assumption that the signal is *approximately* stationary in the time period

Fourier theorem

$$\hat{f}(\xi) = \int_{-\infty}^{\infty} f(x)\, e^{-2\pi i x \xi}\, dx,$$

$$f(x) = \int_{-\infty}^{\infty} \hat{f}(\xi)\, e^{2\pi i x \xi}\, d\xi,$$

- Uncertainty relation between time (x) and frequency (ξ)
- Generally speaking, the more concentrated $f(x)$ is, the more spread out its Fourier transform $\hat{f}(\xi)$ must be.
- Assumes stationarity of the signal



Overview of the Fourier transform of a truncated cosine wave. A theoretically infinte cosine wave (A) multiplied by a rectangular window (B) generates truncated wave C. The Fourier transform of the cosine and the window in the frequency domain are shown in E and (F). The transform of the truncated cosine is the convolution of its components, shown in (D).

- Fourier analysis applied to a non stationary signal (EEG) creates ripple artefacts as shown in previous figure
- Artefactual harmonic frequency components

- Not all peaks in a spectrum correspond to actual physiological events

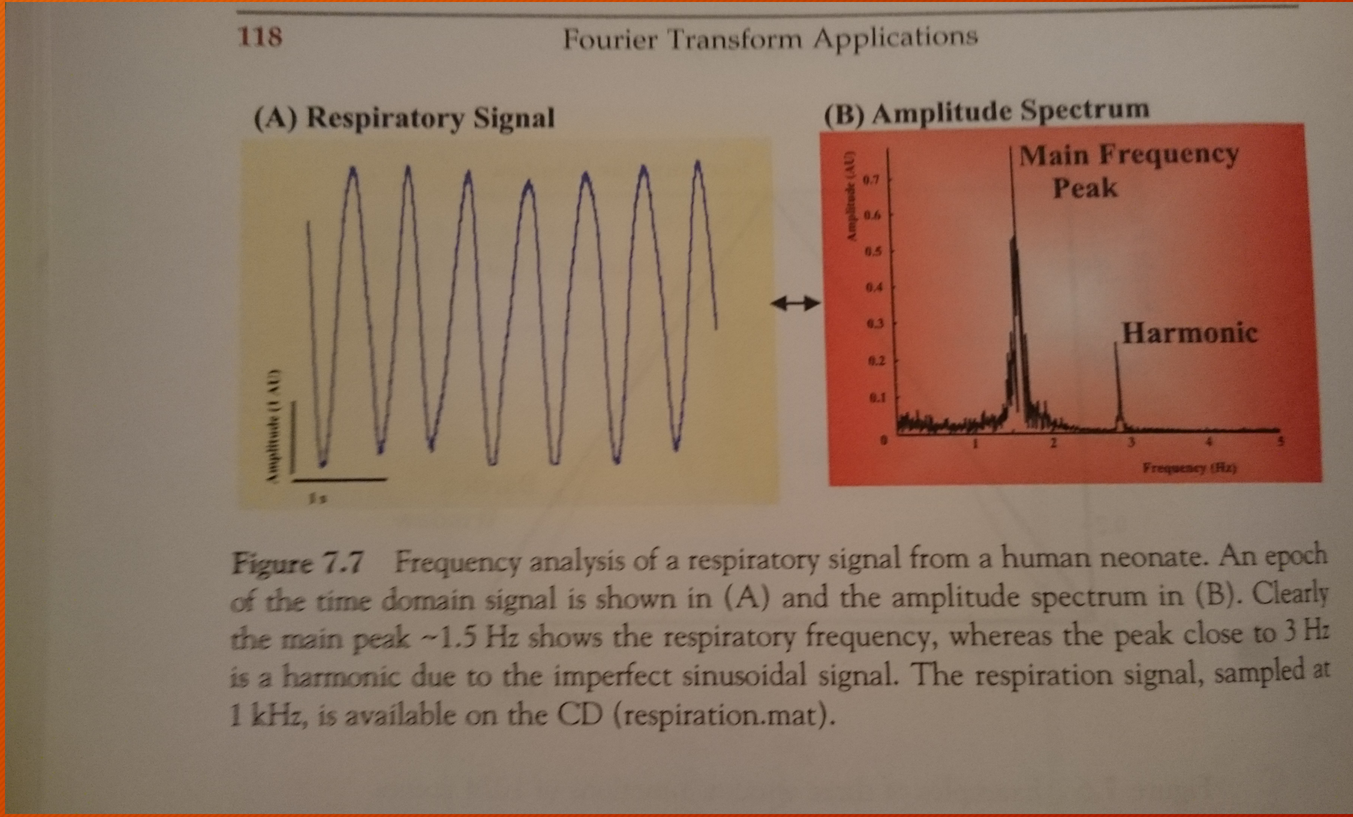
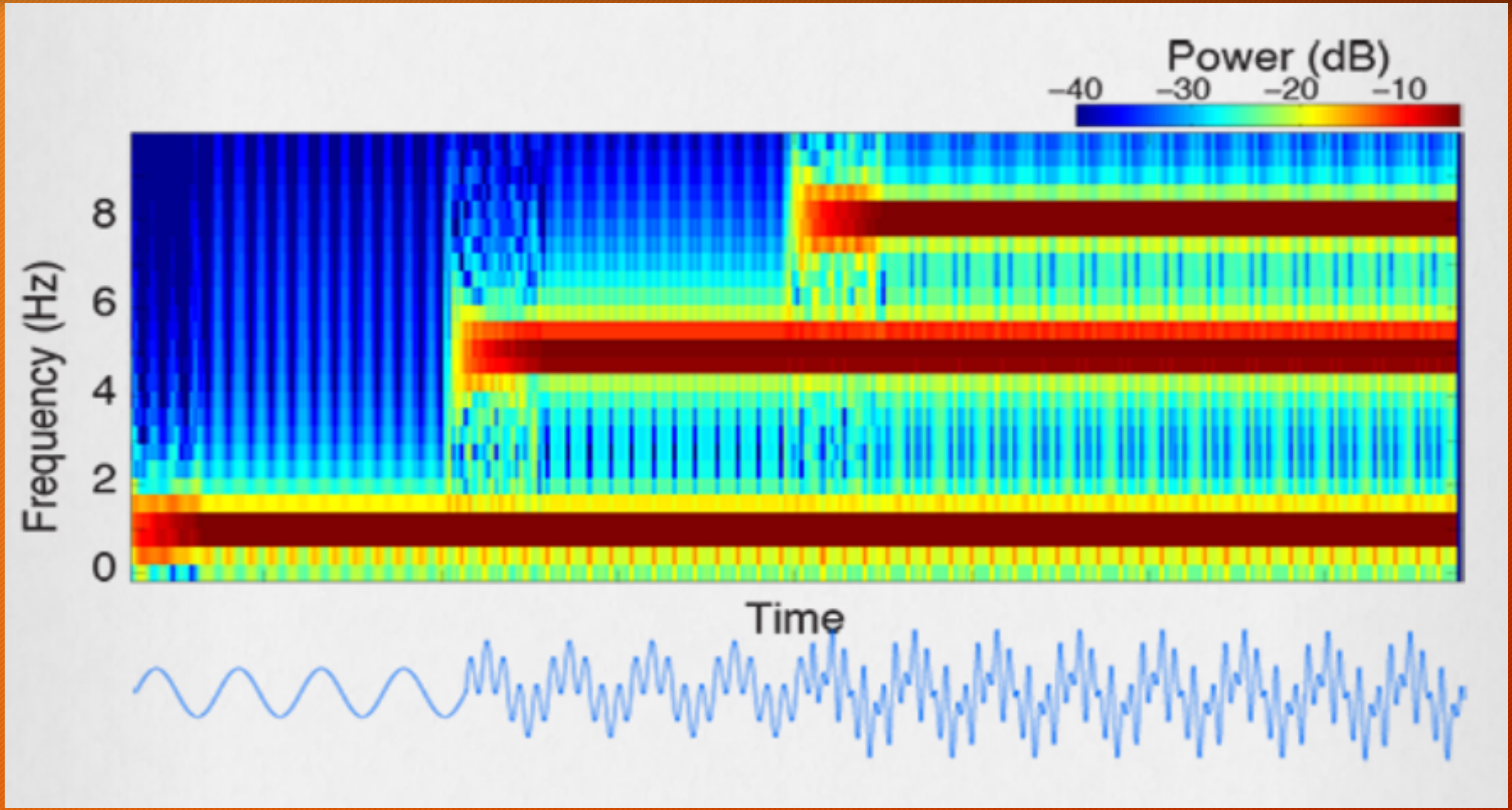

118 Fourier Transform Applications

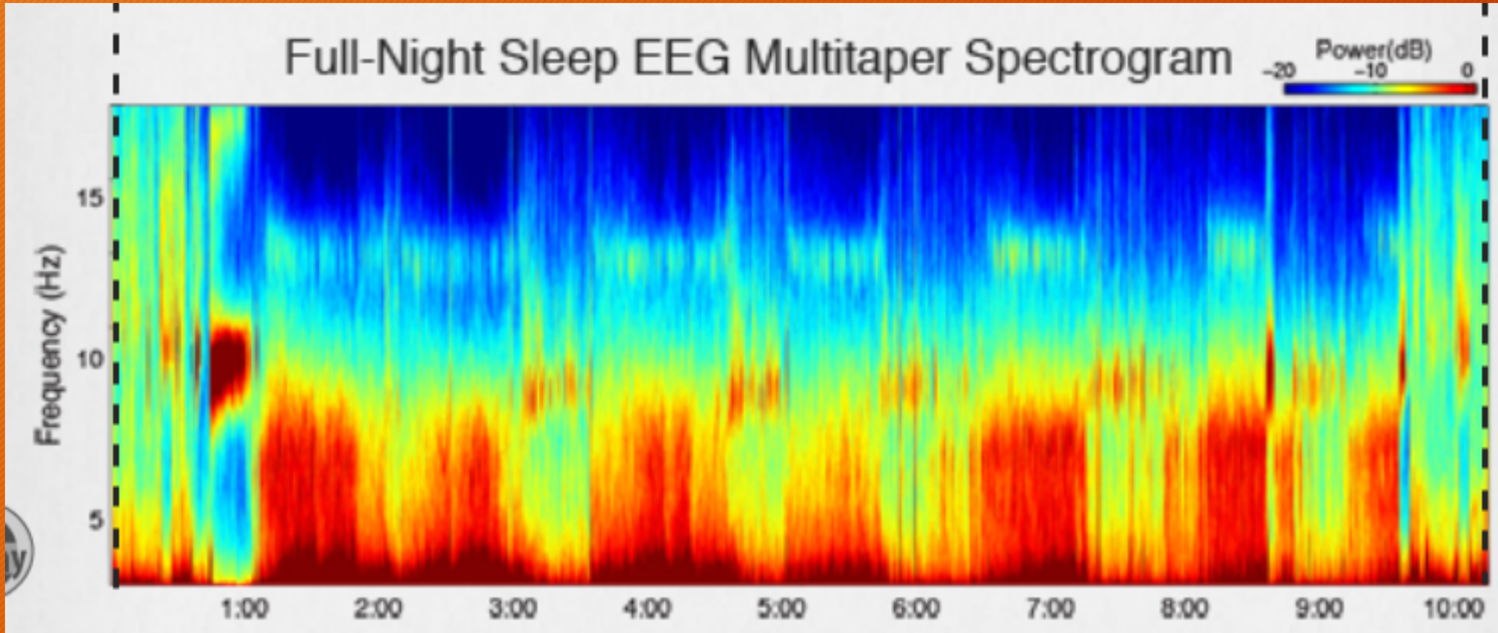
Figure 7.7 Frequency analysis of a respiratory signal from a human neonate. An epoch of the time domain signal is shown in (A) and the amplitude spectrum in (B). Clearly the main peak ~1.5 Hz shows the respiratory frequency, whereas the peak close to 3 Hz is a harmonic due to the imperfect sinusoidal signal. The respiration signal, sampled at 1 kHz, is available on the CD (respiration.mat).

Research and Development by:
Michael J. Prerau, Ph.D.
MASSACHUSETTS GENERAL HOSPITAL
ANESTHESIA, CRITICAL CARE AND PAIN MEDICINE

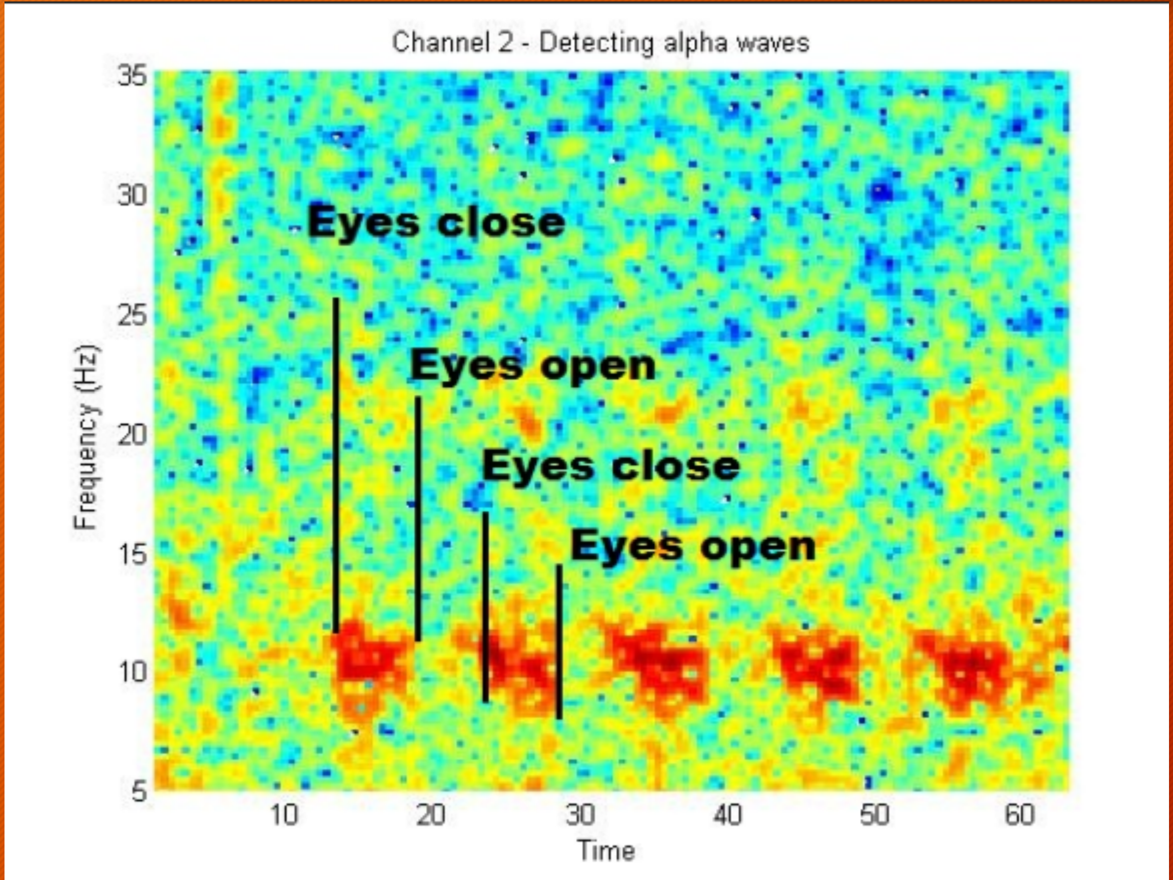
Spectrogram

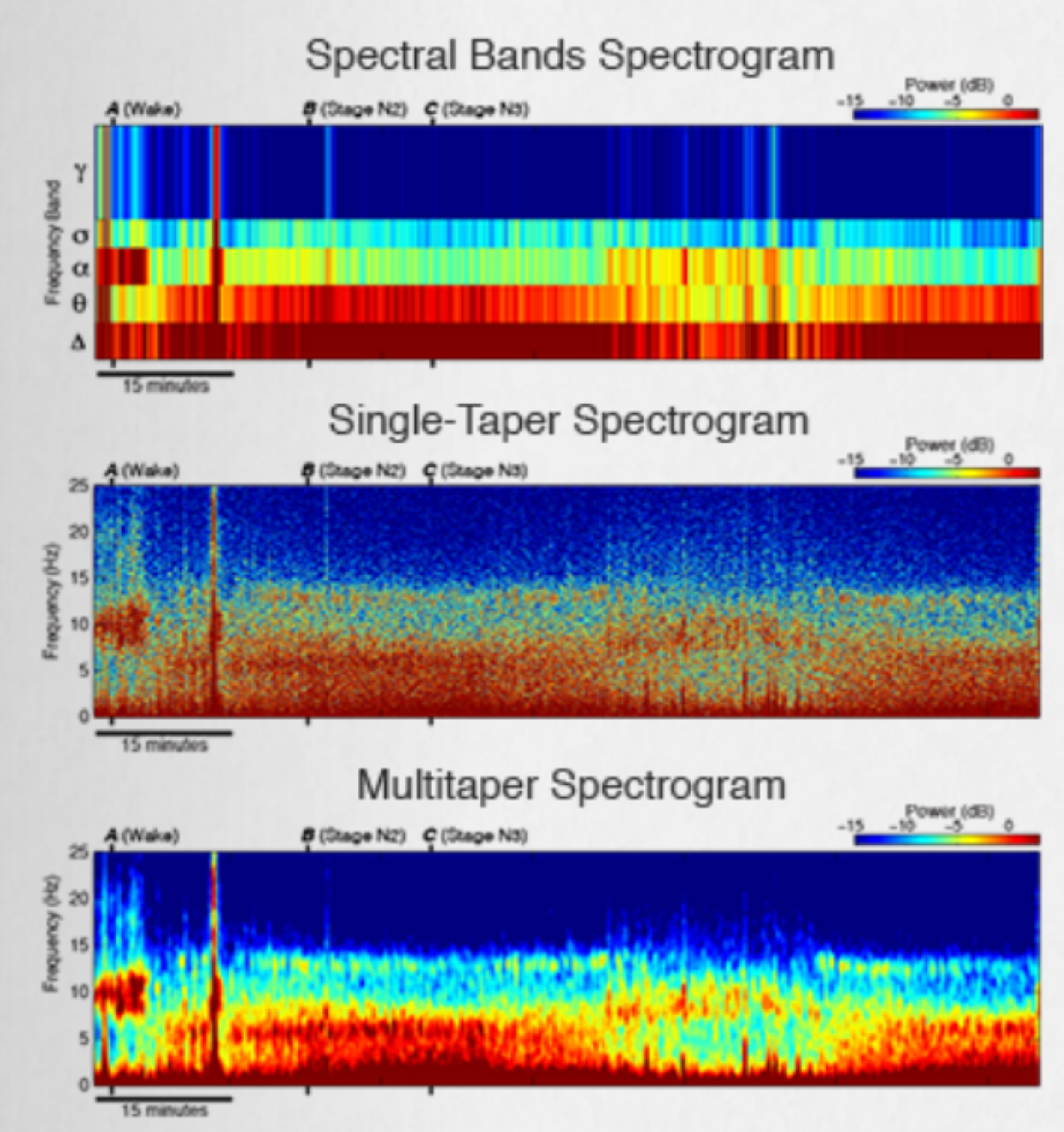


- 10 hours of EEG data at a glance
- Easy to detect which frequencies dominate the data
- Periodic activity



Spectrogram





http://prerau.mgh.harvard.edu/Part%202/Part%202.htm

- Taper function is used to truncate the data
- Shape of taper function affects the data quality
- Multitaper has multiple taper function applied and averaged to increase the resolution

When using spectrograms

- Matlab
- Determine at what time periods the signal can be said to be stationary
- Determine what you need the frequency resolution to be
- Trade-off between frequency and time resolution

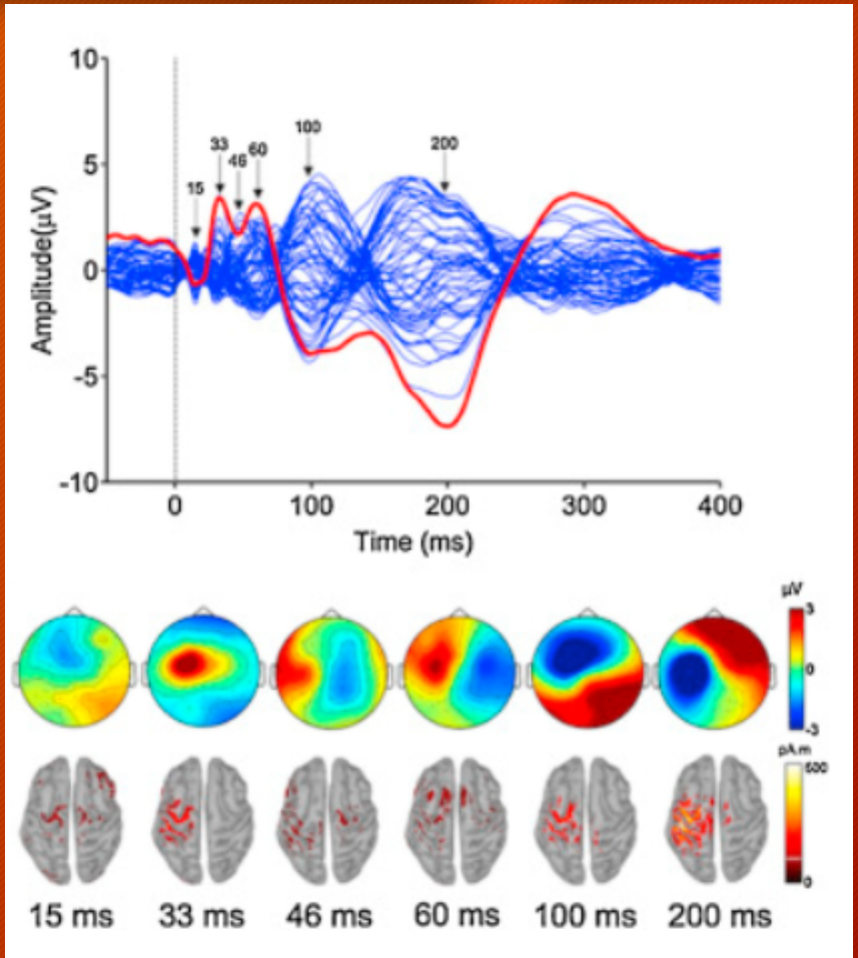
What are spectrographs used for?

- Effective way to analyze complex oscillatory data
- Long-time EEG monitoring in the ICU
- Sleep staging
- Classifying brain responses for e.g. test subject reading/thinking different words – Mind reading?!

Example #2 Evoked potential data analysis

EEG responses to magnetic stimulation

Goal: To probe cortical dynamics, that is, obtain time-amplitude description of the brains response to a magnetic stimulus



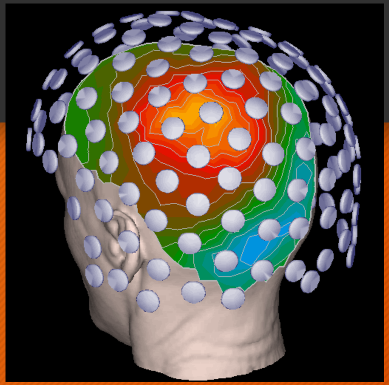
Examples of TMS-evoked potentials following stimulation over the motor cortex (M1). At the top butterfly plots from all electrodes with timing of peaks indicated by arrows (note different amplitude scales between the two plots). The red line indicates the electrode under the coil (C3 for M1). In the bottom half topographic maps of voltage distributions over time across the scalp (top) and following source reconstruction (bottom) for each peak.

A. T. Hill et al, " **TMS-EEG: A window into the neurophysiological effects of transcranial electrical stimulation in non-motor brain regions"**
Neuroscience & Biobehavioral Reviews
Volume 64, May 2016, Pages 175-184

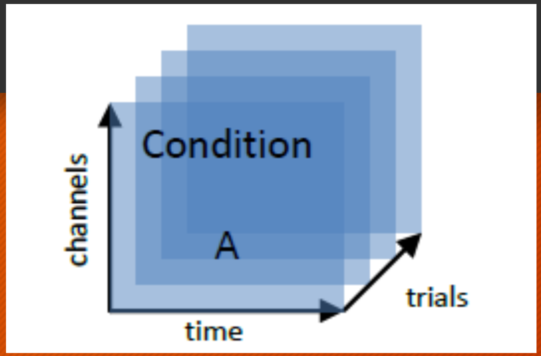
Structure of the Data

Structure of TMS–EEG data

- 1 TMS pulse
- EEG recording
- n TMS pulses
- n EEG recordings

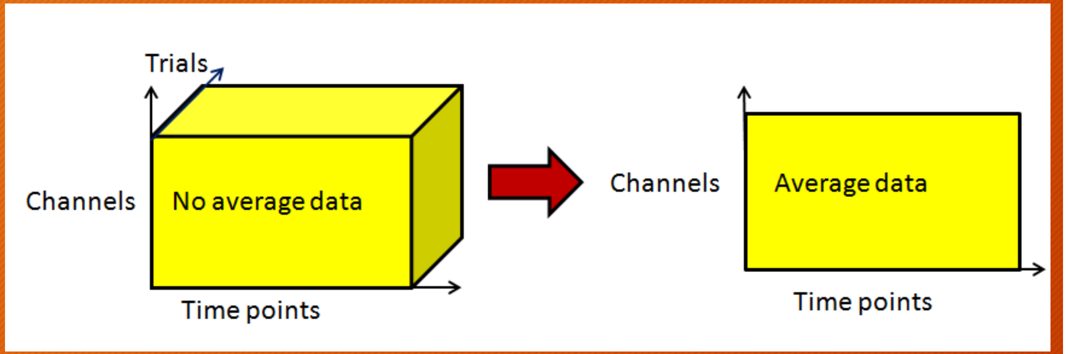


3-Dimensional data

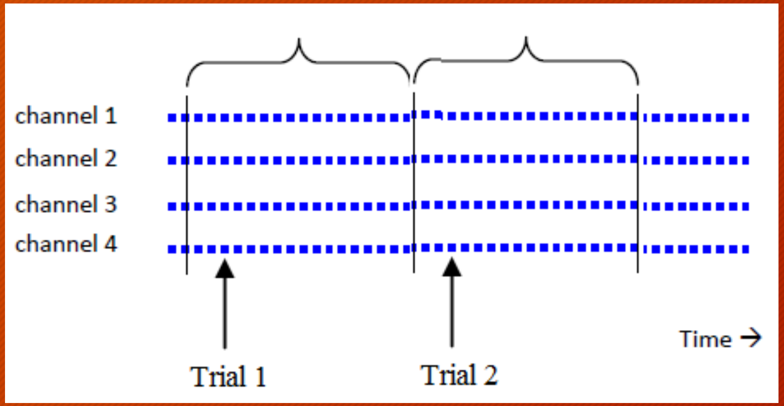


2-Dimensional data

Average over trials

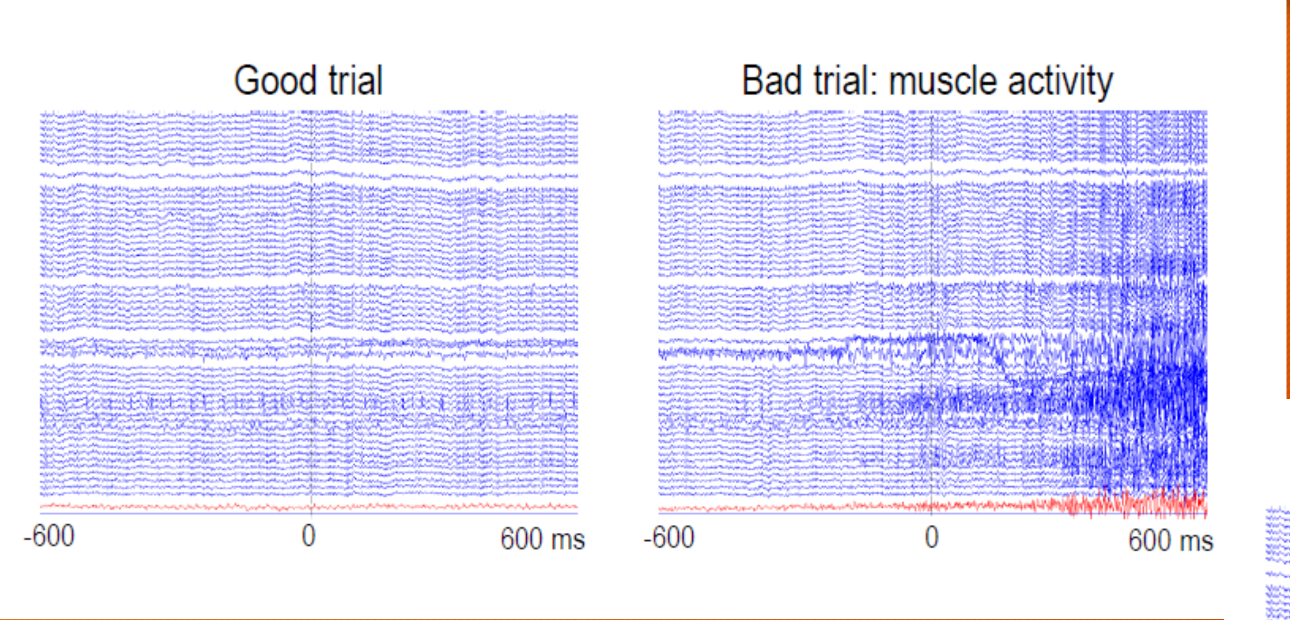


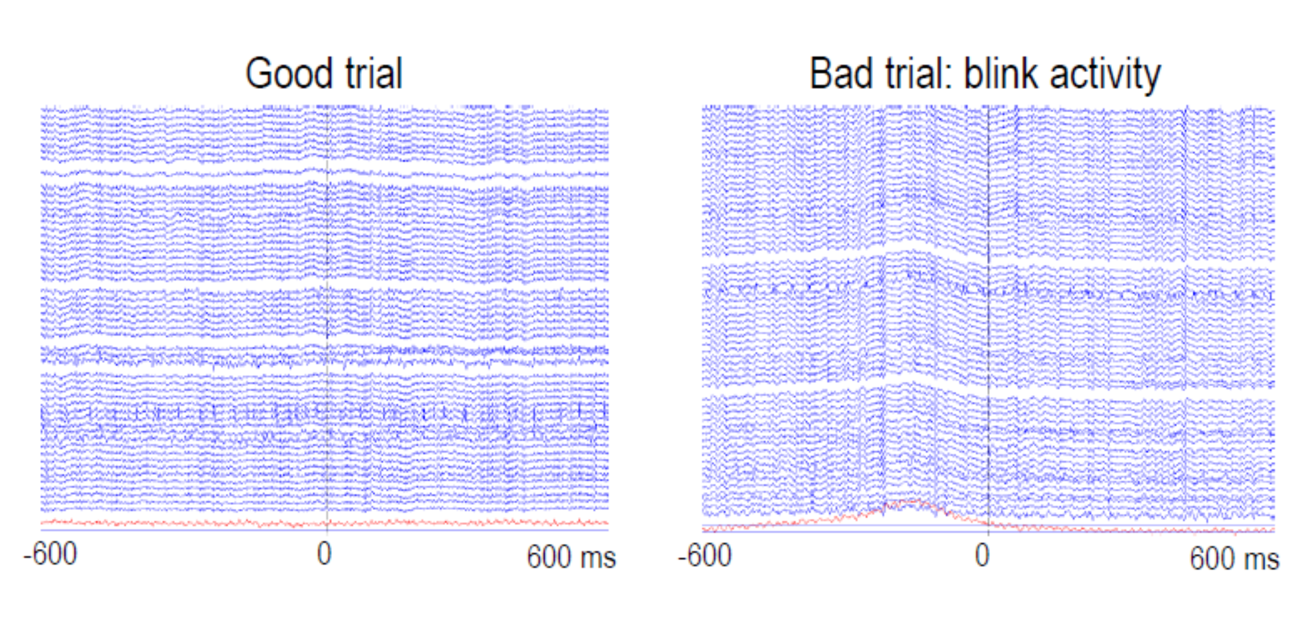
Concatenation of the trials



Signal analysis processing of TMS-evoked EEG

1. Visual inspection of trials: you can reject bad trials if something is wrong...

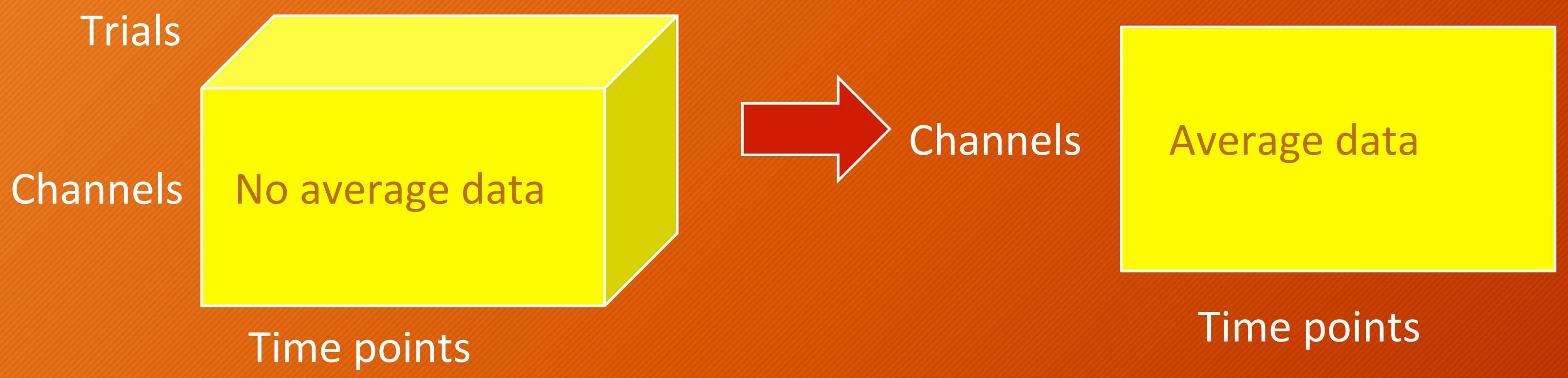




Signal analysis processing of TMS-evoked EEG

Preprocessing steps:

2. Averaging the data

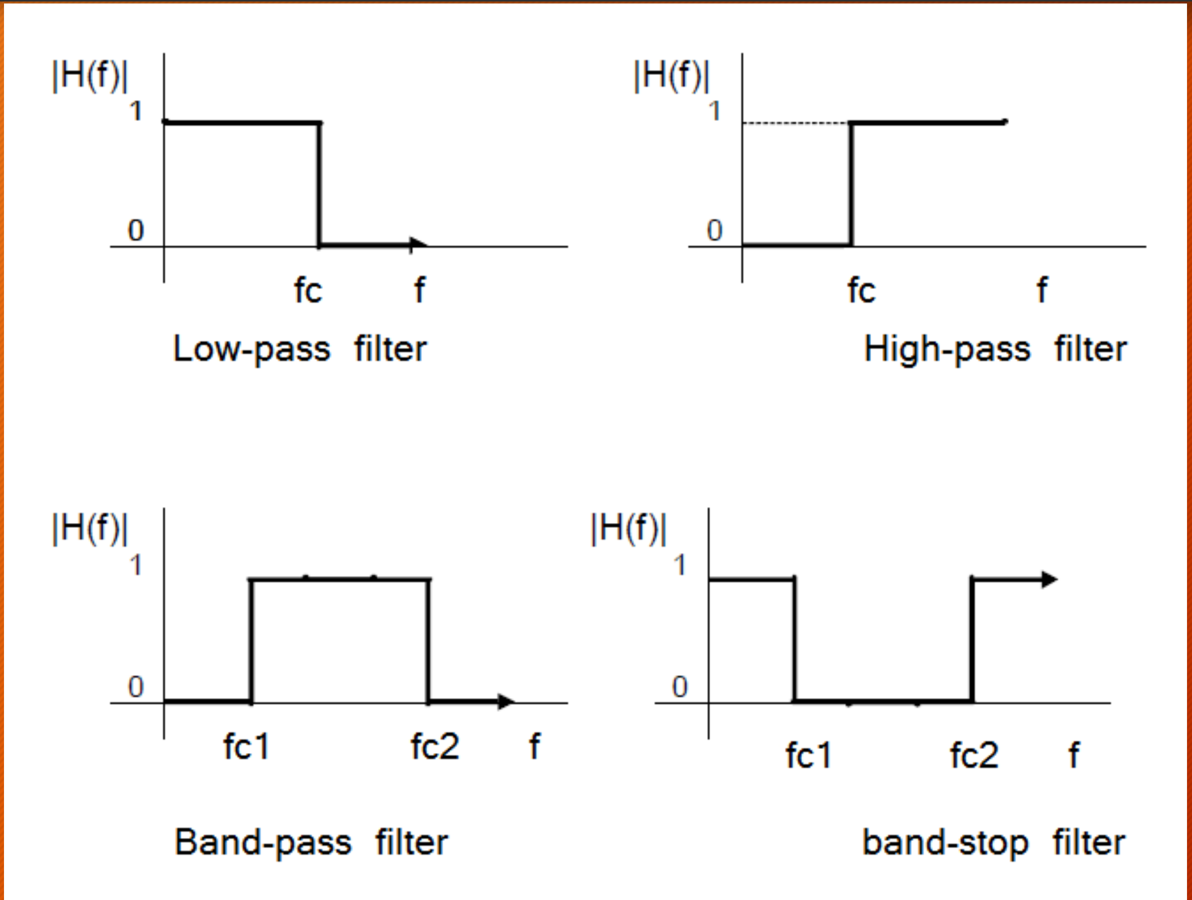


3. Removing bad channels: poor electrodes connection, disconnected channels

4. Filtering

Filtering

Filtering is the process of keeping components of the signal with certain desired frequencies and removing components of the signal with certain undesired frequencies.



fc= cutoff frequency

Preprocessing

4. Referencing the average potential over the channels

$$\boldsymbol{X}_{\mathrm{z}}(j,t) = \boldsymbol{X}_{\mathrm{r}}(j,t) - \frac{1}{M}\sum_{k=1}^{M}\boldsymbol{X}_{\mathrm{r}}(k,t)$$

5. Time centering (baseline correction)

$$\boldsymbol{X}_{\mathrm{c}}(j,t) = \boldsymbol{X}_{\mathrm{z}}(j,t) - \frac{1}{N}\sum_{s=1}^{N}\boldsymbol{X}_{\mathrm{z}}(k,s)$$

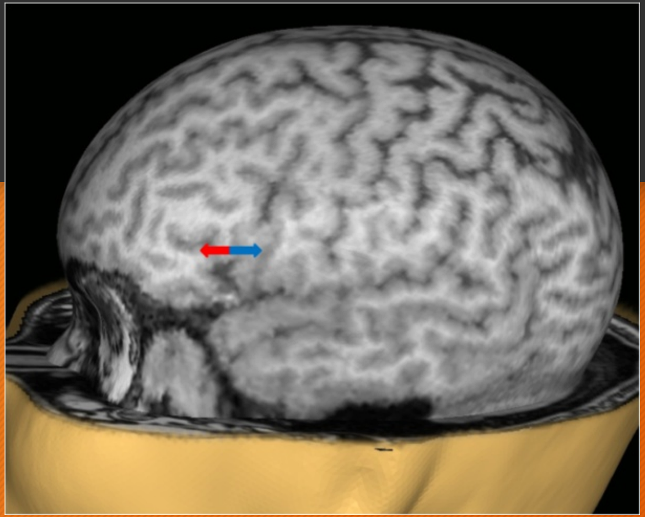
Preprocessing

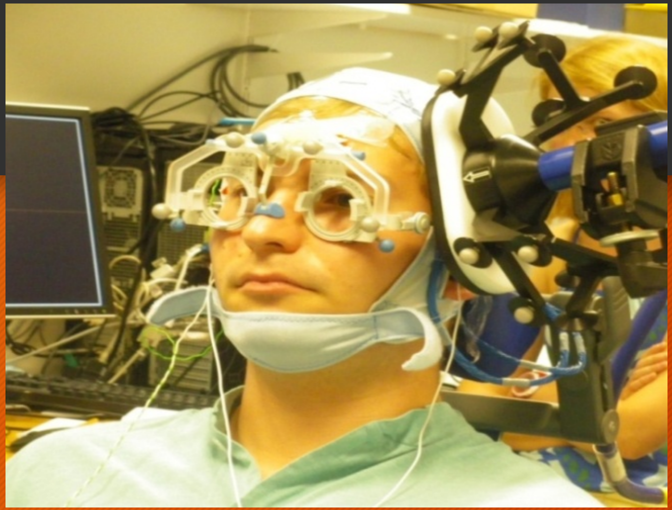
Independent component analysis

5. Artefact removal with ICA

Muscle artifacts in Broca's area

Muscle artifacts

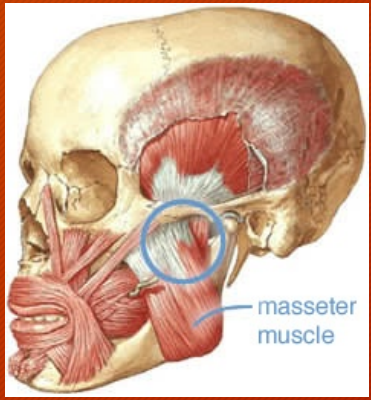




Muscle artifacts:

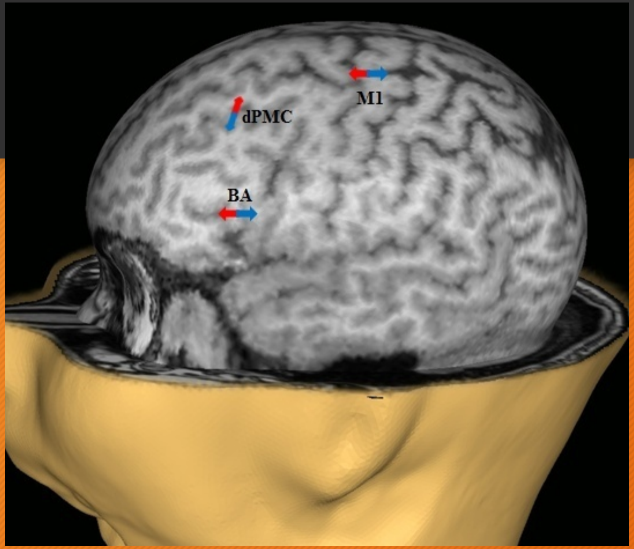
1. Are most prominent when lateral areas of the head or areas near the neck or forehead are stimulated.

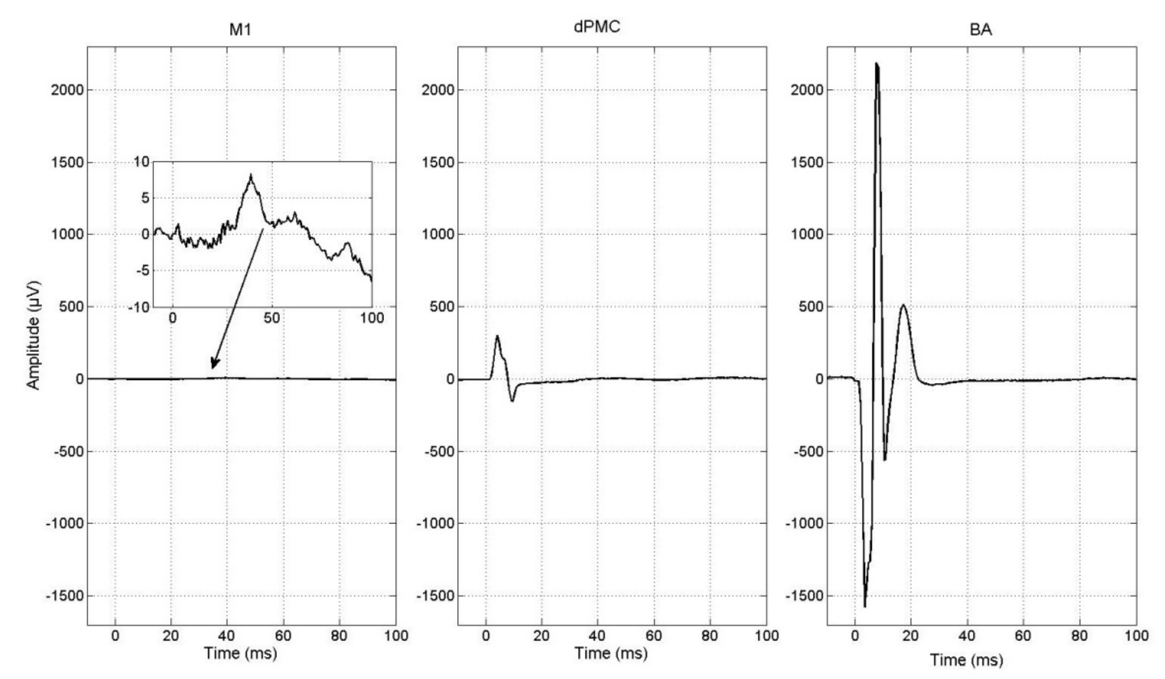
2. **Temporal** and **frontal muscles**, and in some stimulation positions, **masseter muscle** (one of the muscle of mastication) are the most likely to be activated.

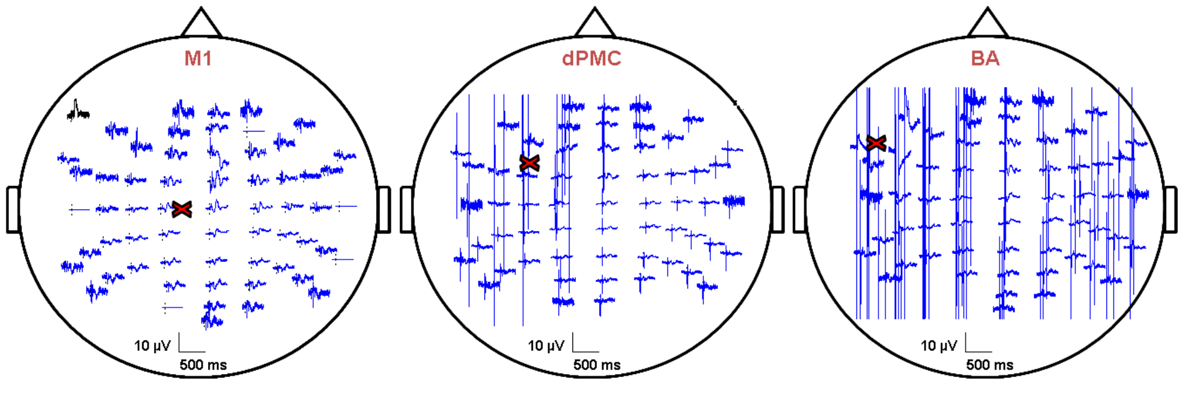


TMS-evoked EEG data from Broca's area

Muscle artifacts:







Muscle artifacts:

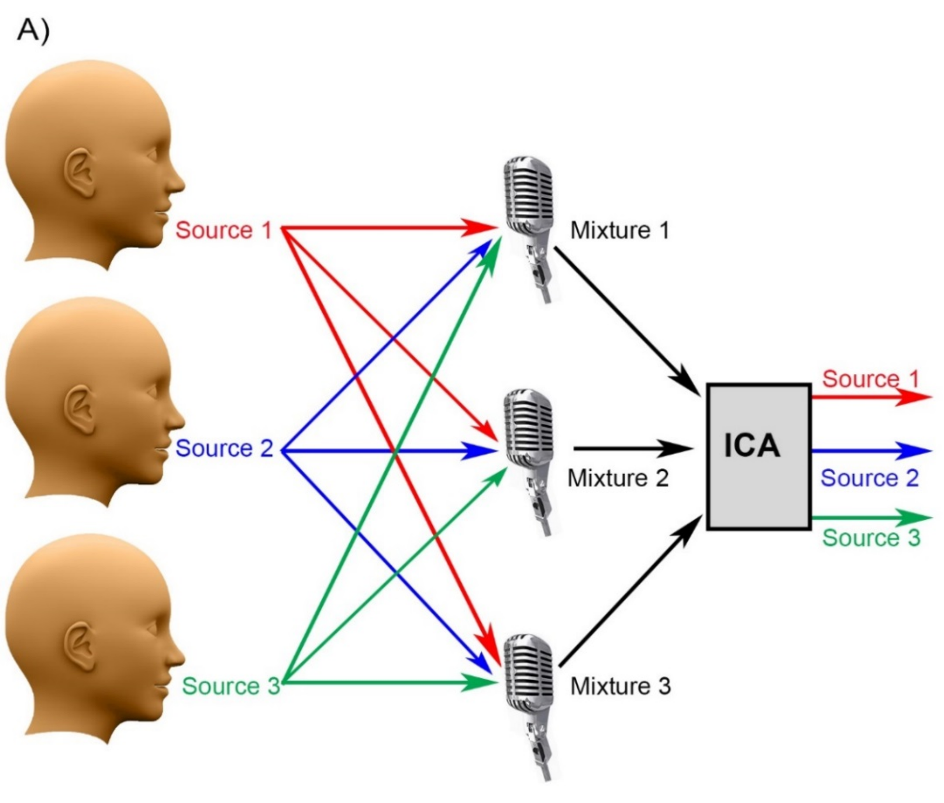
1. They mask the brain signals. 2-3 orders of magnitude larger than brain signals.

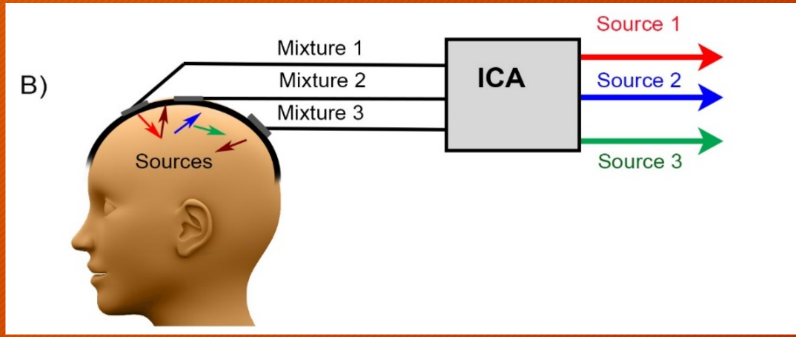
2. They last for tens of milliseconds (30 ms)

Aalto University School of Science

Korhonen, Hernandez-Pavon., et al., 2011; Hernandez-Pavon et al., 2012; Hernandez-Pavon et al., AIP proceedings 2014

Principle of ICA





The EEG recordings are composed of mixed signals, *i.e.*, **brain responses** and **non-brain sources,** such as **<u>muscle artifacts</u>**.

Korhonen, Hernandez-Pavon, *et al*., 2011; Hernandez-Pavon, *et al*., 2012.

Independent component analysis (ICA)

- ICA is a method for finding underlying factors or components from ***multivariate*** (multidimensional) statistical data.

- ICA looks for components that are ***statistically independent and non-Gaussian***

$$\mathbf{X} = \mathbf{A}\mathbf{S} = \sum_{j=1}^{n} a_j \, s_j$$

is an $M \times T$ matrix.

- Matrix of recorded data.

is an $M \times n$ mixing matrix.

- Their columns are the topographies of the n latten sources.

is an $n \times T$ time-courses matrix.

- Their rows are the time-courses (amplitudes) of the latent variables.

Independent component analysis (ICA)

- Applying ICA requires additional steps (compressing extra dimensions, whitening) that we will not go into detail…

Input

X_{white}

in ICA

$\xrightarrow[\text{Algorithm}]{\text{FastICA}}$

$\hat{\mathbf{W}}\hat{\mathbf{S}}$

Estimated

$$\hat{\mathbf{S}} = \hat{\mathbf{W}}\,\mathbf{X}_{\text{white}}$$

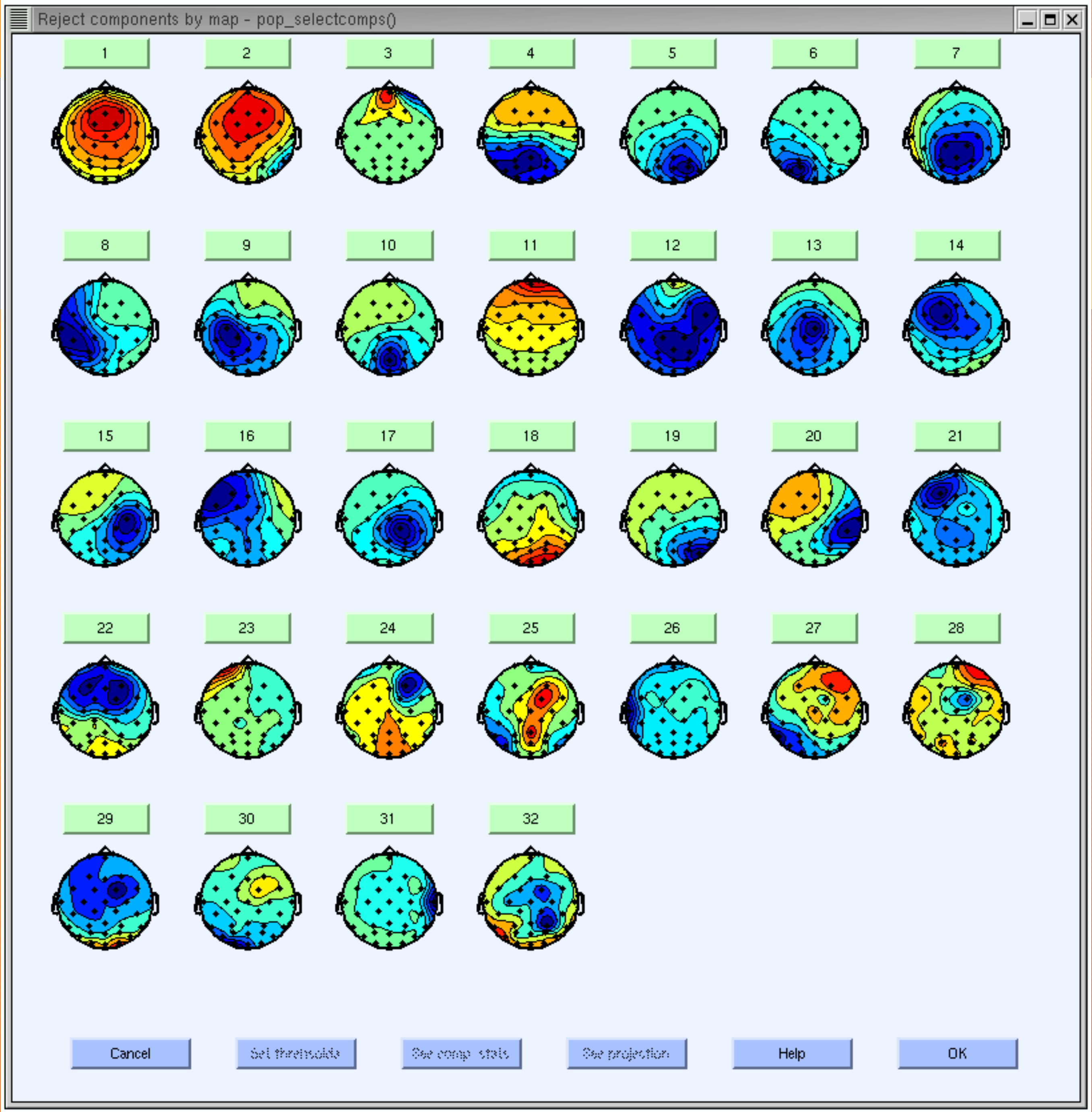
$$\hat{\mathbf{A}} = \frac{1}{T}\,\mathbf{X}\hat{\mathbf{S}}^{T}$$

Preprocessing steps:

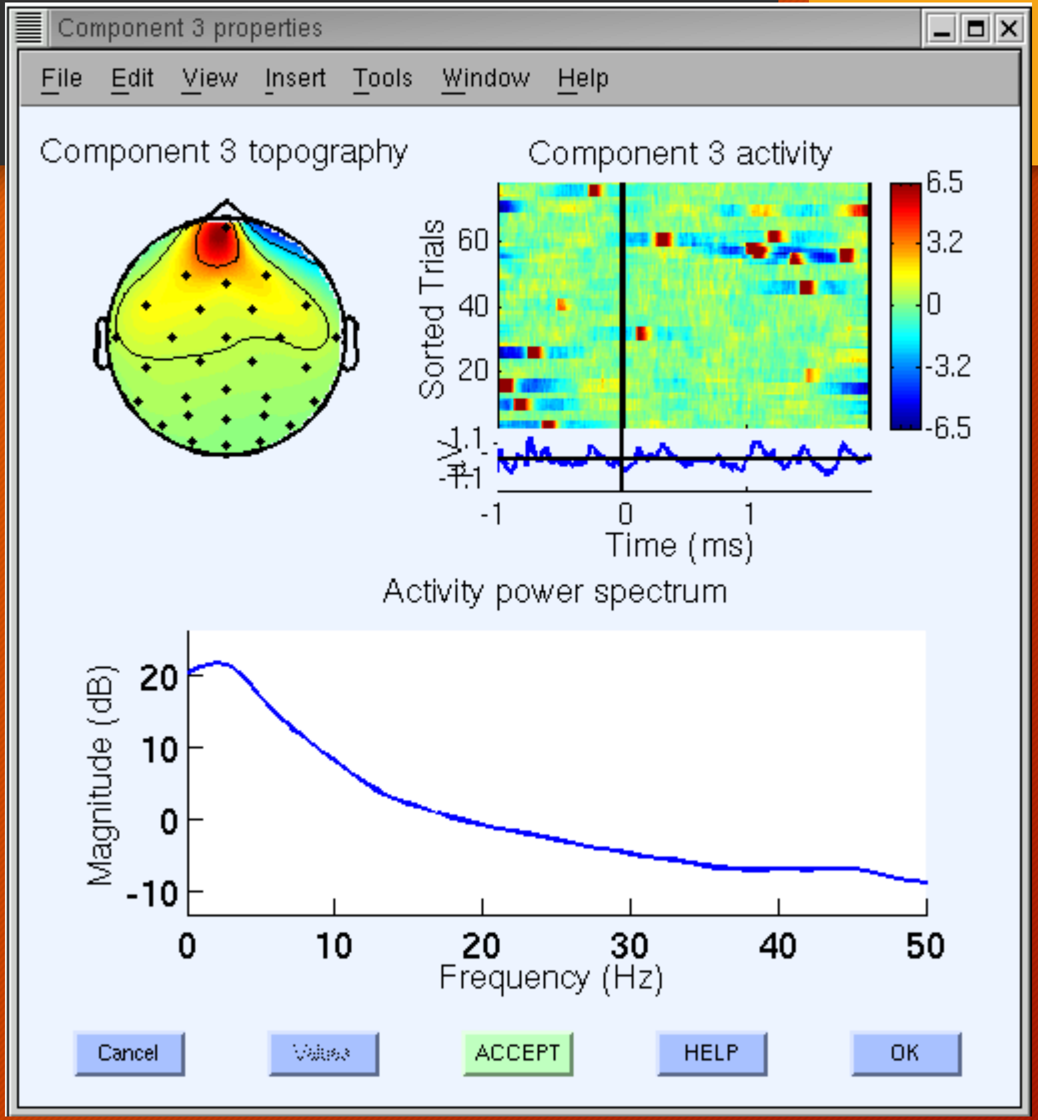
1) Removing bad channels and trials
2) Set the zero potential level or reference potential
3) Centering (zero mean)
4) Compressing extra dimensions
5) Whitening

Results of ICA

- 32 independent components
- Some are EEG components, some are artefacts

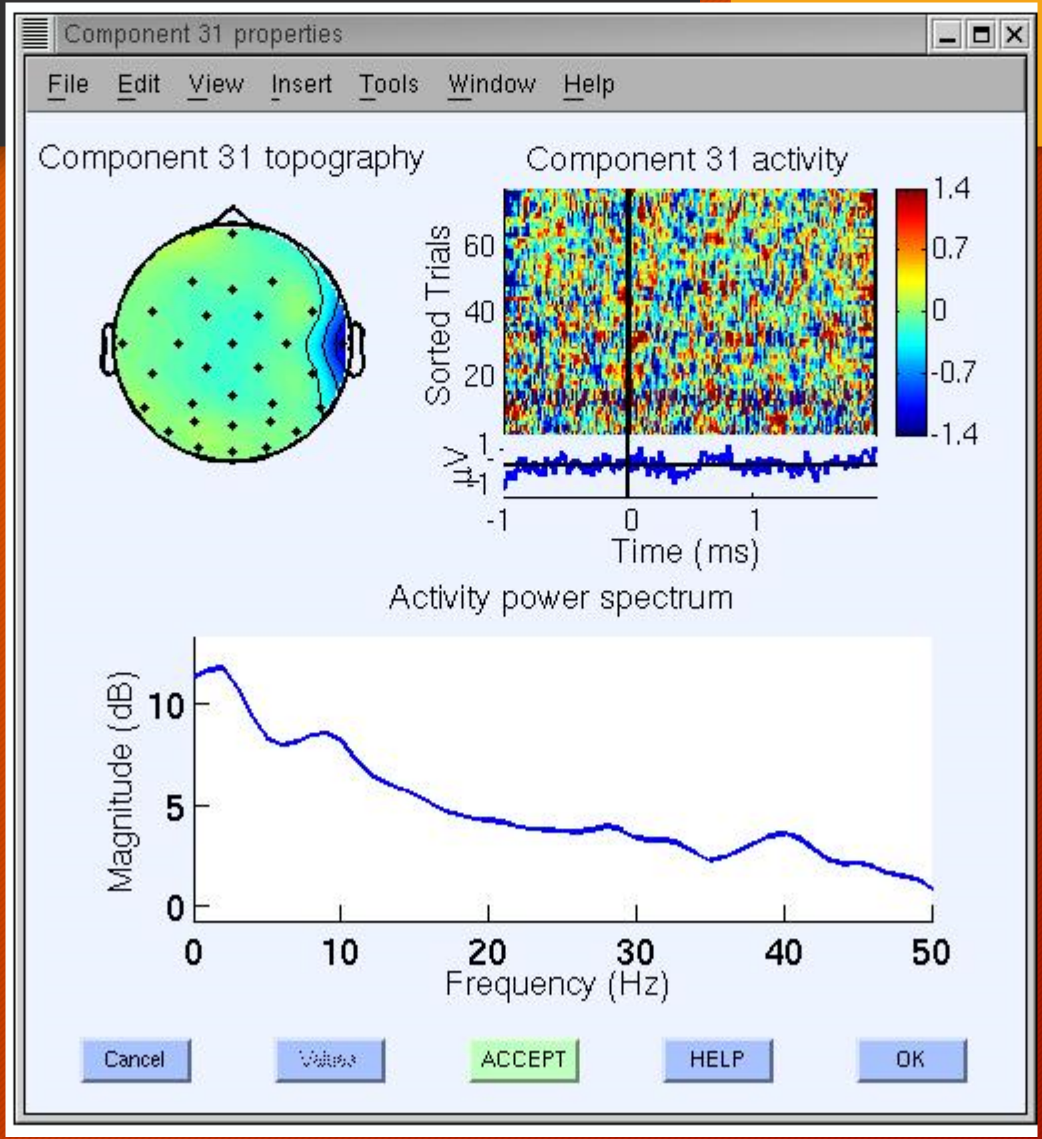


- To help with decising which component to remove, look at additional data
- Eye movement
  - Topoplot frontal
  - Periodicity in spectrum



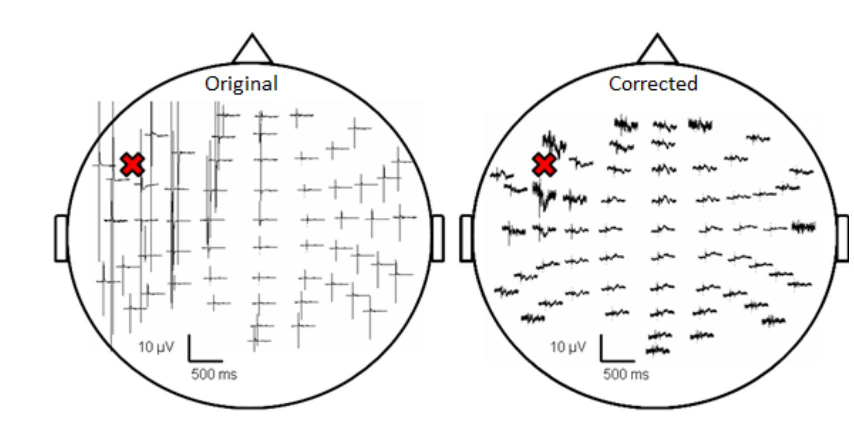
- Muscle artefact
- Topoplot
- High magnitude at 20-50 Hz

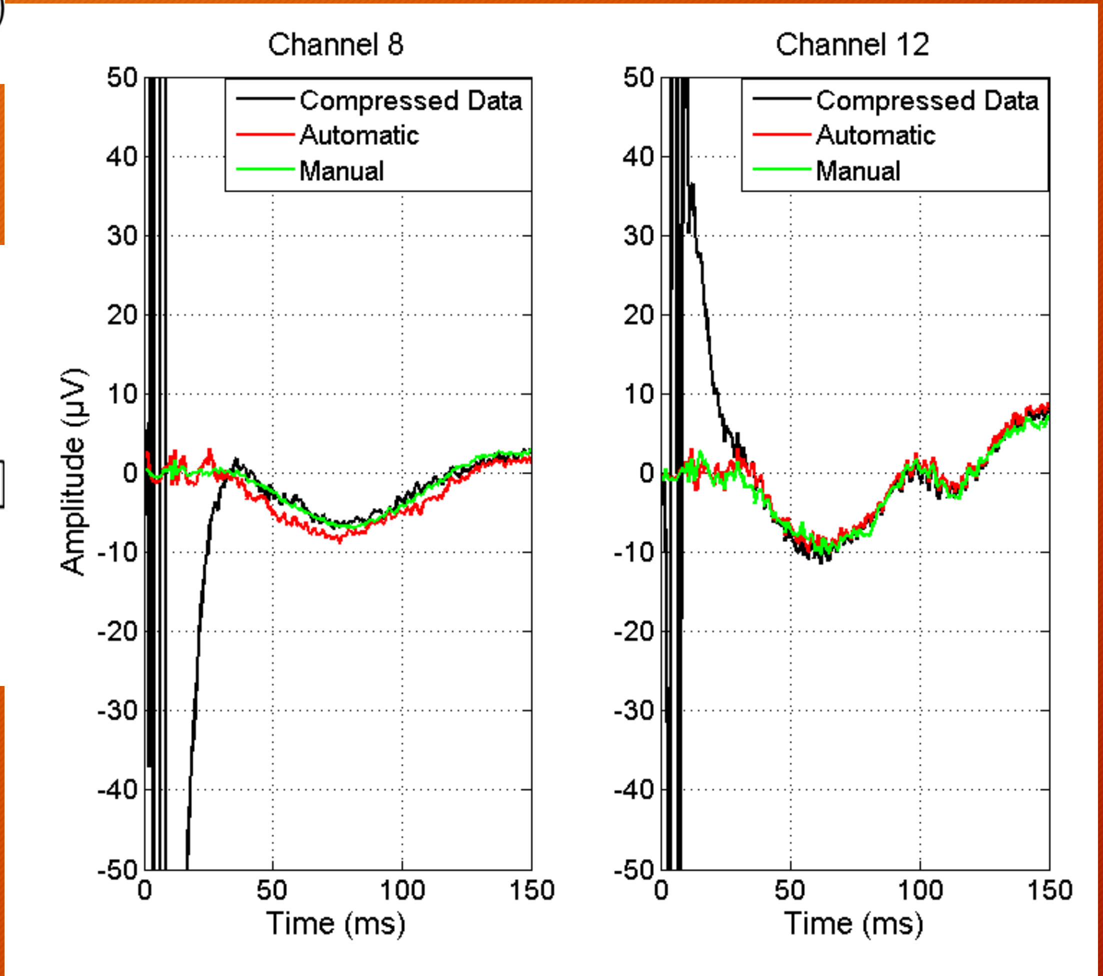
- Tule of thumb: If your’re not sure wether artefact or not, leave it alone!



Removing muscle artifacts with ICA

$$\mathbf{X}_{\mathrm{corr}} = \mathbf{X}_{\mathrm{comp}} - \sum_{j=1}^{p} \hat{\mathbf{A}}(:,j)\,\hat{\mathbf{S}}(j,:)$$





Korhonen R, Hernandez-Pavon JC, et al., Med Biol Eng Comput, 2011

Med Biol Eng Comput (2011) 49:397–407
DOI 10.1007/s11517-011-0748-9

ORIGINAL ARTICLE

Removal of large muscle artifacts from transcranial magnetic stimulation-evoked EEG by independent component analysis

Reeta J. Korhonen · Julio C. Hernandez-Pavon ·
Johanna Metsomaa · Hanna Mäki ·
Risto J. Ilmoniemi · Jukka Sarvas

Journal of Neuroscience Methods 209 (2012) 144–157

Contents lists available at SciVerse ScienceDirect

Journal of Neuroscience Methods

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

Computational Neuroscience

Uncovering neural independent components from highly artifactual TMS-evoked EEG data

Julio C. Hernandez-Pavon[a,c,*,1], Johanna Metsomaa[a,b,1], Tuomas Mutanen[a,b], Matti Stenroos[a], Hanna Mäki[a,b], Risto J. Ilmoniemi[a,b], Jukka Sarvas[a]

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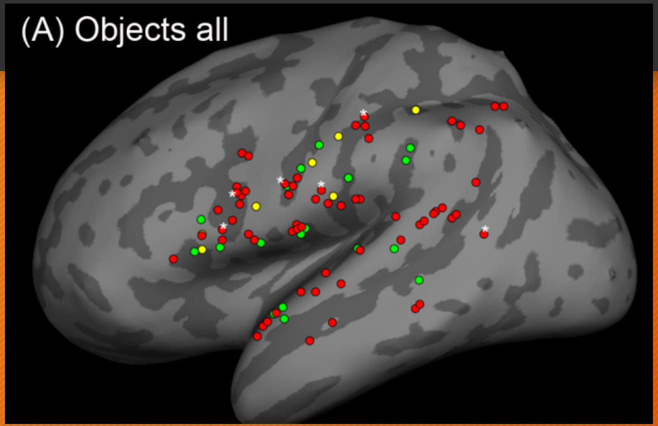
- The muscle artifacts distort the topographies.
- The topographies are useful in source localization.

Connectivity

- TMS-pulse
- After 3 ms activation structure close by are activated
- 20 ms the activation spreads on the opposite side

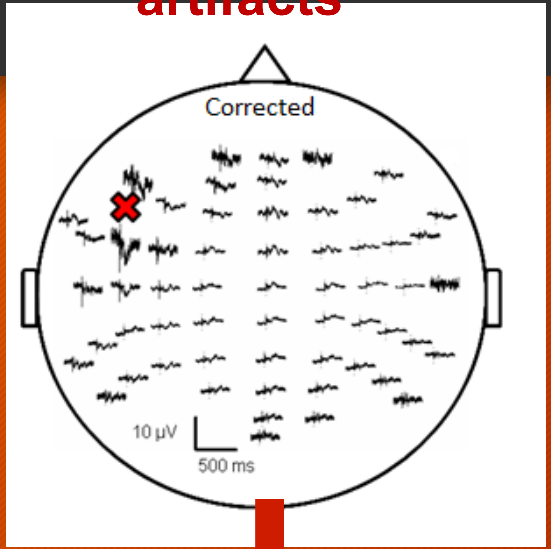
Summary

Functional localization of language areas

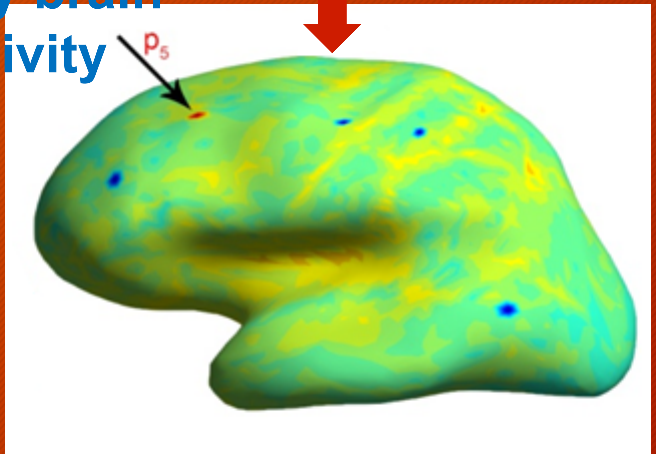


TMS–EEG

Methods for removing or Suppressing artifacts



Source localization to study brain connectivity



Basic Research

Clinical applications

What was achieved?

- Highly artefactual (muscle activation) data was cleaned
- Brain topographies at different time points after the TMS pulse are obtained
- Source localization estimates
- Dynamic information on the underlying brain activity

- Other possible applications include complexity measures that allow the evaluation of conciousness in unresponsive patients (vegetative, minimally conciouss, locked-in?)

Example # 3 Source localization

- Aim: We want to know which are inside the brain is creating some signal, e.g. epileptic spike activity or evoked potential response to a stimulus
- Goal: 3D representation of the activated area within the brain

J. Song et al, Journal of Neuroscience Methods 256 (2015) 9–21
https://doi.org/10.1016/j.jneumeth.2015.08.015

Source localization

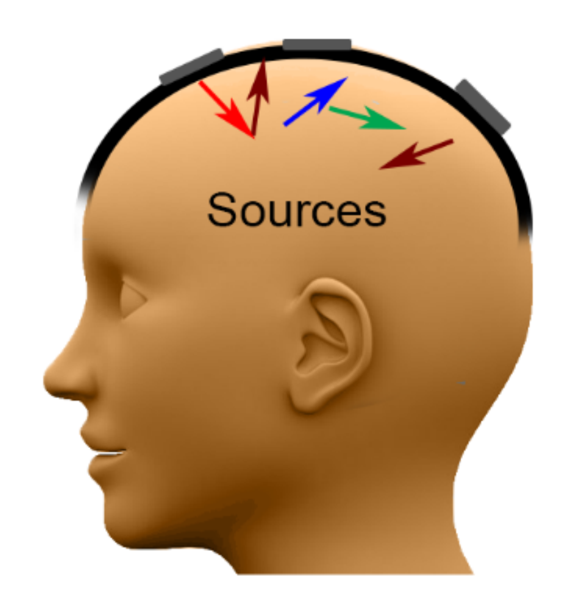
Inverse problem:

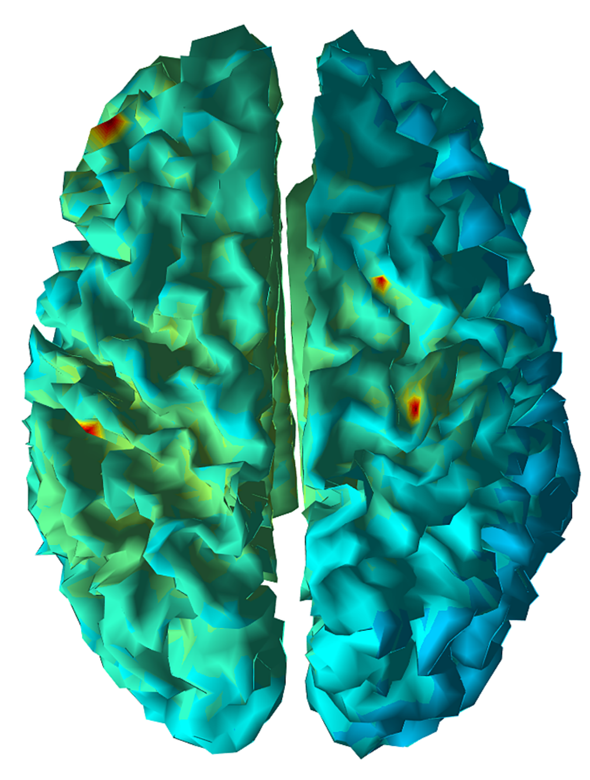
” There are many possible dipole sources that can create the same voltage distribution measured on the scalp. Which is the correct distribution of sources?”

Forward problem describes how the knows dipolar sources propagate to the scalp

Source localization

EEG → Brain sources



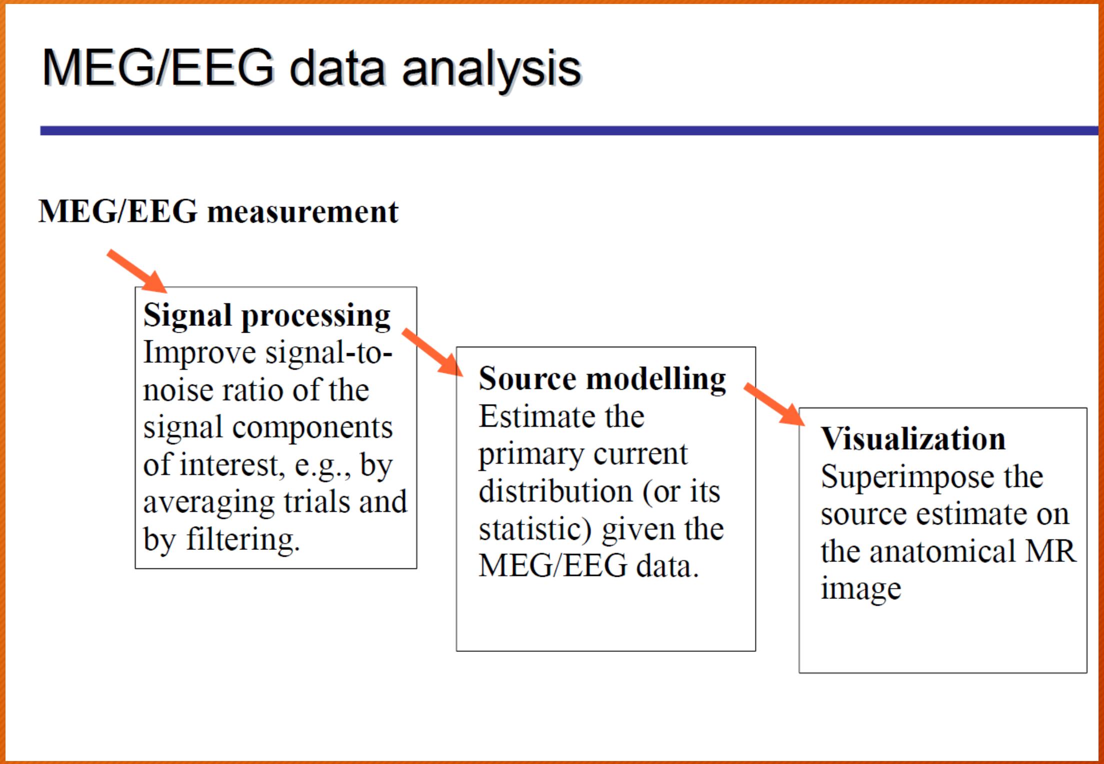


Beamformer

Source localization

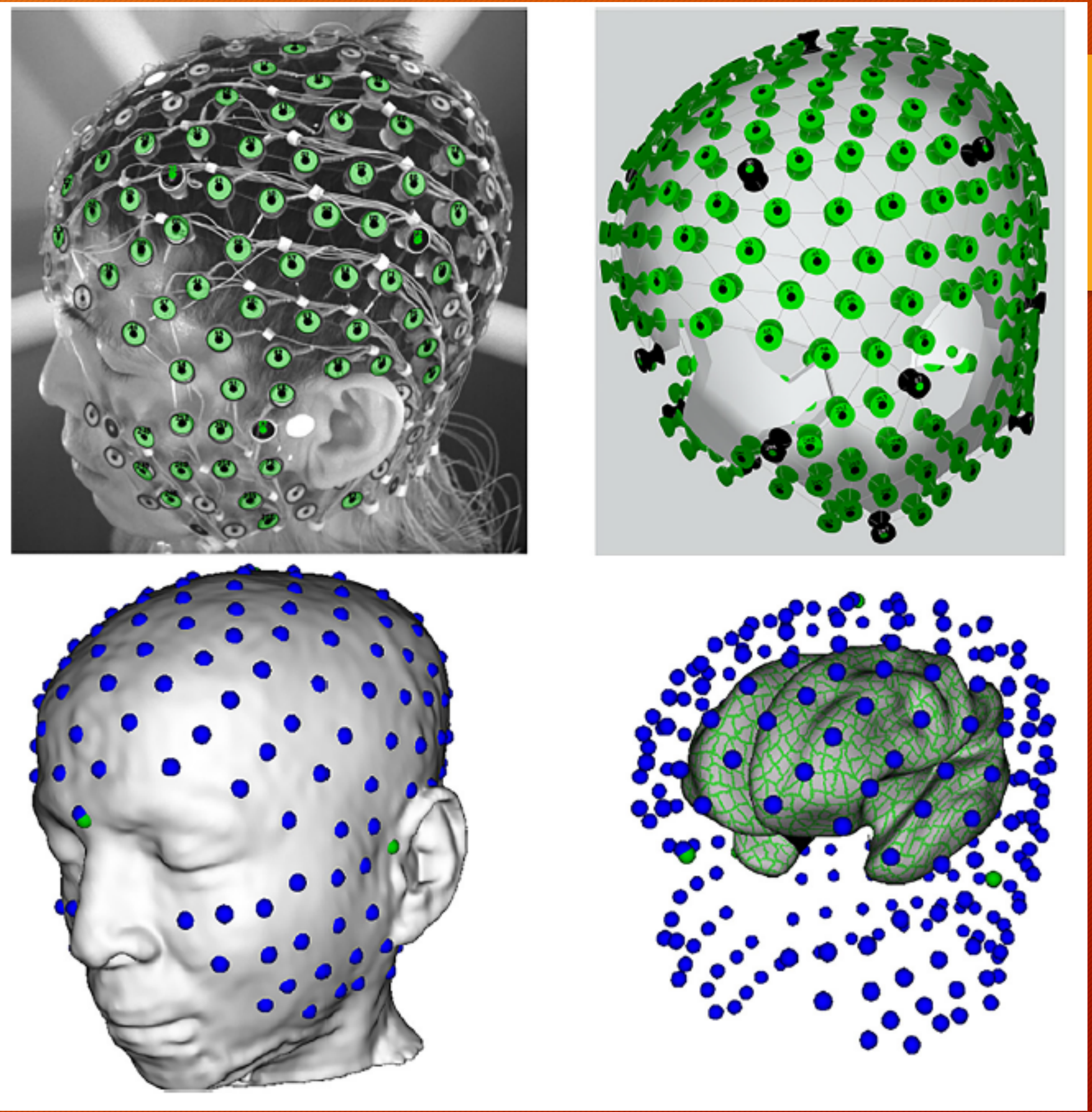
- Spatial sampling density of EEG
- Head conductivity model
- Linear inverse weigh techniques to find the sources
- Matlab (Beamformer, EPIFOCUS, sLORETA)

Source localization, basic steps



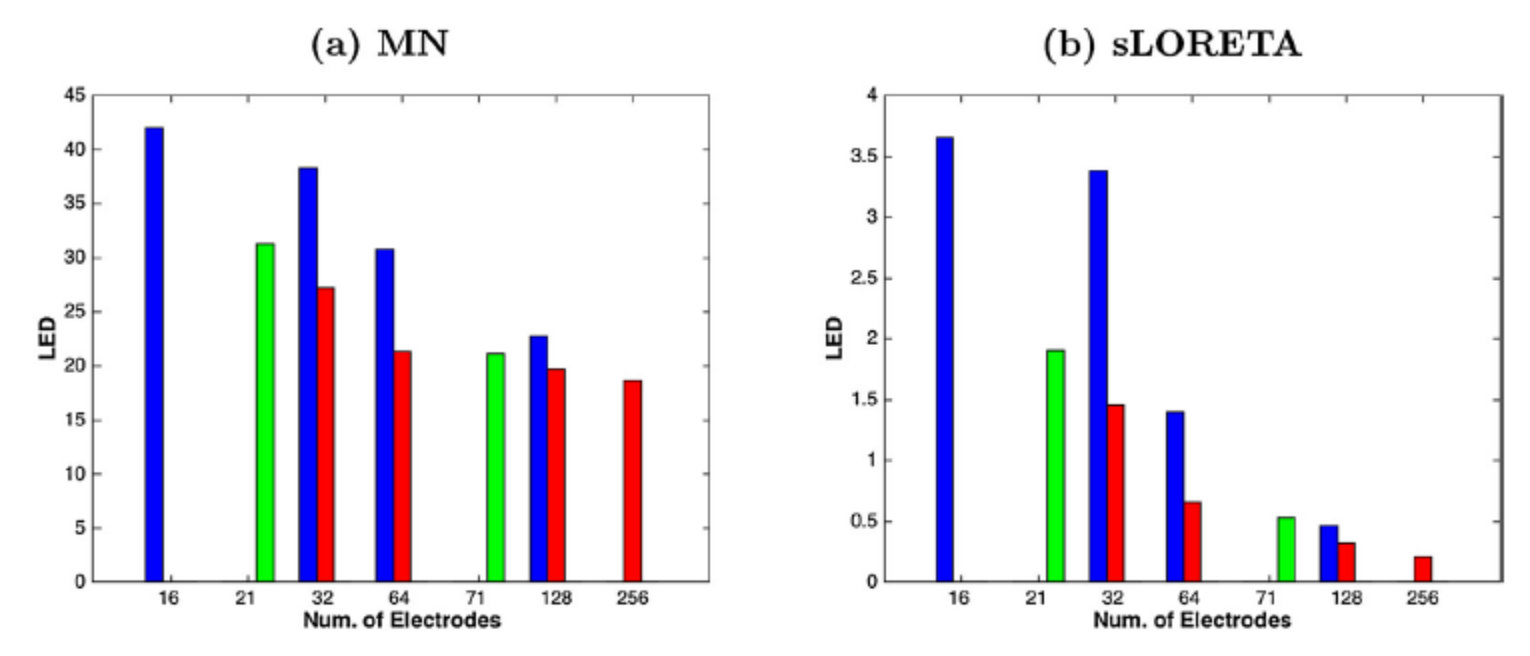
- Traditionally only scalp electrodes were used
- Additional data point from sampling the lower part of the head
- Realistic, individual head model

J. Song et al. / Journal of Neuroscience Methods 256 (2015) 9–21



Spatial sampling

- Using simulated data, the effects of spatial sampling can be shown as Localization Error Distance



J. Song et al. / Journal of Neuroscience Methods 256 (2015) 9–21

RED=whole head
Blue=upper head
Green= 10-20 system

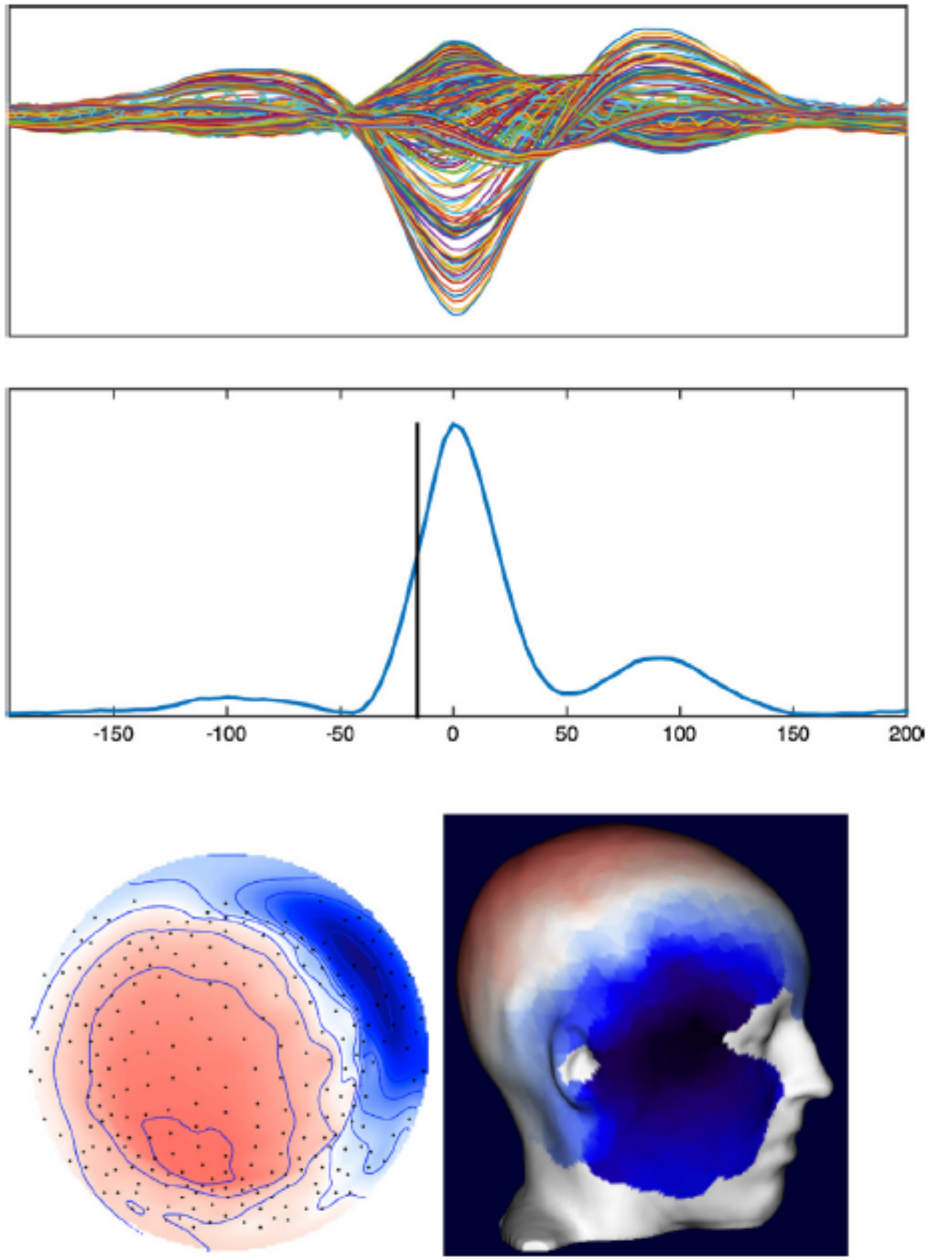
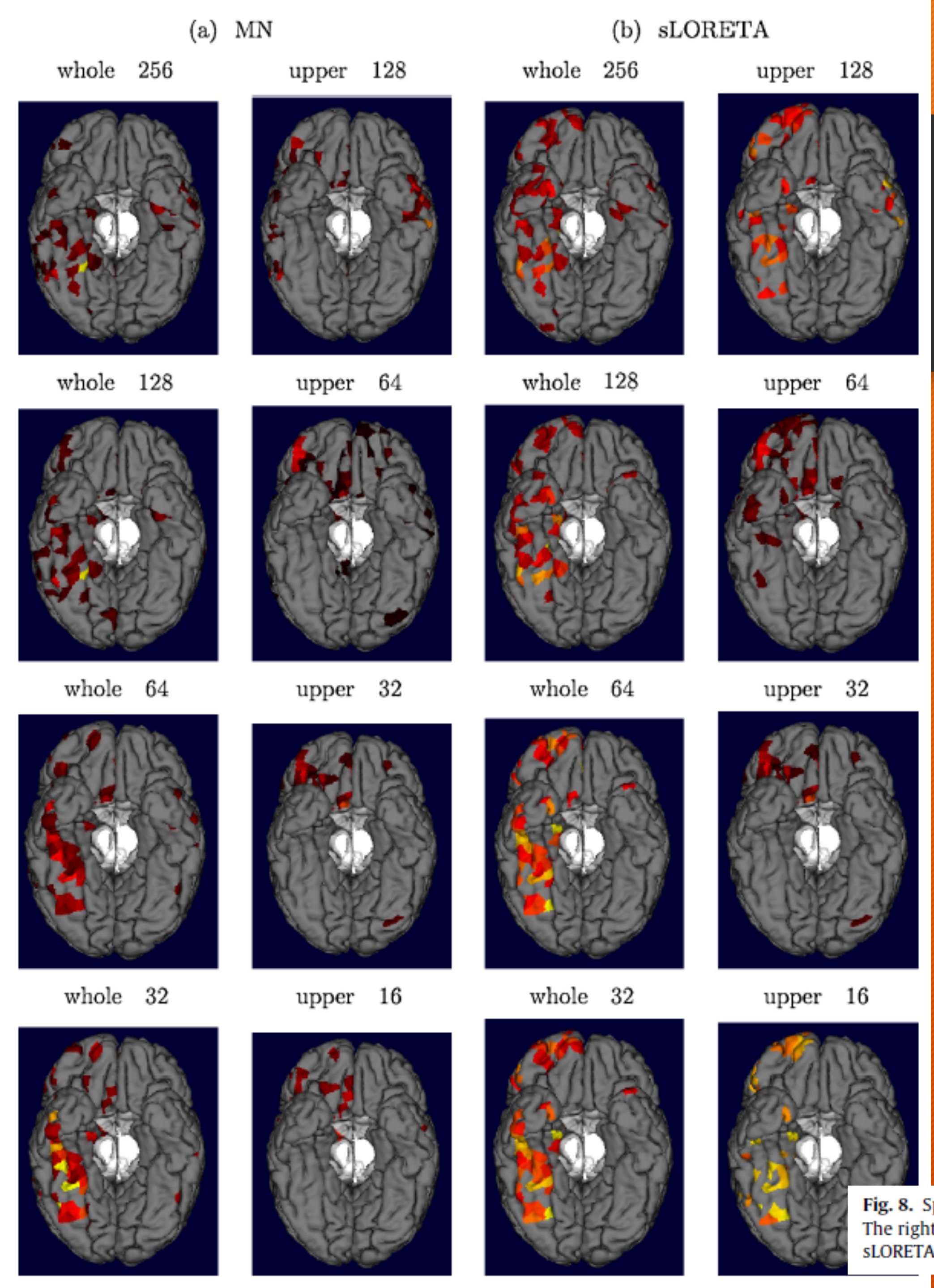


Fig. 7. Spike Onset localized in a patient's individual head model. (Top) 256-channel butterfly plot of average spike waveforms from −200 ms to 200 ms around spike peak and global field power. Black bar indicates time of spike onset used in source localization. (Bottom) Average spike scalp topography at onset.

Patient case

- Epileptic focus localized on the temporal region



- Same patient as before, image showing the bottom of the brain
- Localizations look different with different spatial sampling
- Compare especially upper head vs. whole head (whole 128 vs upper 64)

Fig. 8. Spike Onset localized in a patient's individual head model with MN and sLORETA. (a) MN and (b) sLORETA source distributions with different sensor distributions. The right anterior temporal lobe was independently identified as the epileptogenic spike onset from intracranial data (and surgical outcome). Whole samples with MN and sLORETA are correctly localized.

Example #4 Brain Computer Interface

- Test subject generated patterns in brain signals are recognized and classified by a number of different methods
- https://www.youtube.com/watch?v=7t84lGE5TXA

Conclusions

- Several signal prosessing steps are available
- Application determines which ones to use
- Common ones include filtering not needed frequency components, removing noise (filtering, ICA, spectral properties of the signal)
- Signal processing techniques are being continually developed
- Also new application emerge in clinical and for research purposes