MRC Cognition and Brain Sciences Unit
UNIVERSITY OF CAMBRIDGE

EEG/MEG 1:

Pre-processing

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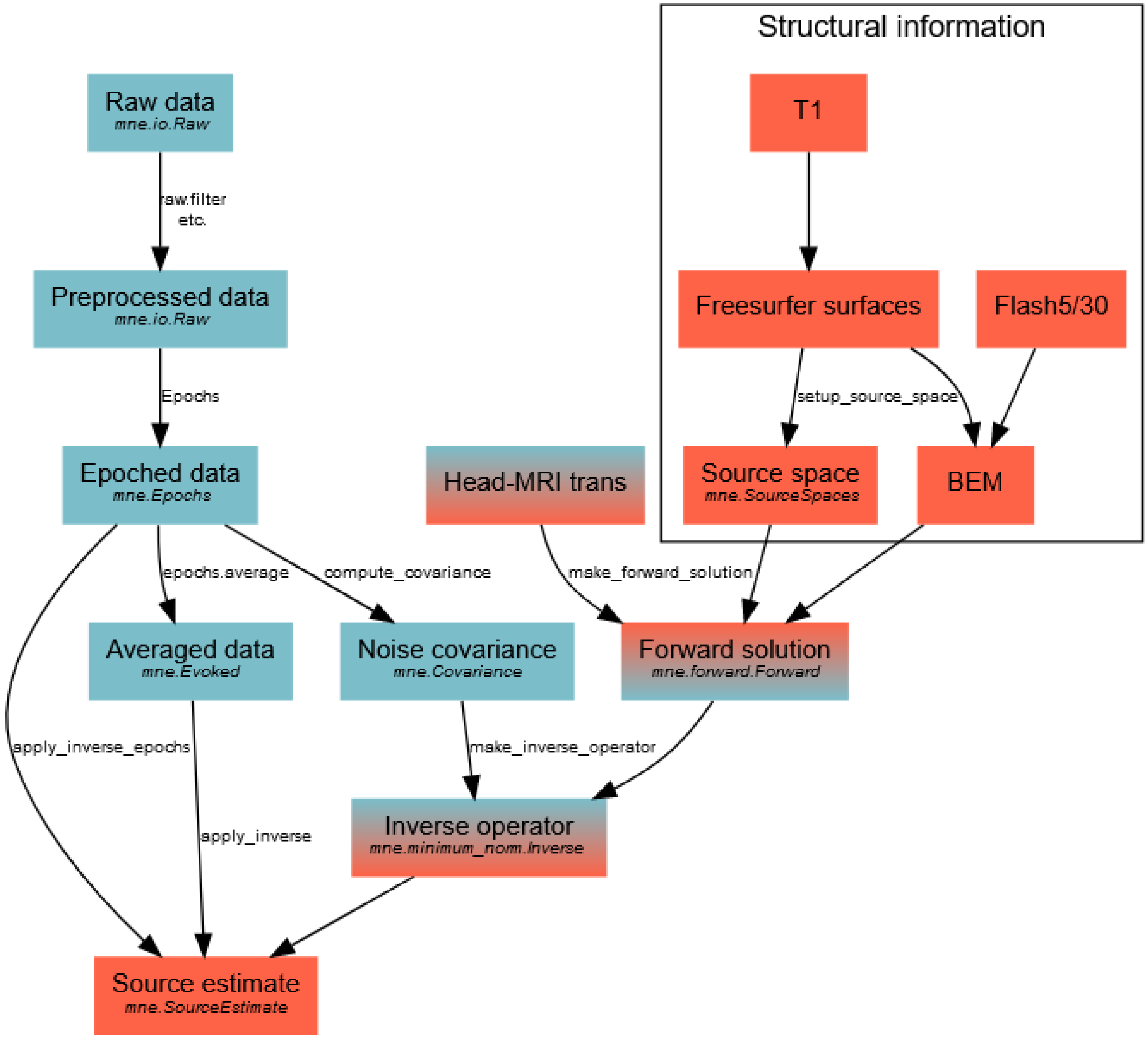
Typical EEG/MEG Analysis Pipeline



https://mne.tools/stable/overview/cookbook.html

Data Pre-Processing - Artefacts

Artefacts

Artefacts can be

- **non-physiological,** i.e. from outside the body (sensor-intrinsic noise, line noise, moving objects, vibrations)
  => Maxfilter (SSS), Frequency-Filtering, SSP, PCA/ICA

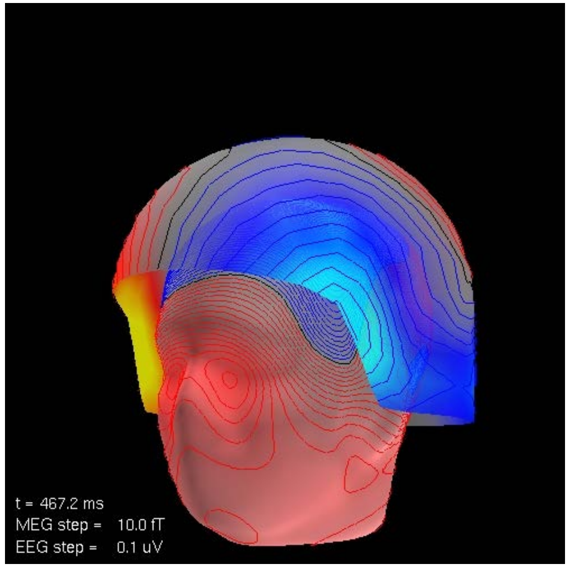
- **Physiological but non-brain**, e.g. eye movements, muscles
  => SSP, PCA/ICA, H/L-Filtering

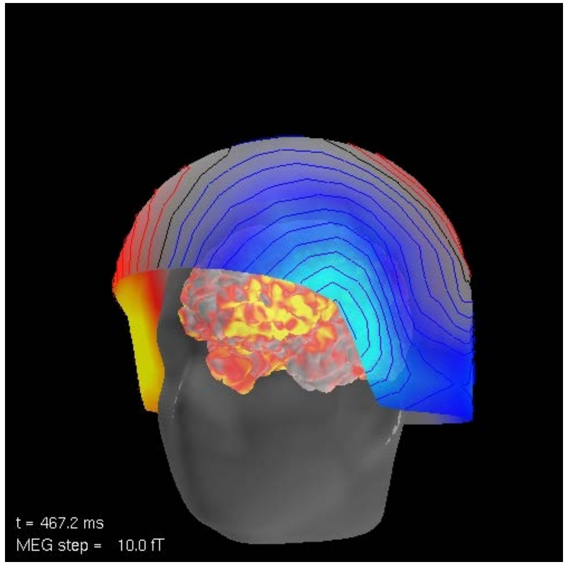
- **Physiological from the brain,** i.e. brain sources that are not of interest or not included in your source model
  => choose appropriate source estimation, regularisation

Wisdoms:
"Some people's signal is other people's noise."
Unfortunately, you cannot just choose what's signals and what's noise.
It's always better to avoid artefacts than to correct them.

Artefacts in EEG and MEG Will End Up in Source Space

Eye Blink





This will affect all source estimation methods –
get rid of your artefacts beforehand.

Separating Signal and Noise Components

If signal and noise have characteristic topographies, several methods can be applied to remove (some) noise or extract signals:

• SSP: Signal Space Projection (needs pre-defined topographies)

The following often go under the term “blind source separation”, because the topographies are not pre-defined, and found by the methods themselves (under certain assumptions):

• PCA: Principal Component Analysis

• SVD: Singular Value Decomposition

• ICA: Independent Component Analysis

Signal Space Projection (SSP)

You know the artefact topography **N** and regress it out of your data.

You decompose your data **D**, such that

D = a***N** + **Signal**

You only analyse **Signal.**

This works well with eye-movement and blink artefacts.

Note:

Brain signals whose topographies are highly correlated with **N** will also be removed or attenuated.

PCA and SVD

• Decompose data into **orthogonal** components $\mathbf{T}_1$, $\mathbf{T}_2$, etc. (topographies or time courses), i.e. data

$\mathbf{D} = a*\mathbf{T}_1 + b*\mathbf{T}_2 + \ldots$

• Find the components you don't like (e.g. correlate highly with EOG and ECG, or components that explain little variance).

• Reconstitute your data only with the "good" components,

e.g. $\mathbf{D} = a*\mathbf{T}_1 + c*\mathbf{T}_3 + \ldots$ if component 2 reflects eye blinks.

Also:

• Components have an order according to the variance they explain (e.g. $var(\mathbf{T}_1)>var(\mathbf{T}_2)>\ldots$)

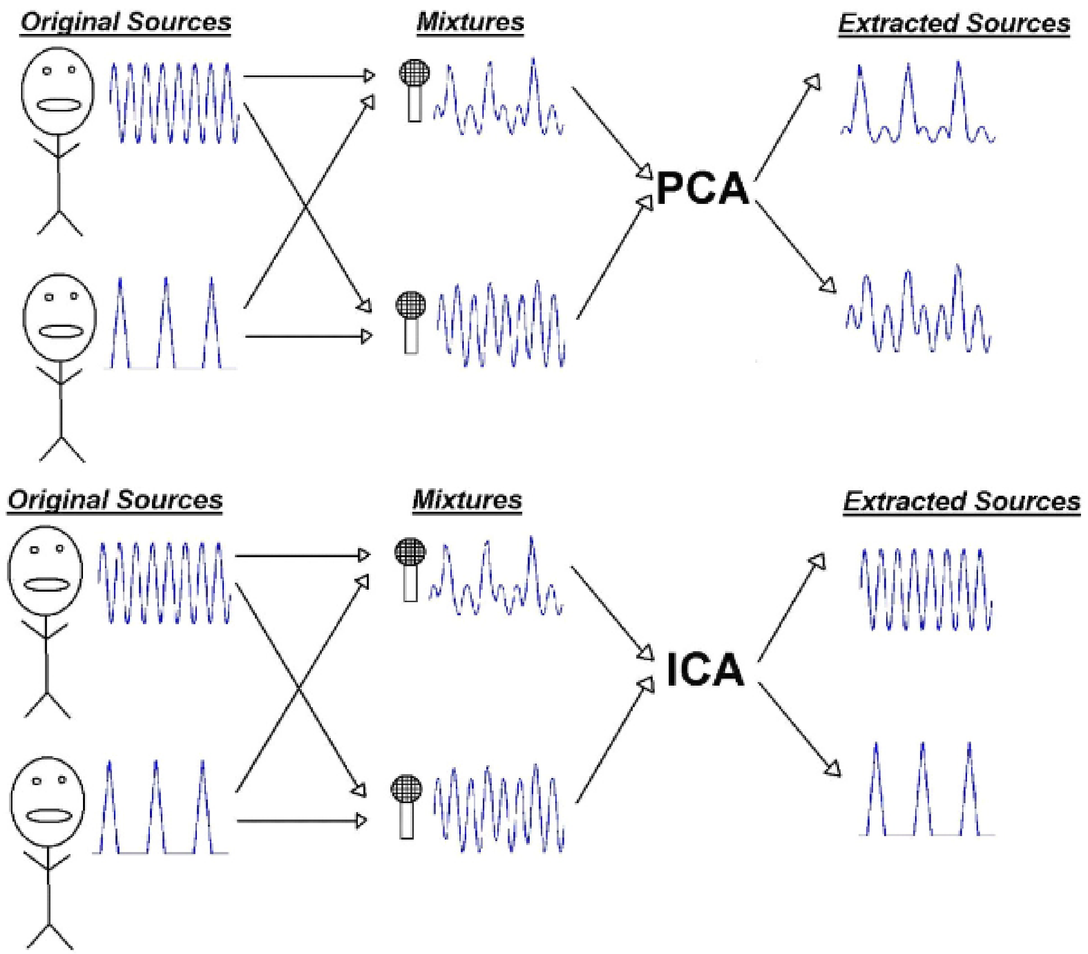
• Can be used to determine the number of independent components (according to specified criteria)

• Relatively fast (try svd() or princomp() in Matlab).

•**Unfortunately: Orthogonality and variance ordering is not physiologically plausible.**

Independent Component Analysis

Example: (De-)mixing of sources in the cocktail party effect



http://www.tqmp.org/Content/vol06-1/p031/p031.pdf

Independent Component Analysis

Basic idea is similar to PCA and SVD:

Decompose data into components $\mathbf{T}_1$, $\mathbf{T}_2$, etc. (topographies or time courses), i.e. data

$\mathbf{D} = a*\mathbf{T}_1 + b*\mathbf{T}_2 + \ldots$

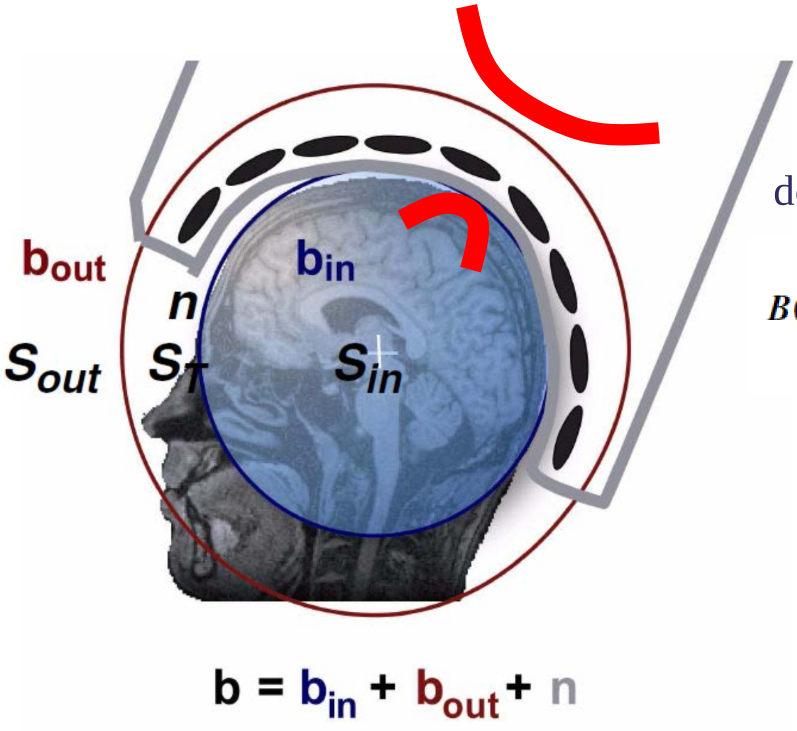
But:

ICA does not produce orthogonal components, and does not assume Gaussianity of signals.

There are number of ICA algorithms available that have been optimised for EEG/MEG data.

They usually work well for example to remove eye movement and heart beat artefacts.

"Maxfilter"
Suppressing Signals From Distant Sources (MEG only)



The mathematical basis of Maxfilter:

decomposition of magnetic field into spherical harmonics)**:**

$$B(r) = -\mu_o \sum_{n=1}^{\infty} \sum_{m=-n}^{n} \alpha_{nm} \frac{\nu_{nm}(\theta, \varphi)}{r^{n+2}} - \mu_o \sum_{n=1}^{\infty} \sum_{m=-n}^{n} \beta_{nm} r^{n-1} \omega_{nm}(\theta, \varphi).$$

$$\nu_{nm}(\theta, \varphi) = -(n+1) Y_{nm} e_r + \frac{\partial Y_{nm}}{\partial \theta} e_\theta + \frac{imY_{nm}}{\sin\theta} e_\varphi,$$

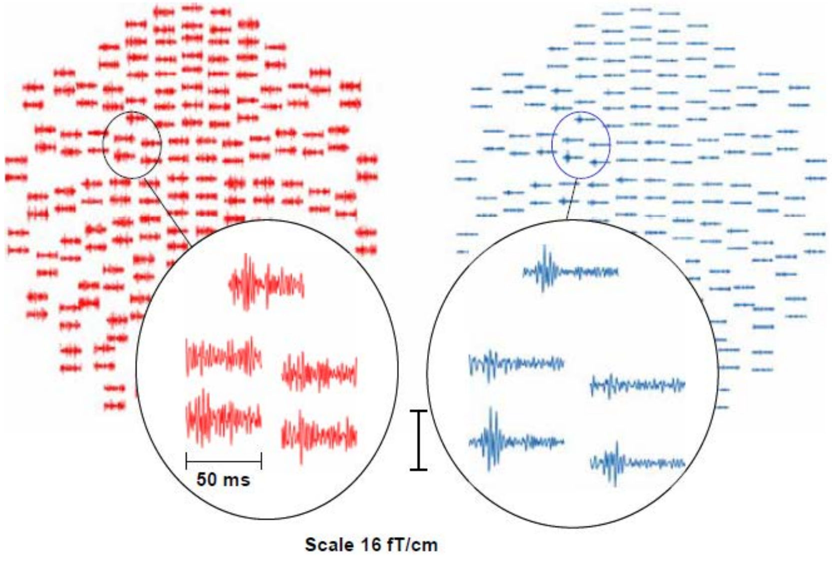
$$\omega_{nm}(\theta, \varphi) = nY_{nm} e_r + \frac{\partial Y_{nm}}{\partial \theta} e_\theta + \frac{imY_{nm}}{\sin\theta} e_\varphi,$$

The measured magnetic field distribution is decomposed into "inside" (the helmet) and "outside" components, and the outside components are removed.

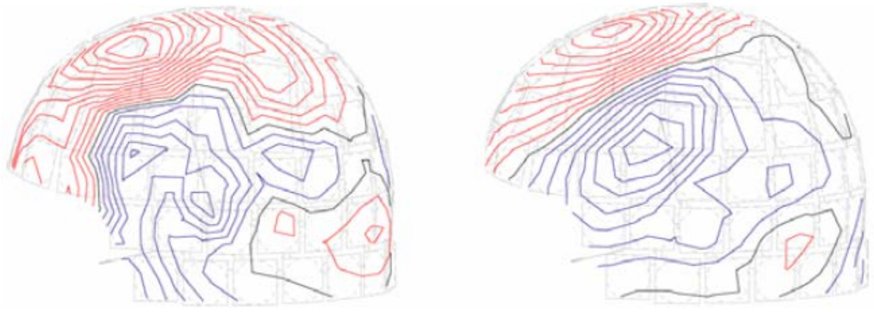
Taulu & Kajola, Journal of Applied Physics 2005

Maxfilter

Without With



Without With



Original Field Map

SSS Reconstructed Field Map

Latency 20 ms
Q = 2 nAm

Taulu & Kajola, Journal of Applied Physics 2005

Maxfilter Software

Software shielding (Signal Space Separation, SSS)
By subtracting the outer SSS components from measured signals, the program suppresses artifacts from distance sources.

Automated detection of bad channels
By comparing the reconstructed sum with measured signals, the program can automatically detect if there are MEG channels with bad data that need to be excluded from Maxwell-filtering.

Spatio-temporal suppression of artifacts (“-st”)
By correlation the time courses of SSS artefact components with the cleaned signal, the program can identify and suppress further artefacts that arise close to the sensor array.

Notch Filter to remove 50/60 Hz line noise.

Transformation of MEG data between different head positions (“-trans”)
By transforming the inner components into harmonic amplitudes (i.e. virtual channels), MEG signals in a different head position can be estimated easily.

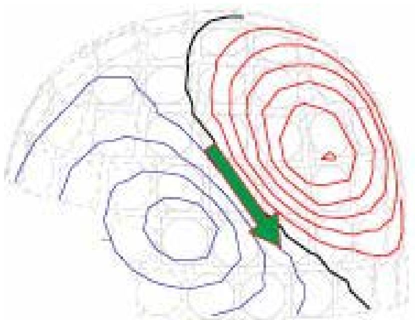
Compensation of disturbances caused by head movements (“-movecomp”)
By extracting head position indicator (HPI) signals applied continuously during a measurement, the data transformation capability is utilized to estimate the corresponding MEG signals in a static reference head position.

Maxfilter – Movement Compensation

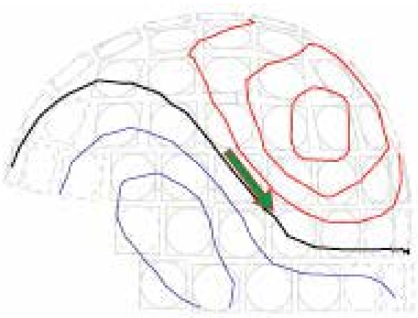
Head movement is tracked continuously (well, every 200 ms) via HPI (Head Position Indicator) coils.

We can take Maxfilter parameters from any time point t,
and estimate the MEG signals at sensor positions of time point t_0.

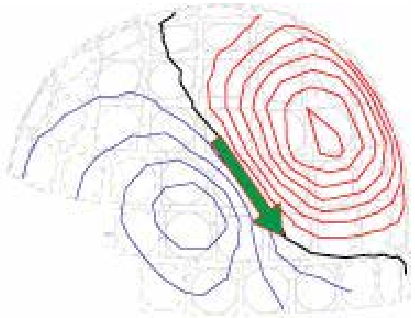
This compensates – to some degree – for spatial variation caused by head movements.



Stable subject



Moving subject,
No compensation



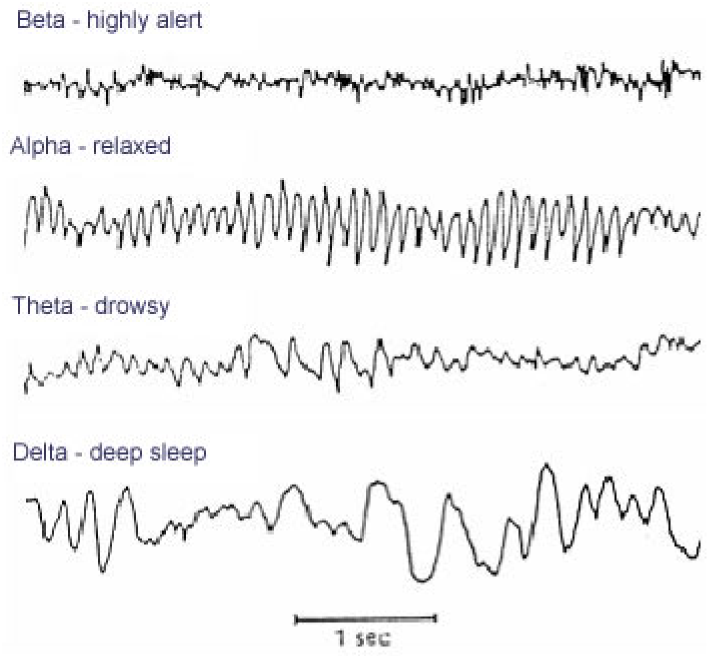
Moving subject,
with compensation

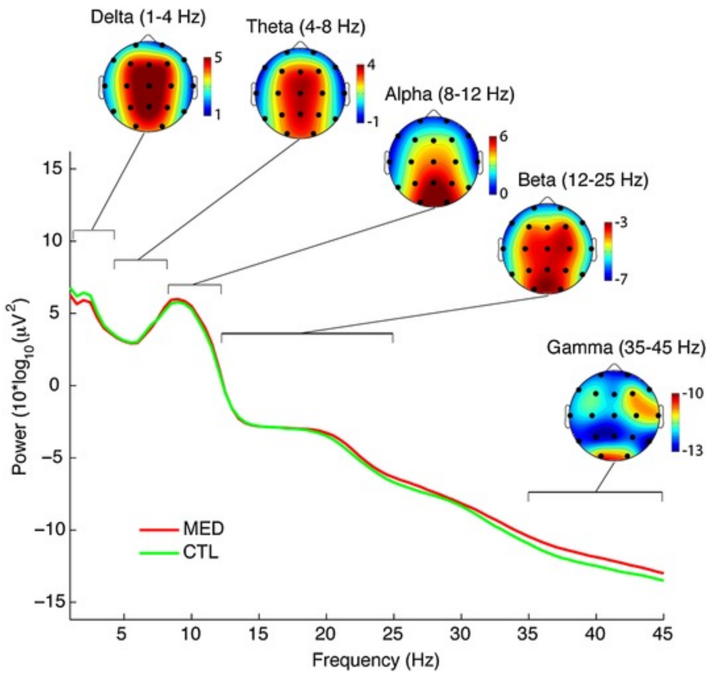
Data Pre-Processing
Frequency and Time-Domain Filtering

Frequency Spectrum of EEG Data

Time course and topography may differ among different frequency bands

(and may depend on task, environment, subject group etc.)

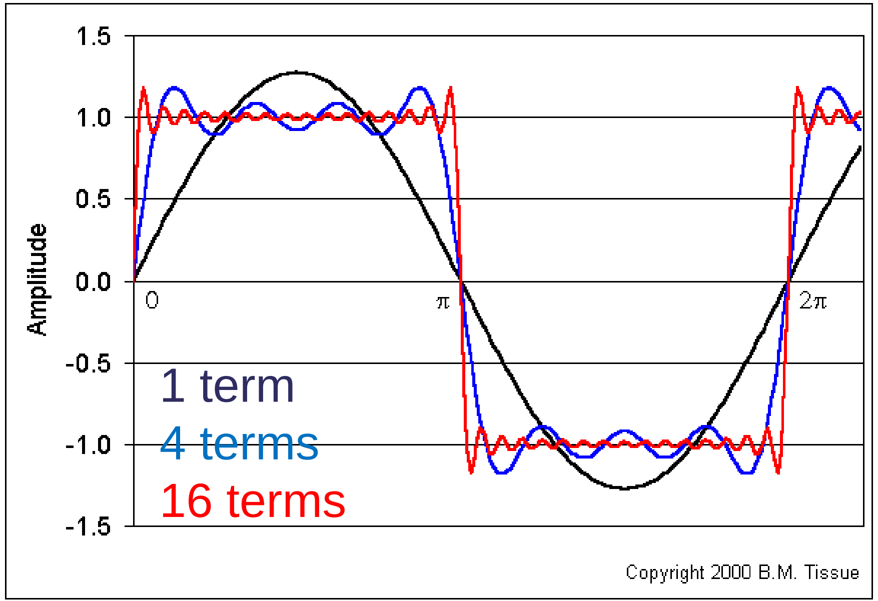




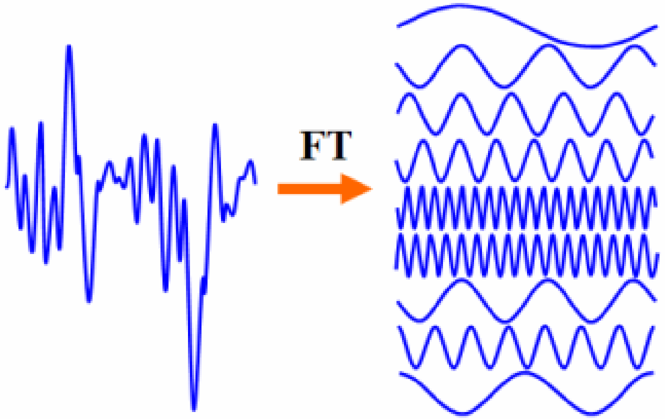
Cahn et al., Cogn Proc 2010, http://link.springer.com/article/10.1007%2Fs10339-009-0352-1/

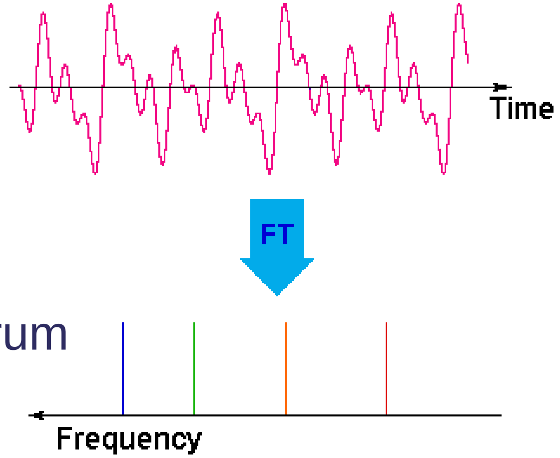
Time-Domain Signals Can Be Represented in the Frequency Domain - and Vice Versa

Approximating a step function
with Fourier terms



Decomposing signals
into sine/cosine terms





Frequency Spectrum

Basic Principals of Frequency Filtering

If you signals of interest and artefacts occur in separate frequency bands:

- Decompose your signal into its frequency spectrum
- Remove the part of the frequency spectrum that represents artefacts
- Recompose your time domain signal from the remaining frequency spectrum

Examples:

- Line Noise from electrical equipment (50 or 60 Hz): Notch filter
- Muscle artefacts are commonly high frequency (> 30 Hz): Low-pass filter

Basic Principals of Frequency Filtering

Unfortunately, signal and artefacts often overlap in the frequency domain (e.g. eye movements, head movements, heart activity). Thus:

- Avoid artefacts wherever possible
- Control for artefacts (e.g. EOG electrodes, movement parameters)
- Use spatial artefact correction methods where appropriate (ICA, Maxfilter, etc.)

Basic Principals of Frequency Filtering

Filtering changes the time course of your data. Thus:

“Filter as much as necessary but as little as possible.”

Common types of filters:

“High-pass”: Lets higher frequencies pass, suppressses lower frequencies (incl. “detrending”)

“Low-pass”: Lets lower frequencies pass, removes higher frequencies

“Band-pass”: Lets frequencies within a frequency band pass, suppresses frequencies above and below the band

“Notch” filter: A very sharp band-pass filter, e.g. for 50 or 60 Hz line noise

(e.g. Cheveigen & Nelken, Neuron 2019, https://www.sciencedirect.com/science/article/pii/S0896627319301746), Widmann et al., Journal of Neuroscience Methods 2015, https://www.sciencedirect.com/science/article/pii/S0165027014002866, Tanner et al., Psychophysiology 2016, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4506207/).

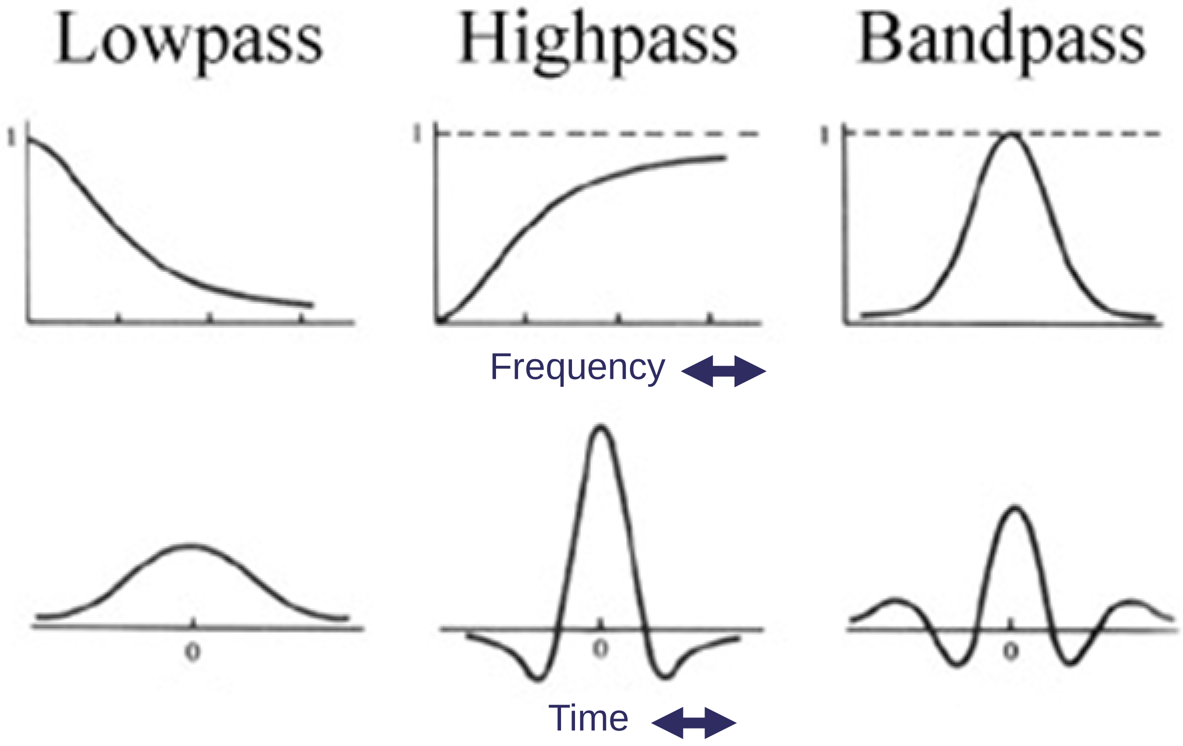
Basic Principals of Frequency Filtering

Time-domain and frequency-domain filtering are two sides of the same coin:

One type of frequency-domain filtering corresponds to one type of time-domain filtering.

Frequency domain

Time domain

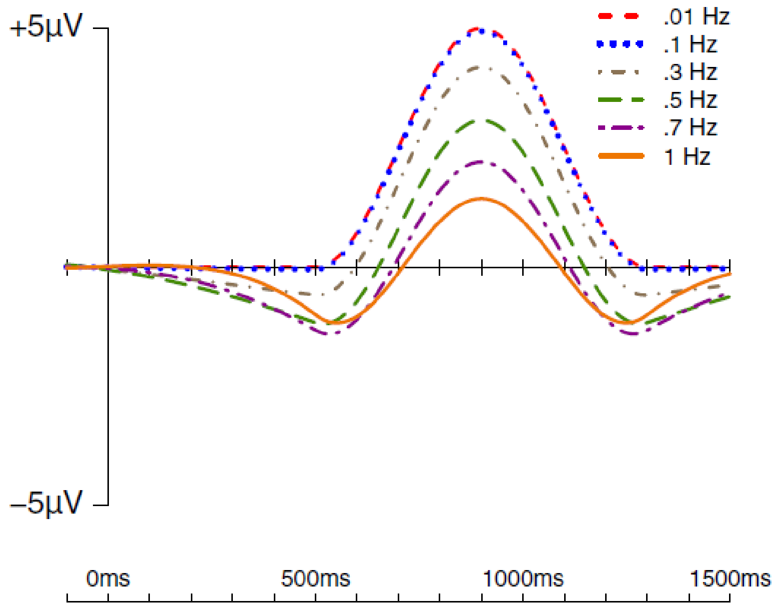


https://uk.mathworks.com/matlabcentral/fileexchange/51155-time-domain-filtering-vs-frequency-domain-filtering-in-images

Filtering can affect both signal and artefact

High-pass filtering:

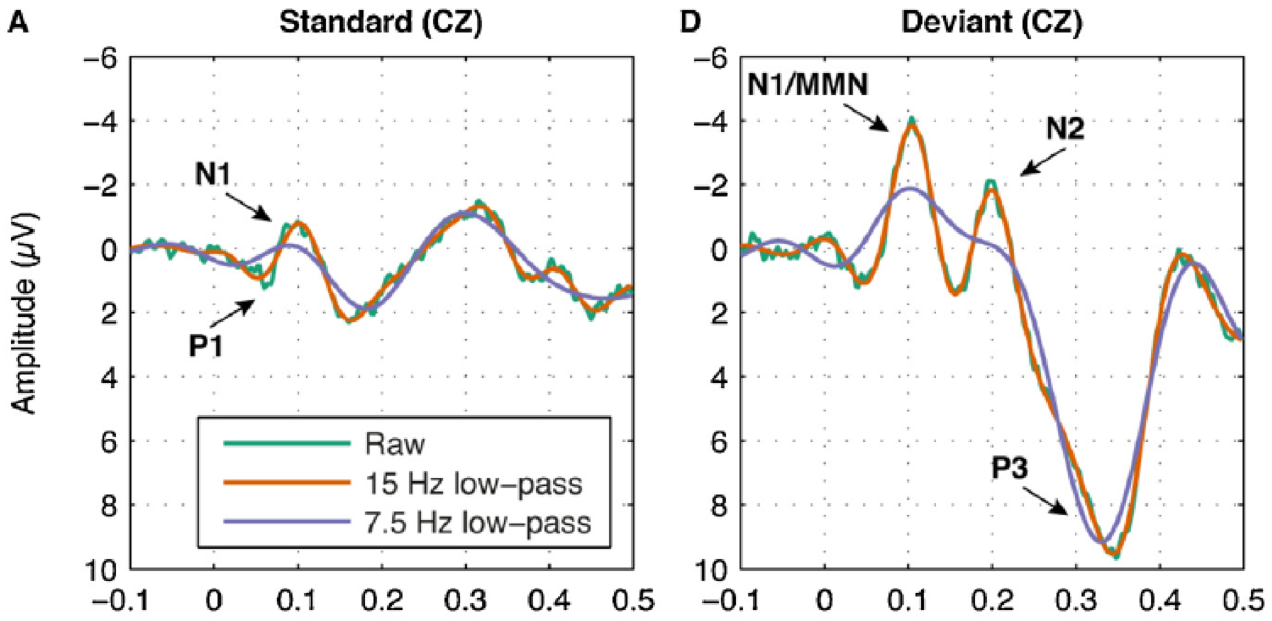
“(linear/polynomial) Detrending”
“Removing slow drifts”



Tanner et al., Psychophysiology 2016,
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4506207

Low-pass filtering:

“Smoothing”

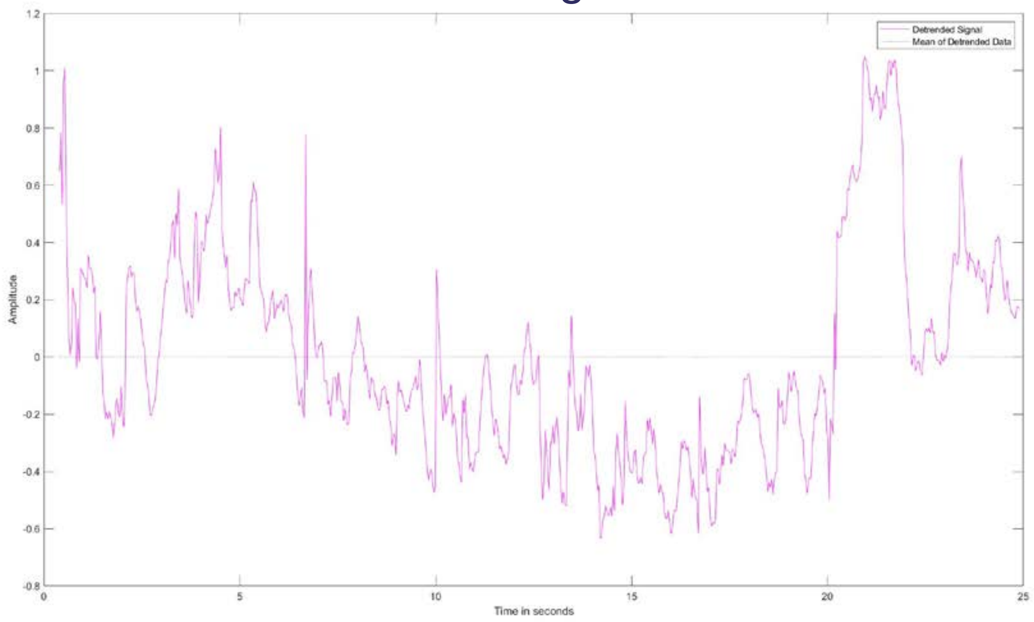


Widmann et al., Journal of Neuroscience Methods 2015,
https://www.sciencedirect.com/science/article/pii/S0165027014002866

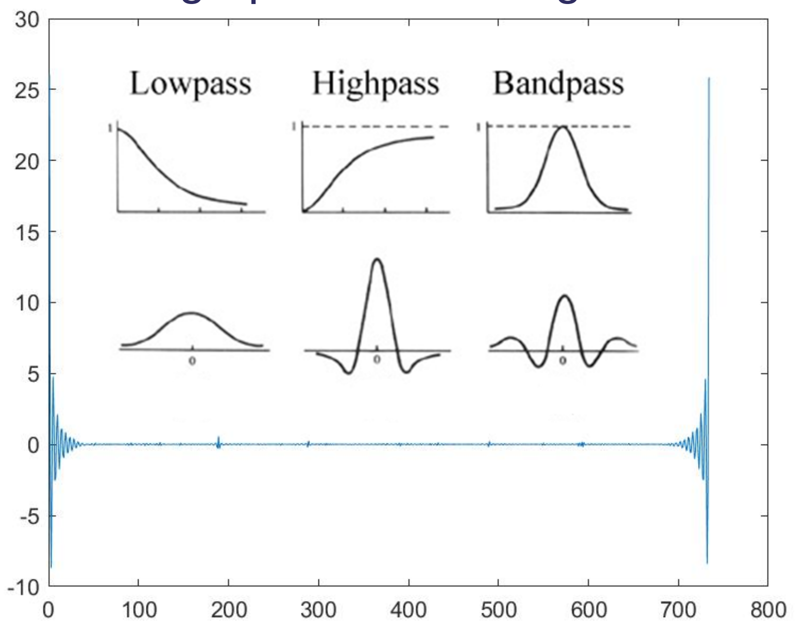
Edge Artefacts of Filters

- Filtering artefacts occur at signal discontinuities, e.g. at the beginning and the end of the data.
- Thus, filter the “longest possible data segment”, ideally the raw data as early as possible.
- If you have to filter epochs, consider filtering longer epochs than you actually need.
- Be careful with “effects” close to the border of epochs.

Raw signal



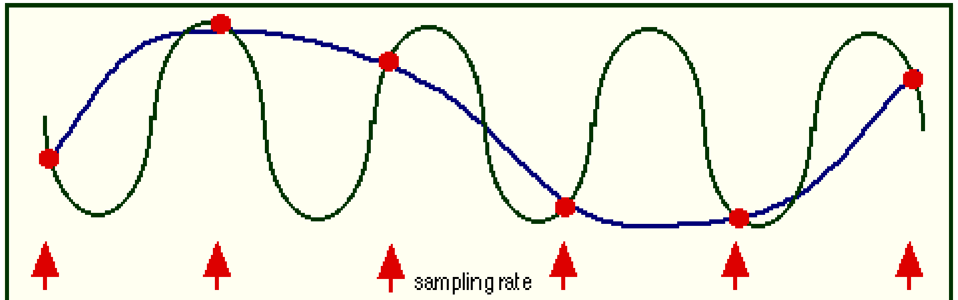
High-pass filtered signal



Filtering and Downsampling: “Aliasing”

- Downsampling can lead to “aliasing” if the data are not filtered appropriately (Nyquist theorem): Filter at least below half of the sampling frequency before downsampling.

Aliasing



Aliasing produces waveform (blue) at 1/4 the original signal's frequency (green).

Also watch:
https://www.youtube.com/watch?v=R-IVw8OKjvQ
Thanks to Alessandro.

Thank you