EEG/MEG 1:
Measurement, Pre-Processing and Data Reviewing

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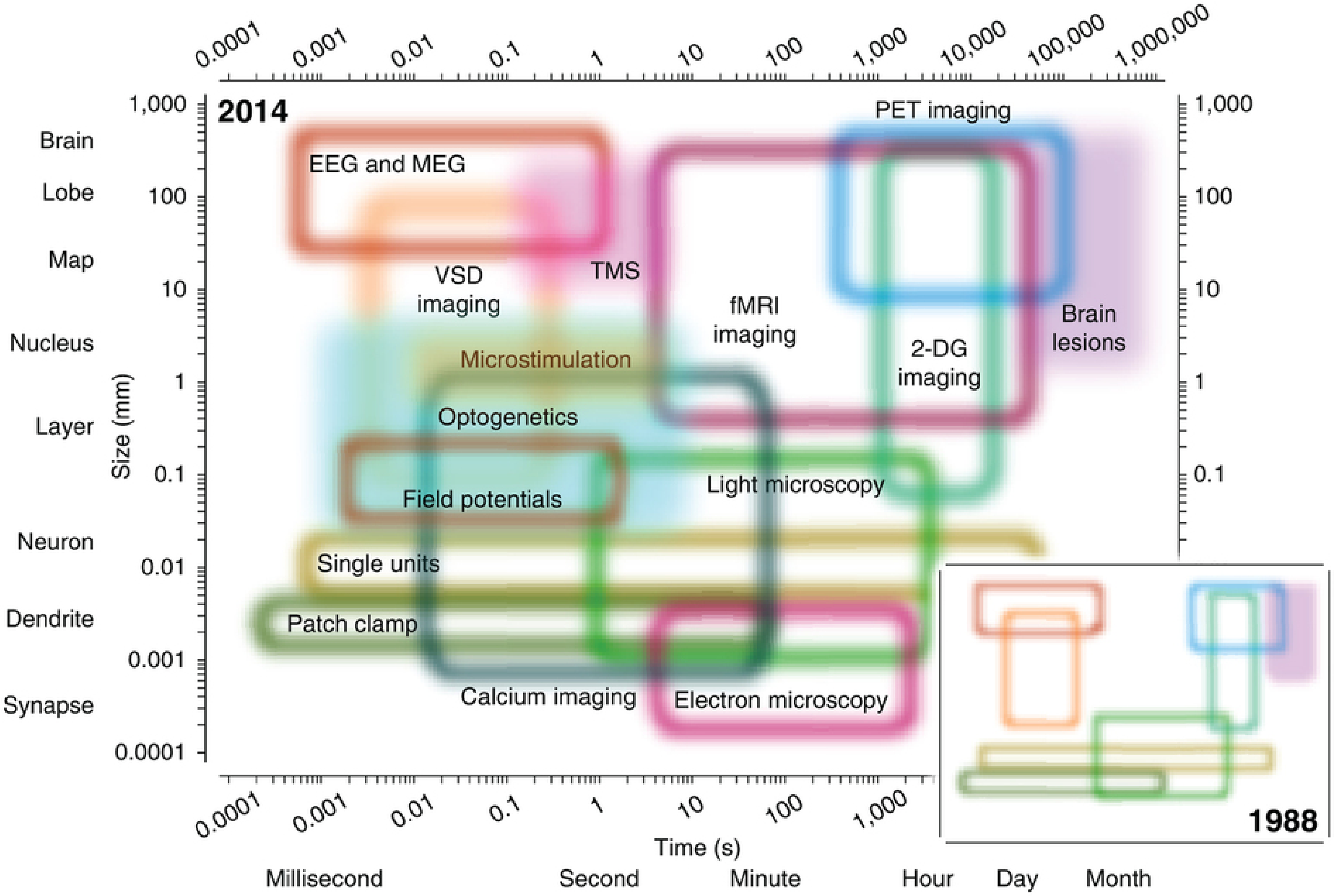
http://imaging.mrc-cbu.cam.ac.uk/methods/IntroductionNeuroimagingLectures

A Big Picture: Spatial vs Temporal Resolution

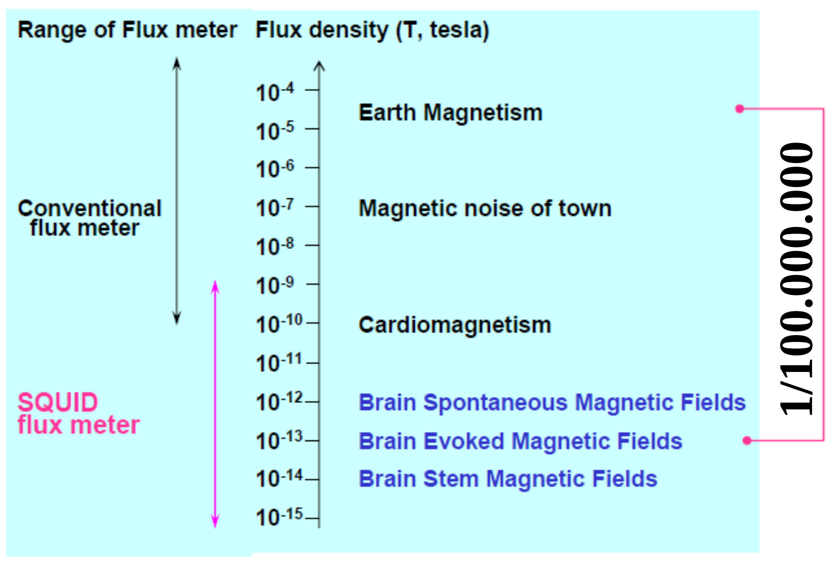


Seijnowki, Churchland, Movshon, Nat Nsc 2014

What We are Measuring

Magnetoencephalography (MEG)

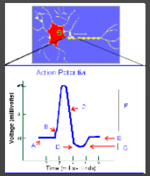
Tiny magnetic fields



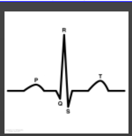
Electroencephalography (EEG)

Small electric potentials

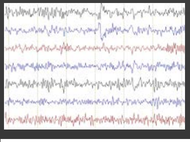
Household Batteries
~ 1-12 V



Cell Membrane Potentials
~ 70 mV



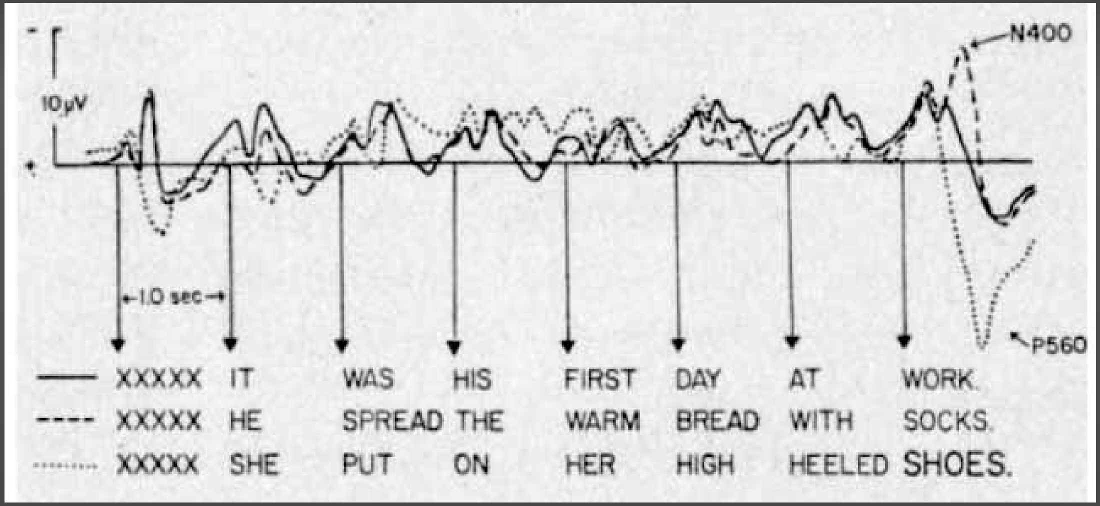
ECG:
~ 1mV



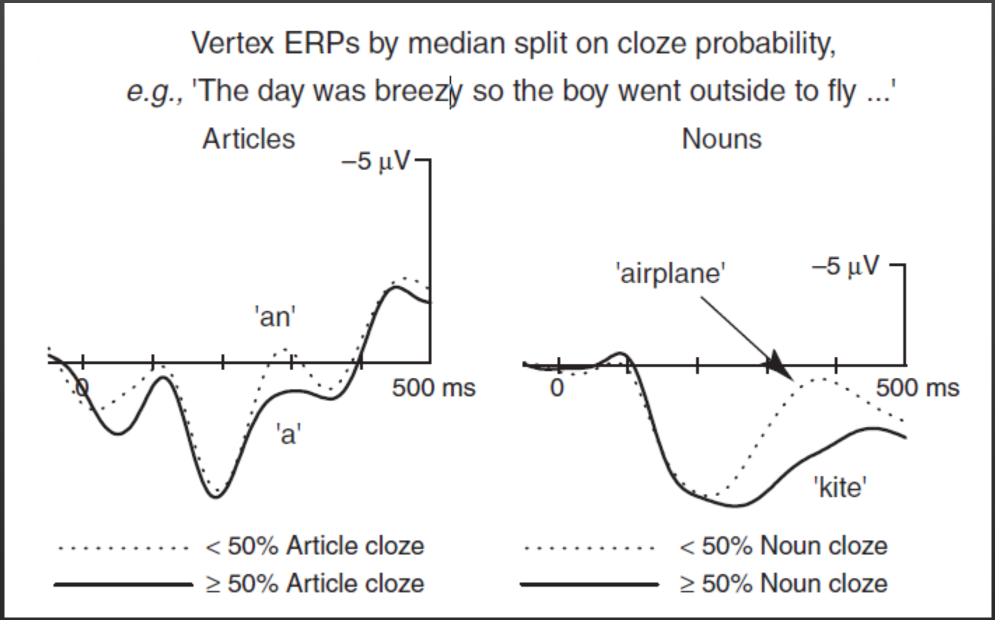
Raw EEG: ~ 30 µV
Eye blinks: > 100 µV

ERPs: ~ 0-10 µV

When Timing Is Of The Essence:



Kutas&Hillyard, Science 1980



deLong, Urbach, Kutas, Nat Nsc 2005

EEG/MEG Introductory Literature

http://imaging.mrc-cbu.cam.ac.uk/meg/MEGpapers

Books:
Hansen, Kringelbach, Salmelin: “MEG: An Introduction to Methods”, OUP 2010
SJ Luck: “An Introduction to The Event-Related Potential Technique”, MIT 2005
TC Handy: “Event-Related Potentials”, MIT 2004

Guidelines for MEG and EEG research:
Gross et al., “Good practice for conducting and reporting MEG research.“, Neuroimage 2013
Picton et al., “Guidelines for using human event-related potentials to study cognition: recording standards and publication criteria.“, Psychophysiology 2000

Timing Is Essential

… so here is a bit of history:

Ancient Egypt, 2750 BC:

Electric Fish ("Thunderer of the Nile")
Some Roman writers mention electric shocks as an ailment for headaches (~ 0 AC)...

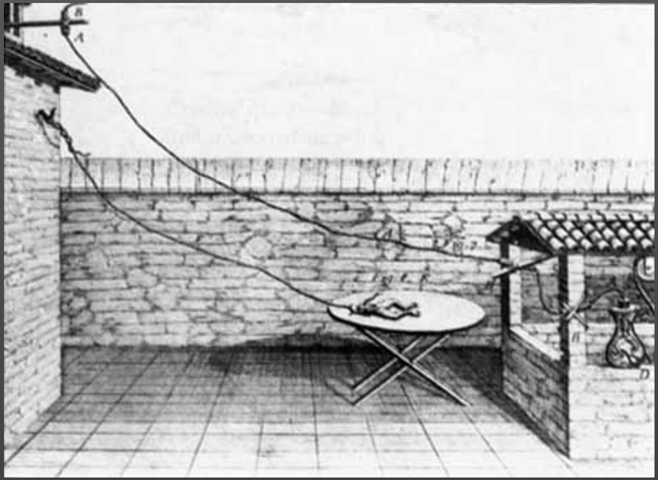
Ancient Greece, 600 BC:

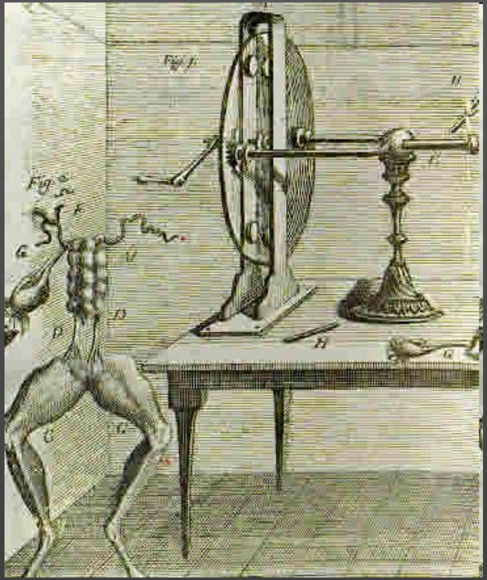
Thales describes static electricity
"electron"

Early Science

1771

Luigi Galvani, Bologna, “animal electricity”





In 1803:

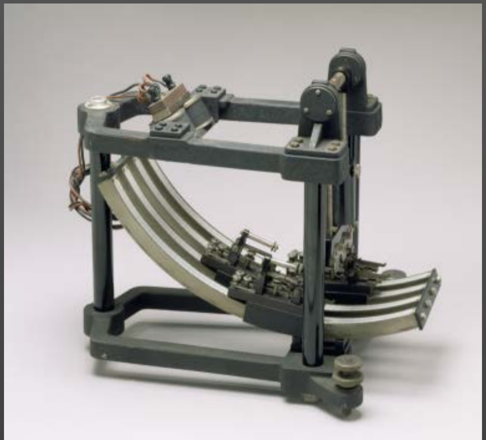
“On the first application of the process to the face, the jaws of the deceased criminal began to quiver, and the adjoining muscles were horribly contorted, and one eye was actually opened. …

Mr Pass, the beadle of the Surgeons’ Company, who was officially present during this experiment, was so alarmed that he died of fright soon after his return home.”

http://www.executedtoday.com/2009/01/18/1803-george-foster-giovanni-aldini-galvanic-reanimation/

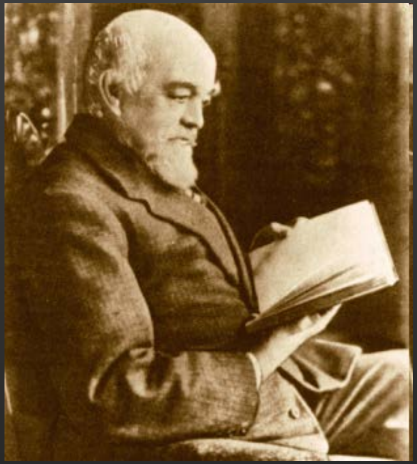
Early Electrophysiology

1842: Du Bois-Reymond, Berlin
nerve action potentials
neurons



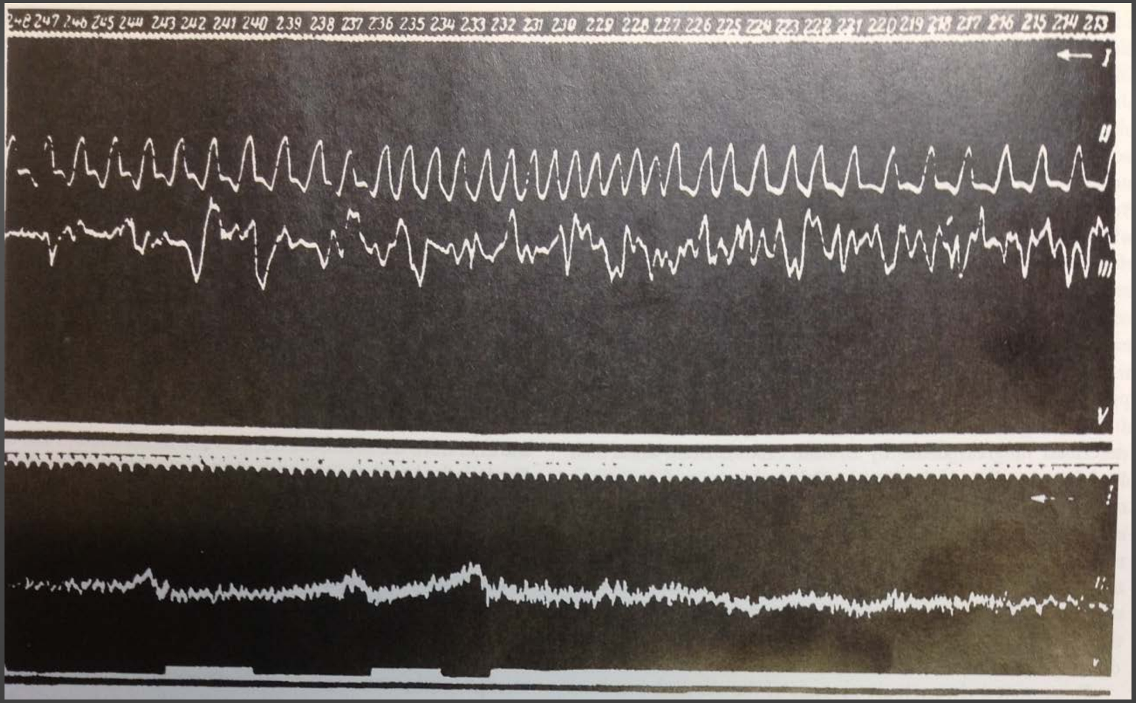
1852: Helmholtz, Berlin
speed of action potentials in frogs
neurons

1875: Richard Caton, Liverpool
first “ECoG” from animals



http://www.sciencemuseum.org.uk/broughttolife/objects/display.aspx?id=4360

Early EEG



Time marker

Artery pulsation

Brain potential

Response to sciatic nerve stimulation

Stimulation signal

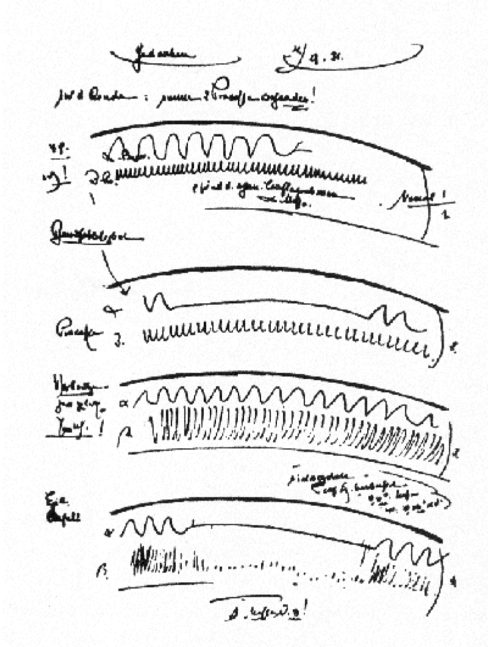
“Danilevsky (1852-1939) … finished his thesis entitled “Investigations into the Physiology of the Brain (1877). … He published an extensive textbook of human physiology in 1915. … He saw his high hopes unfulfilled as far as the spontaneous electrical activity of the brain was concerned. … He was not the only EEG researcher with shattered hopes in the field of psychophysiology”.
From: Niedermeyer and Schomer, 2011

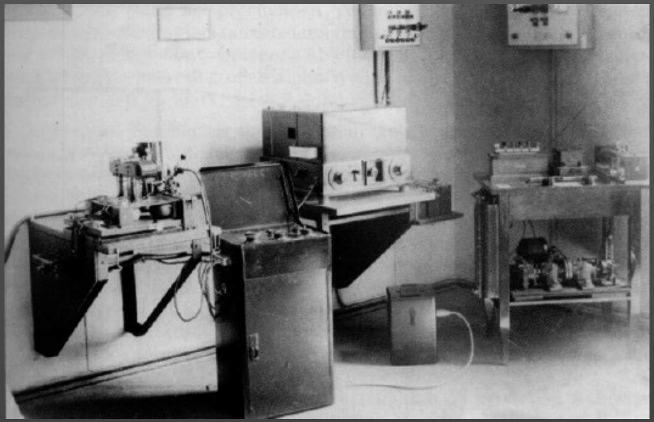
Pravdich-Neminsky, 1913

Early EEG

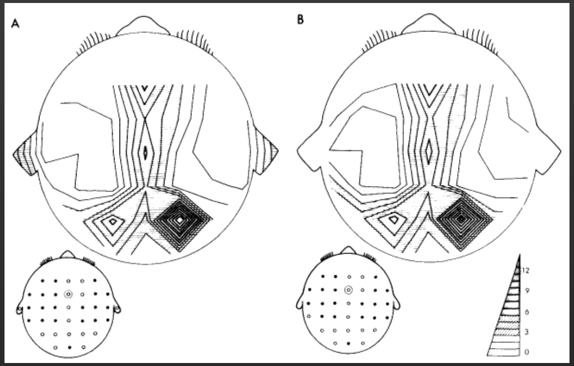
Hans Berger, Jena 1924

First Fourier Analysis of EEG: Berger&Dietsch 1931



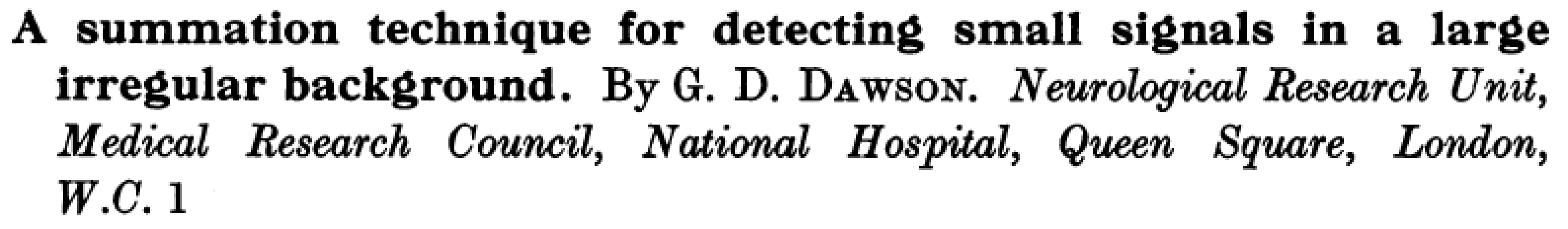


1969/70: 32/48-channel EEG, “generators”



Lehmann, 1971

Early ERPs



A summation technique for detecting small signals in a large irregular background. By G. D. Dawson. *Neurological Research Unit, Medical Research Council, National Hospital, Queen Square, London, W.C.* 1

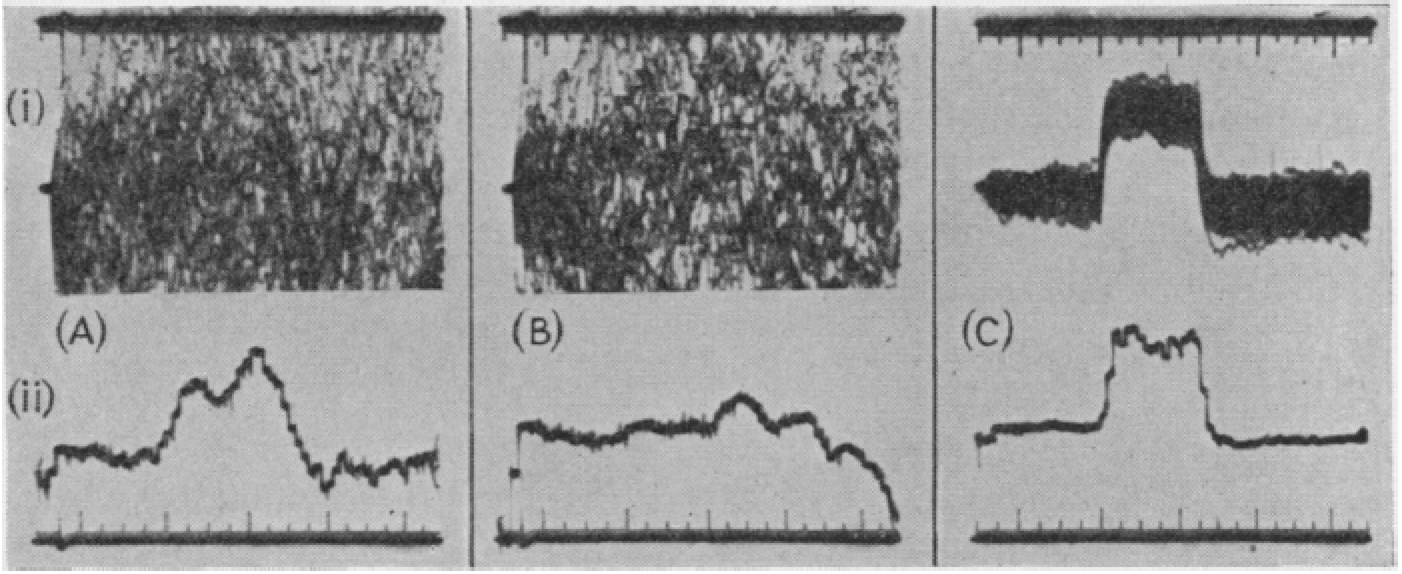


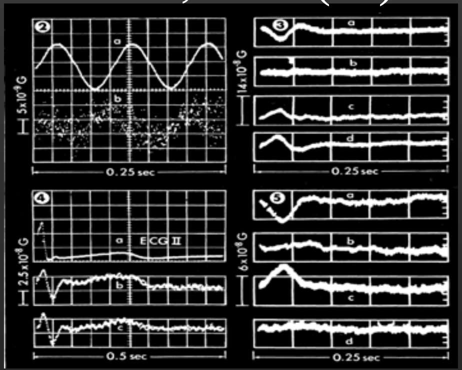
Fig. 1. An experiment to detect cerebral responses when the left ulnar nerve was stimulated at the wrist once per second. The upper line of traces shows sets of 55 records superimposed and the lower line the averages of these given by the machine. In A, from the contralateral scalp, there was one electrode on the midline and one over the right central sulcus. In B, from the ipsilateral scalp, the record was taken from the same midline electrode and one over the left central sulcus. In C is shown the result of making the electrode over the central sulcus positive to that on the midline by 5 μV. The largest spikes in the time scales show intervals of 20 msec., and the stimulus was applied 5 msec. after the start of each sweep.

Dawson, Proceedings of the Physiological Society, 1951

First MEG: Pre-SQUID age

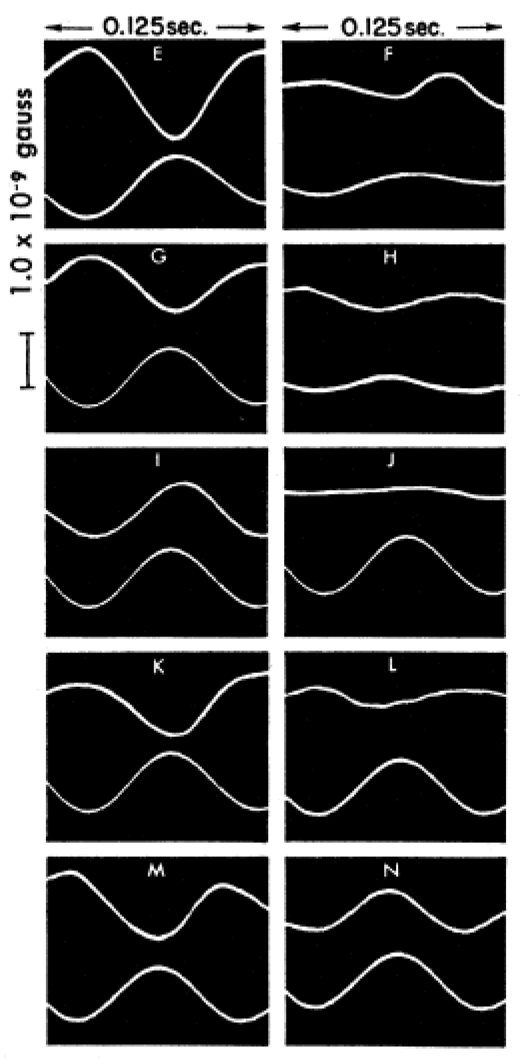
MEG pioneers
MIT

MCG, 1967/(63)



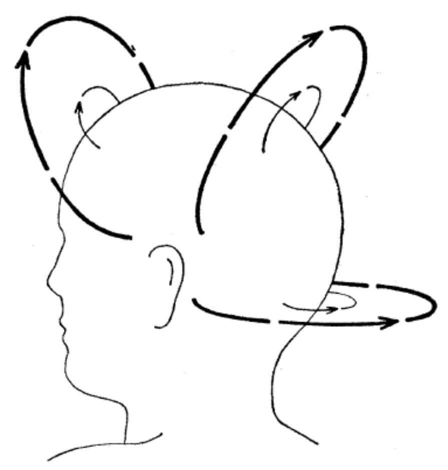
Cohen, Science 1967

MEG, 1968

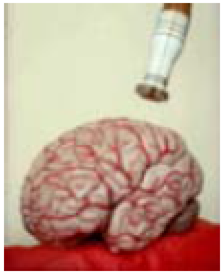


Cohen, Science 1968

Alpha Rhythm

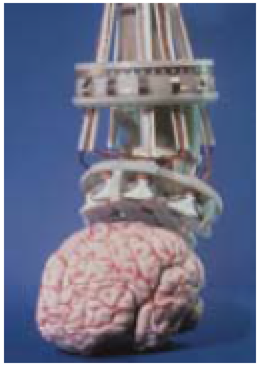


The Fast Evolution of MEG



1983
by HUT
4 channels
30 mm in diameter
(coverage: 7 cm^2)
Axial

1986
by HUT
7 channels
93 mm in diameter
(coverage: 68 cm^2)
Axial



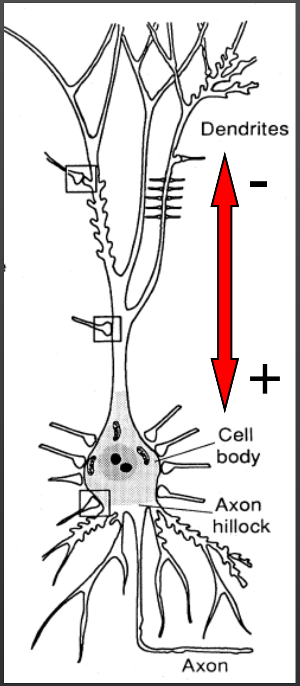
1989
by HUT
24 channels
125 mm in diameter
(coverage: 123 cm^2)
Planar

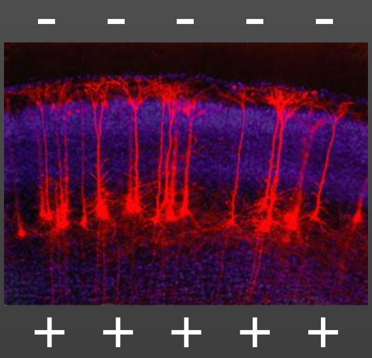
1991
by Neuromag
122 channels
whole head
(coverage: 1100 cm^2)
Planar
12 Deliveries

1997
by Neuromag
306 channels
whole head
(coverage: 1220 cm^2)
Planar &
Magnetometers

Main Generators of Electrical Activity in the Brain

- **Apical dendrites of pyramidal cells**
- **NOT action potentials** (too short-lived and quadrupolar)
- **EEG/MEG: same generators, different sensitivity**

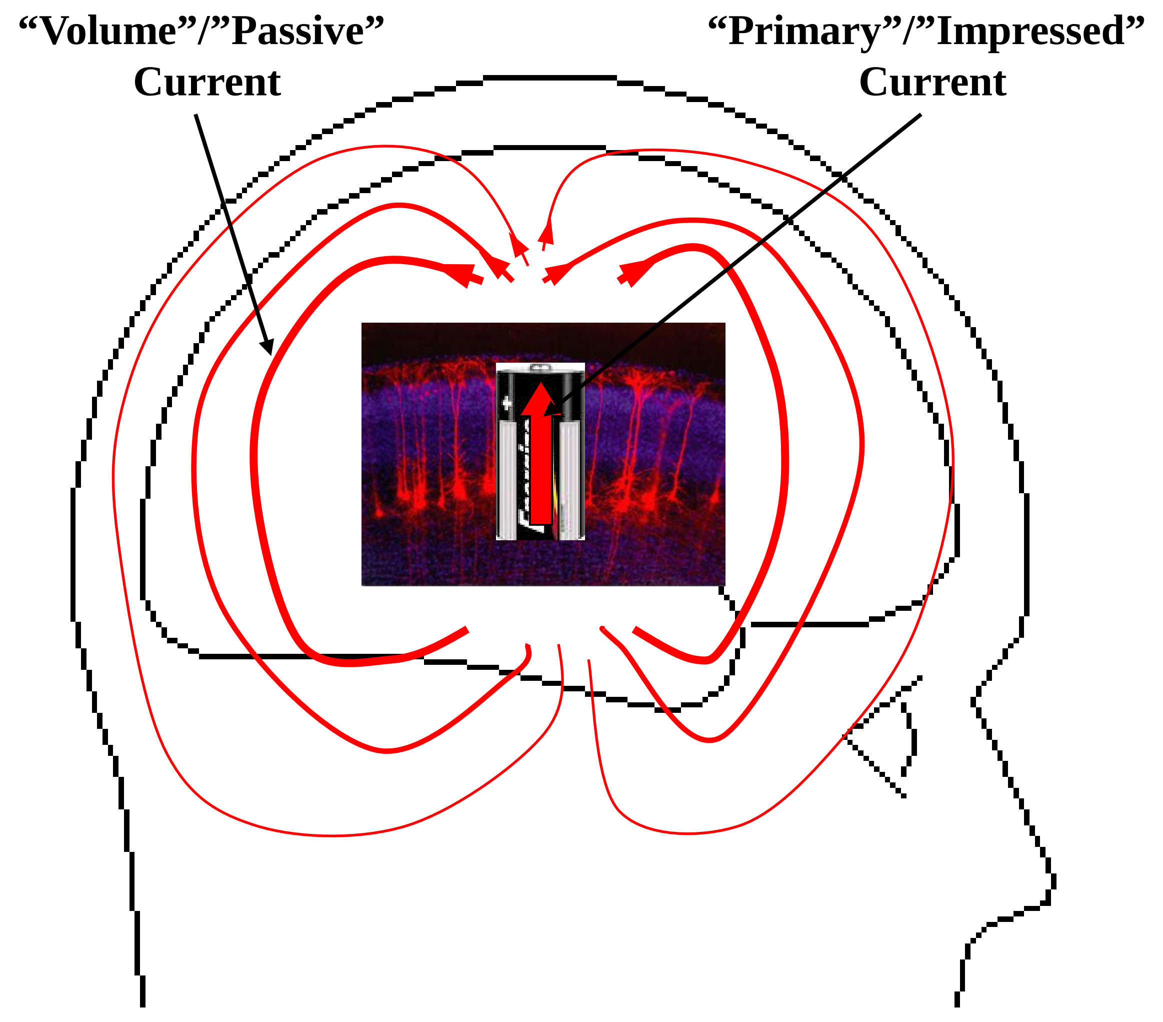




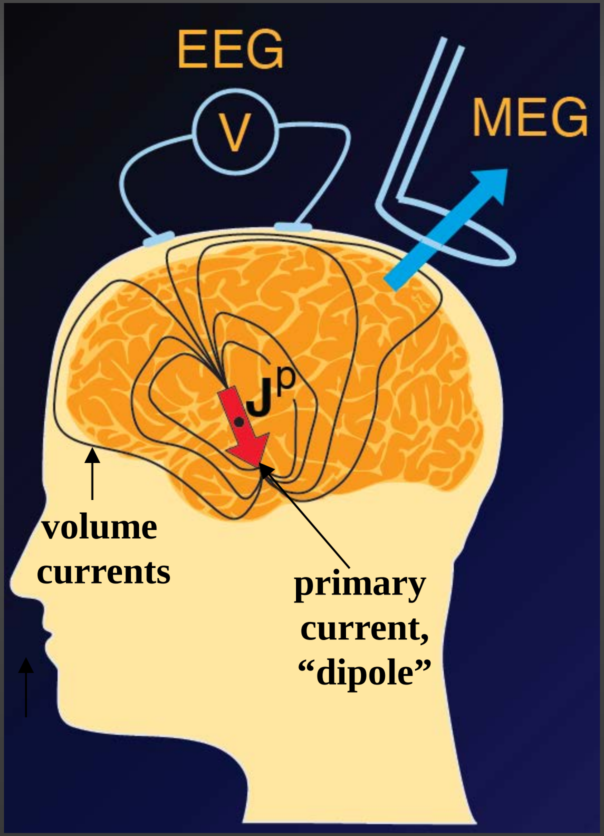
- ~ 1 Million synapses needed to activate simultaneously
- Luckily: ~10000 cells per mm^2, ~ 1000 synapses per cell

=> several mm^2 can produce measurable signal

Current Flow in the Head



EEG/MEG Measurements



Volume currents affect both EEG and MEG –

but EEG more than MEG

http://www.nmr.mgh.harvard.edu/meg/pdfs/talks/

The Neuromag Vectorview System

306 channels in 102 locations

1 magnetometer and 2 planar gradiometers at each location

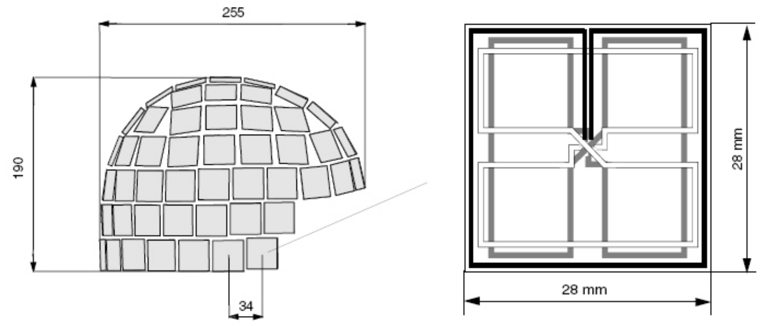
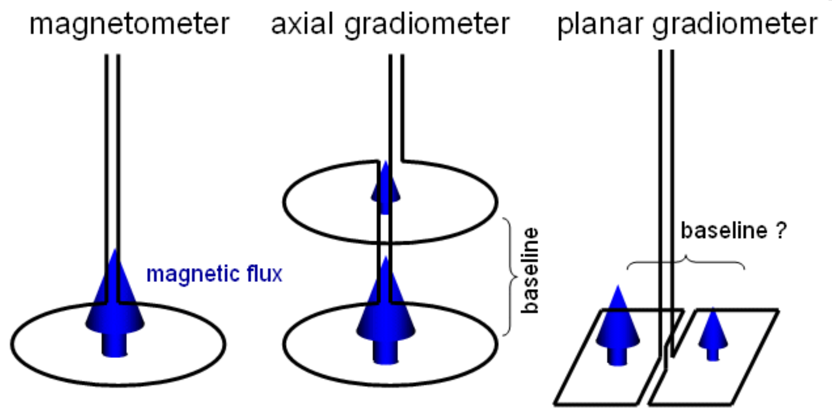


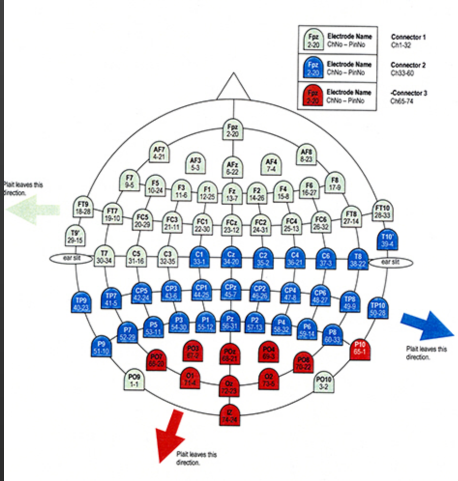
Figure 1.6. (left) Detector array, side view. Average distance between sensor elements : 34,6 mm. (right) Triple sensor detector unit.

MEG sensor types



http://meg.aalip.jp/scilab/CoilType.html

Up to 120 EEG electrodes (we typically use 70, plus EOG/ECG)



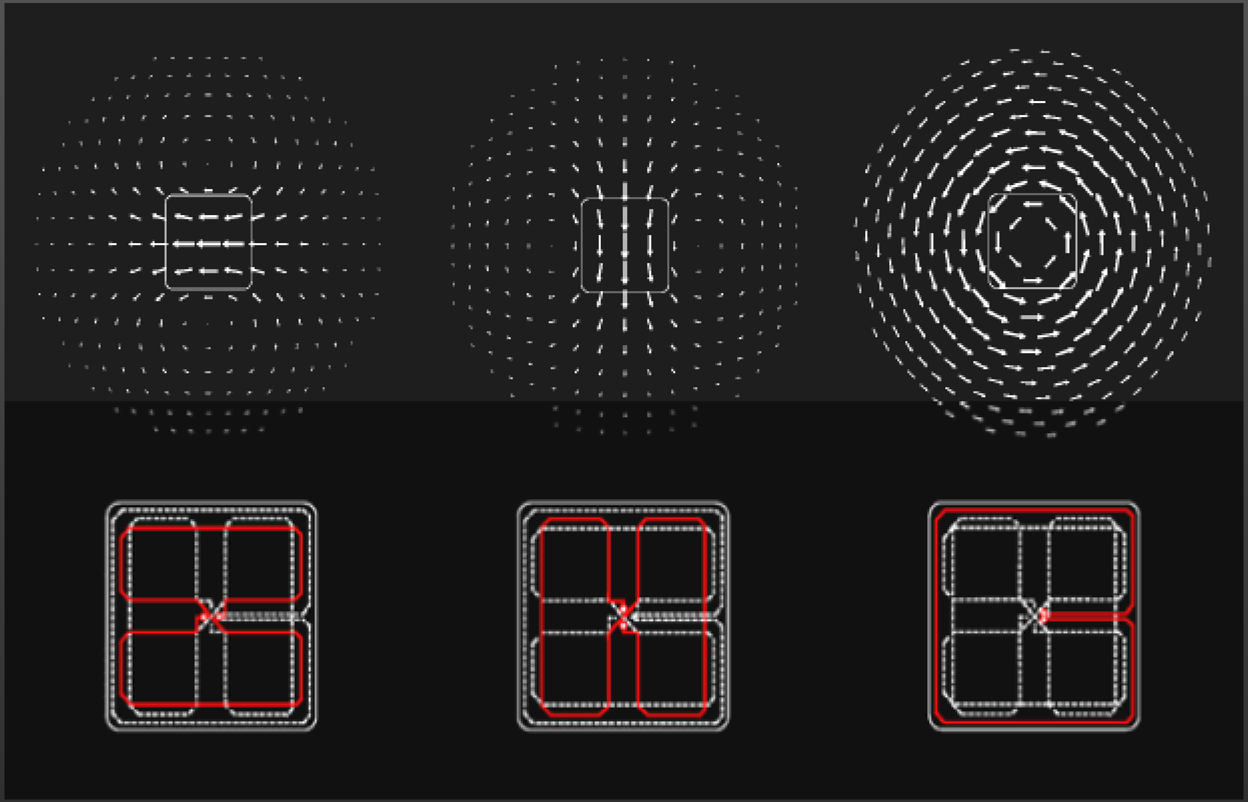
http://imaging.mrc-cbu.cam.ac.uk/meg/VectorviewDescription

Leadfields

Leadfields are sensitivity profiles of individual sensors.

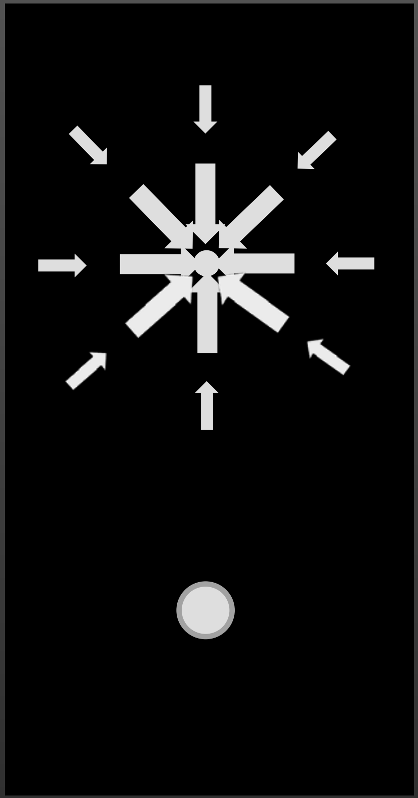
Each sensor is maximally sensitive to sources oriented along the arrows, and insensitive to sources perpendicular to the arrows.

Gradiometer | **Gradiometer -** **Magnetometer**



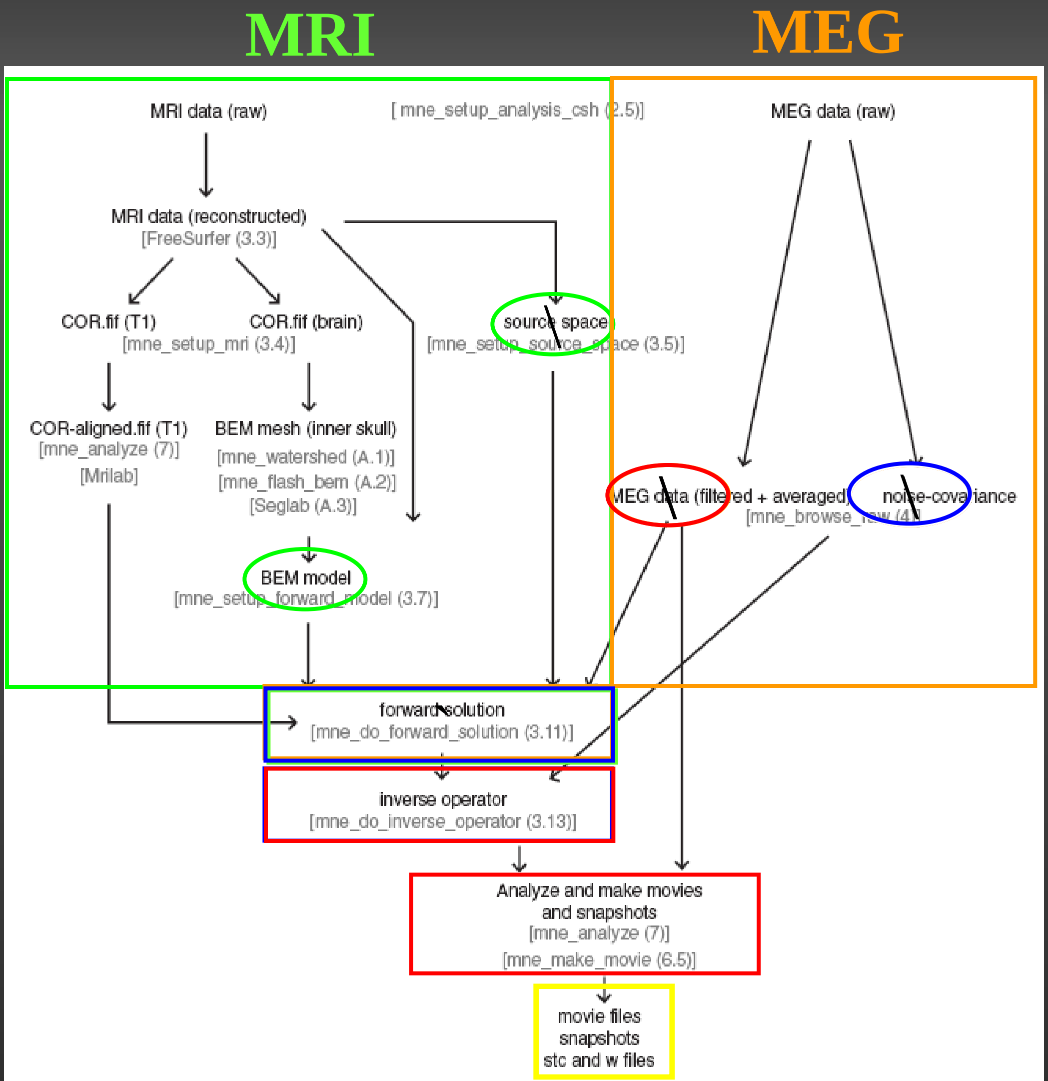
The “right-hand-rule” comes in handy here.

EEG



This bit I made up.

Typical EEG/MEG Analysis Pipeline



Artefacts

Artefacts can be

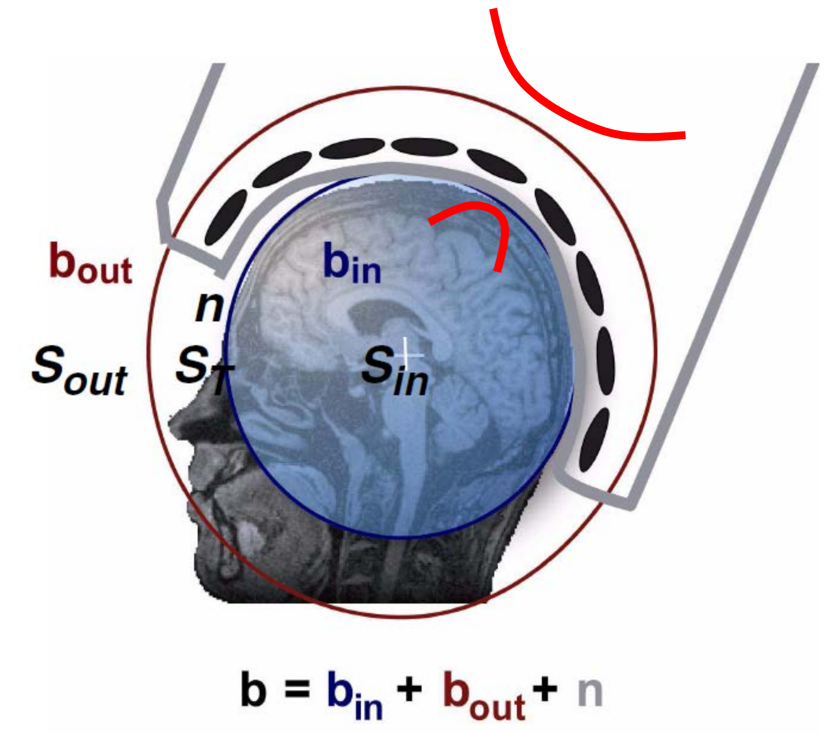
- **non-physiological,** i.e. from outside the body (sensor-intrinsic noise, line noise, moving objects, vibrations)
  => Maxfilter (SSS), Frequency-Filtering, SSP, PCA/ICA

- **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.”
It’s always better to avoid artefacts than to correct them.

Maxfilter



Maxmagic (spherical harmonics)**:**

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

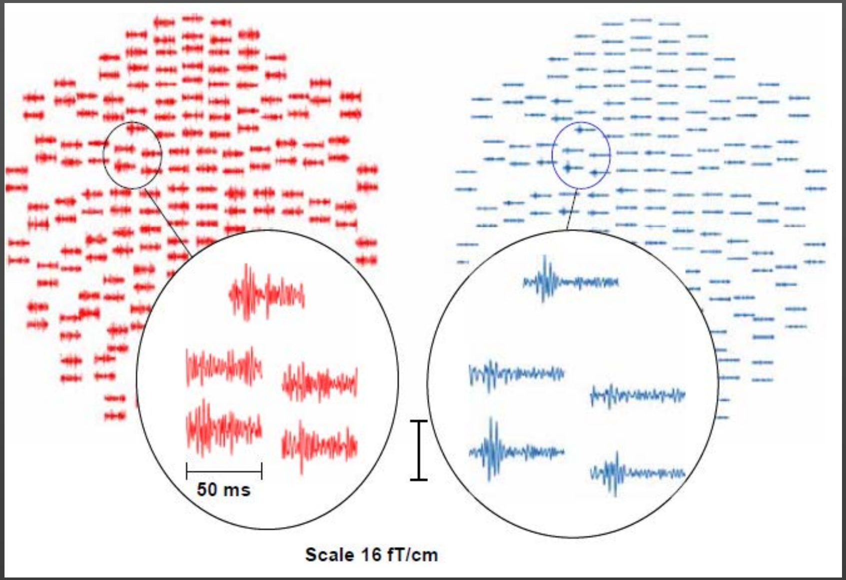
$$\nu_{nm}(\theta, \varphi) = -(n+1) Y_{nm} e_r + \frac{\partial Y_{nm}}{\partial \theta} e_\theta + \frac{i m Y_{nm}}{\sin\theta} e_\varphi,$$

$$\omega_{nm}(\theta, \varphi) = n Y_{nm} e_r + \frac{\partial Y_{nm}}{\partial \theta} e_\theta + \frac{i m Y_{nm}}{\sin\theta} e_\varphi,$$

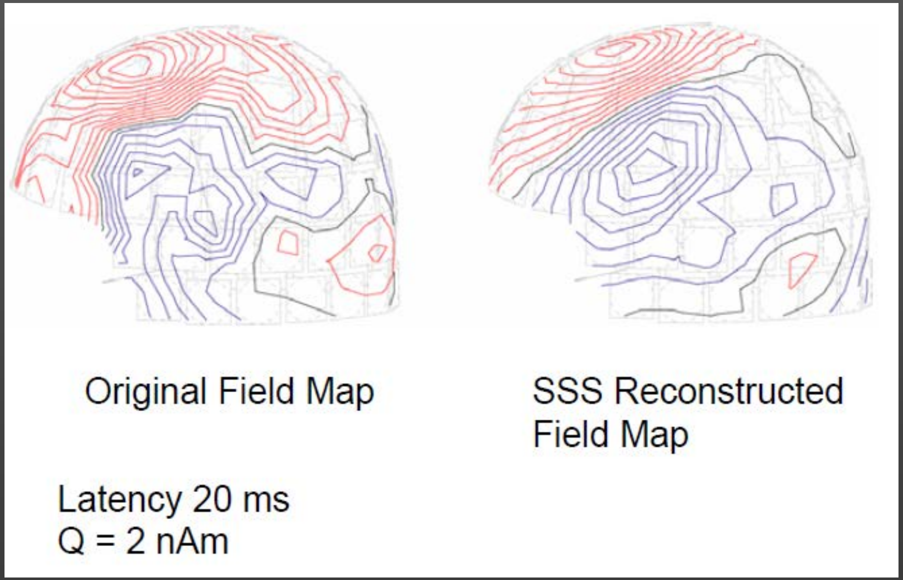
Elekta Neuromag

Maxfilter

Without With



Without With



Elekta Neuromag

Maxfilter

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 50Hz 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.

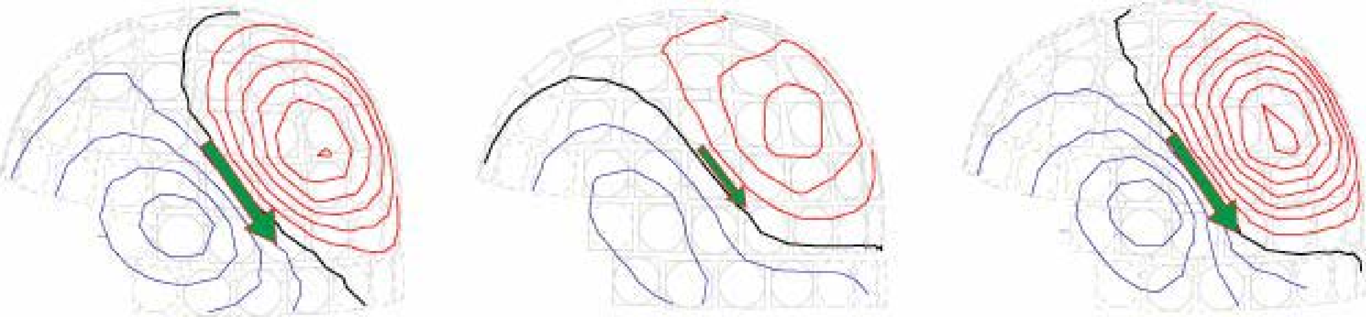
http://imaging.mrc-cbu.cam.ac.uk/meg/Maxfilter_V2.2
Maxfilter Manual

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

Filtering and Downsampling

- Choose a “convenient” sampling rate with respect to processing speed and storage (usually 250 Hz to 500 Hz ok)
- We have to sample at 1000 Hz during acquisition because of head position indicator (HPI) signals
- Downsampling can lead to “aliasing” if the data are not filtered appropriately (Nyquist theorem)
- Filtering can reduce (possibly remove) some artefacts such as sensor noise, muscle artefacts, line noise.

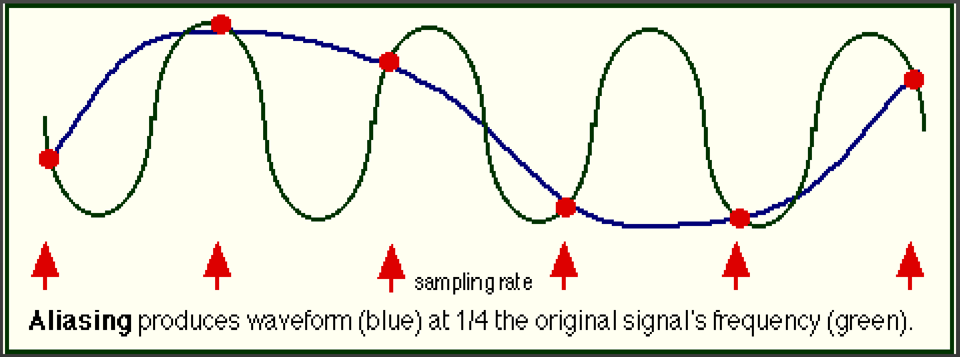
Further reading:

Widmann et al., “Digital filter design for electrophysiological data – a practical approach”, Journal of Neuroscience Methods 2015

Aliasing

- Downsampling can lead to “aliasing” if the data are not filtered appropriately (Nyquist theorem)

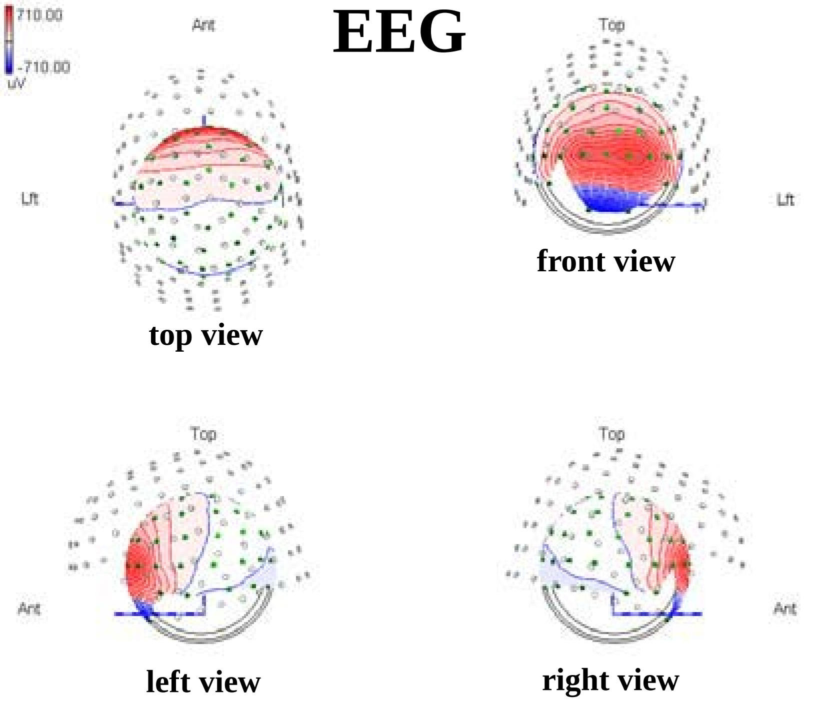
Aliasing

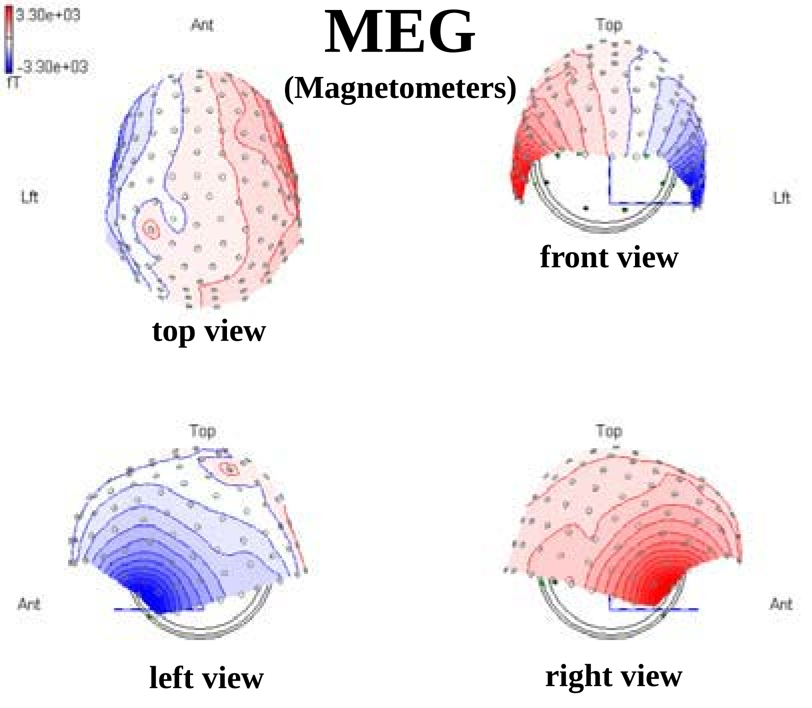


Aliasing produces waveform (blue) at 1/4 the original signal's frequency (green).

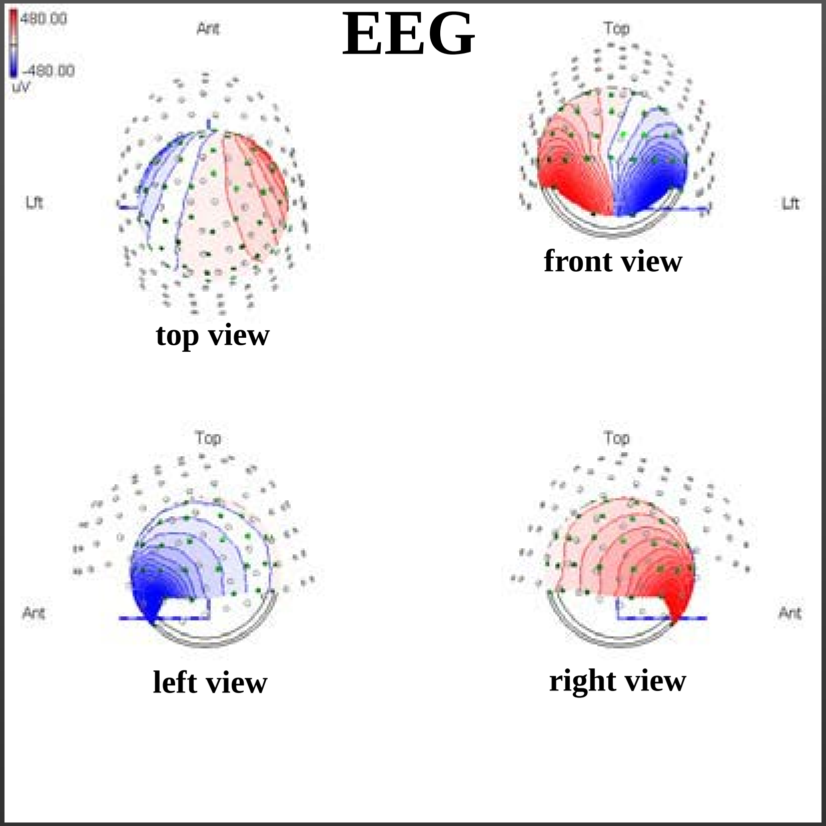
Watch:
https://www.youtube.com/watch?v=R-IVw8OKjvQ
Thanks to Allessandro

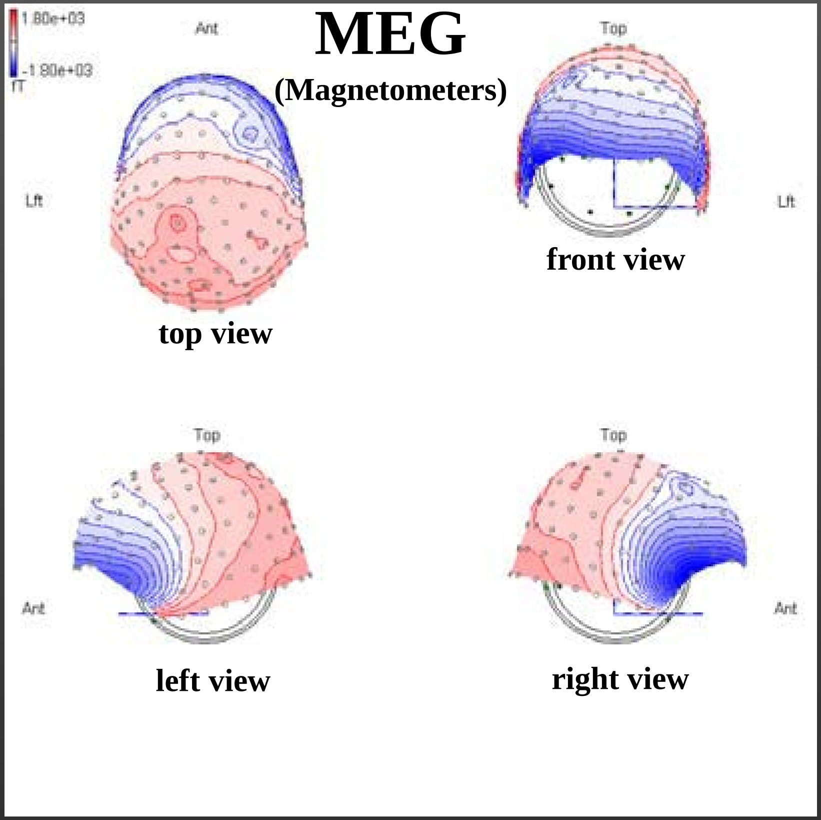
Common Artefacts: Eye Blink



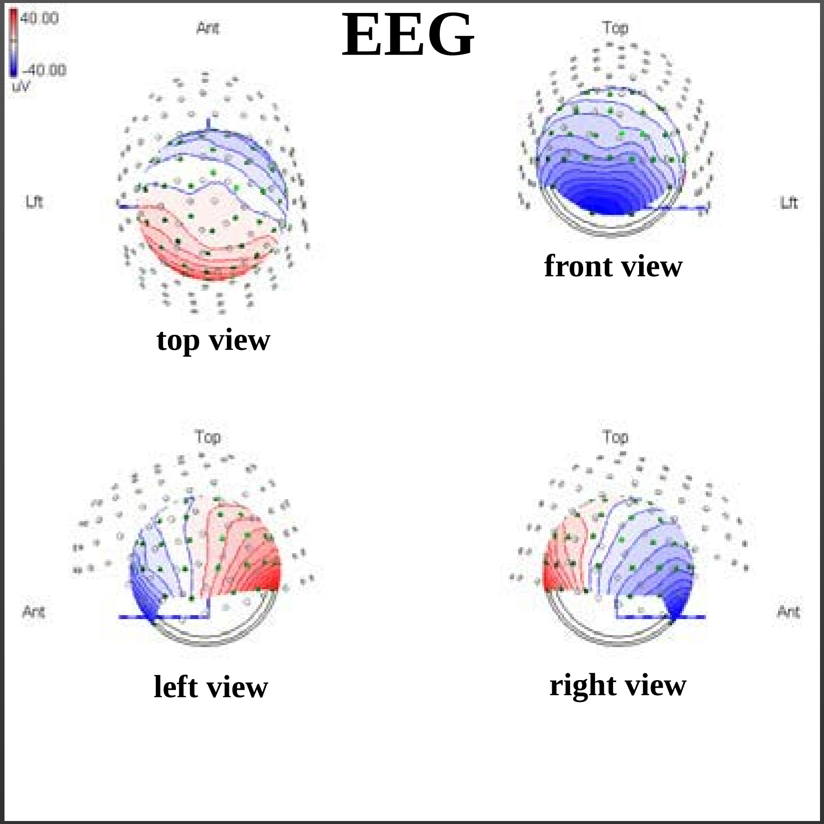


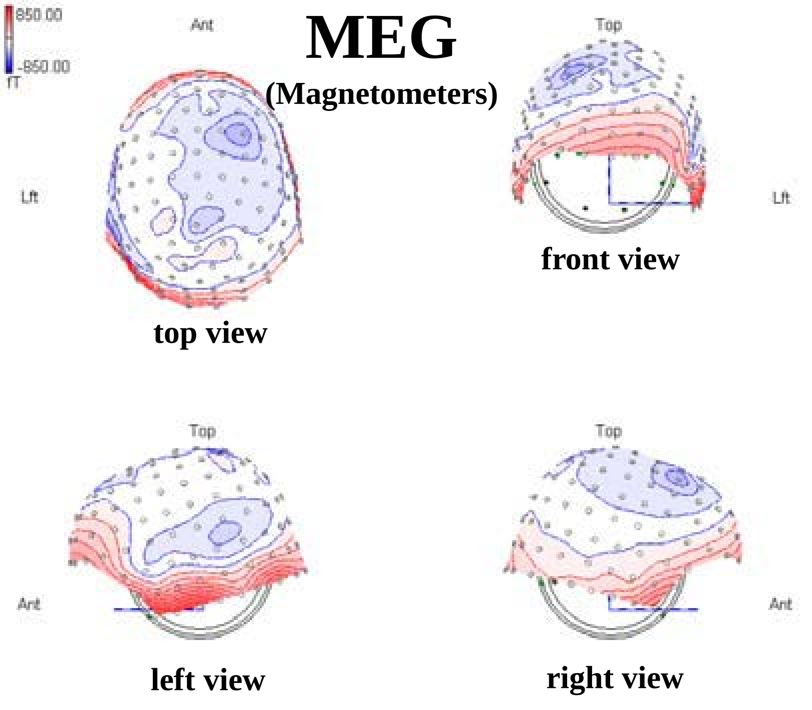
Common Artefacts: Eye Movement to the Right



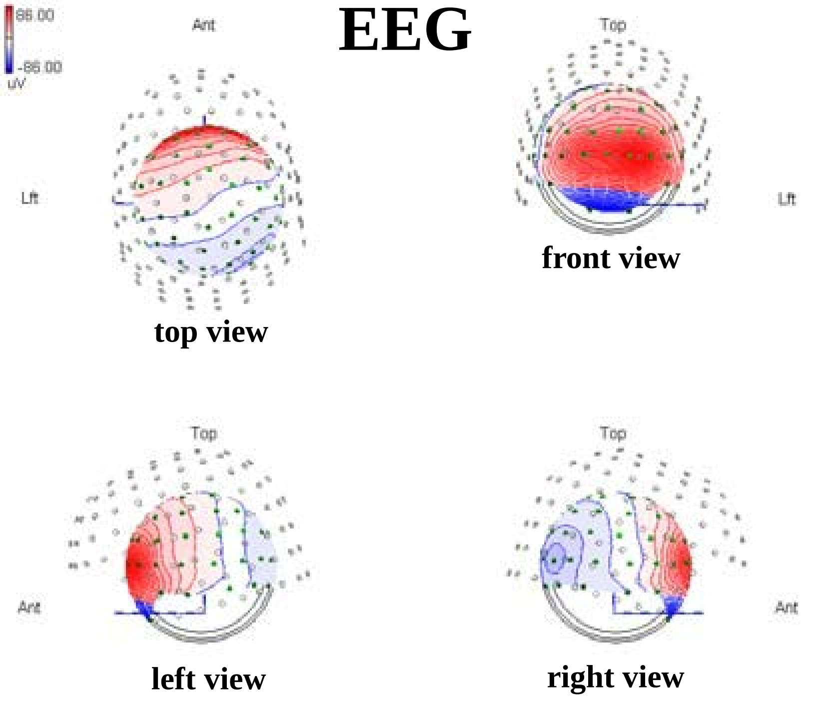


Common Artefacts: Heart Beat





Common Artefacts: Mouth Movement

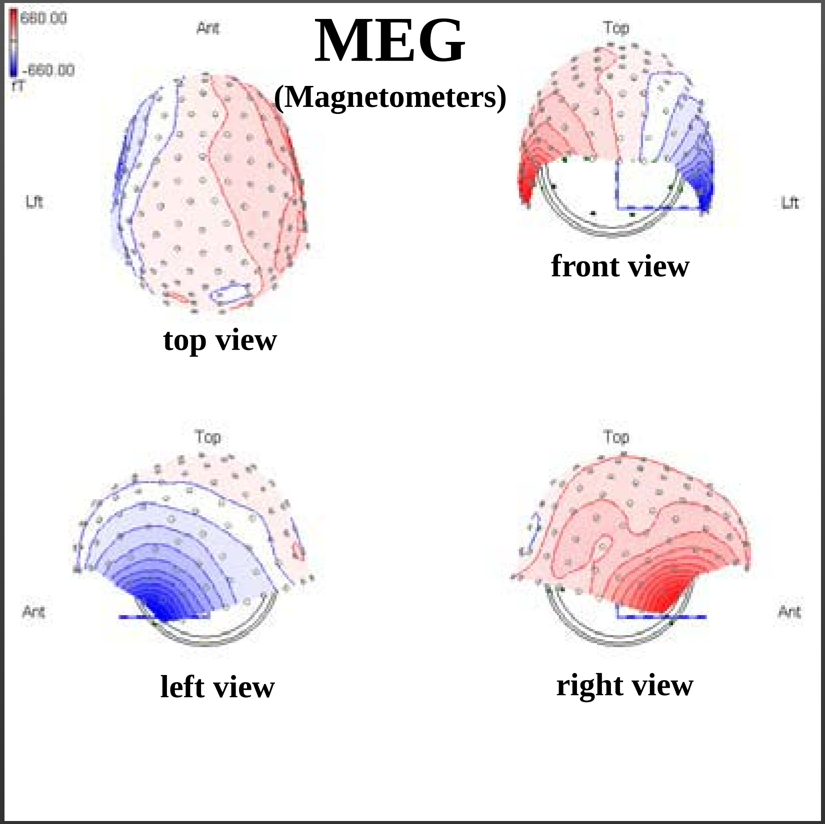

EEG

top view

front view

left view

right view


MEG

(Magnetometers)

top view

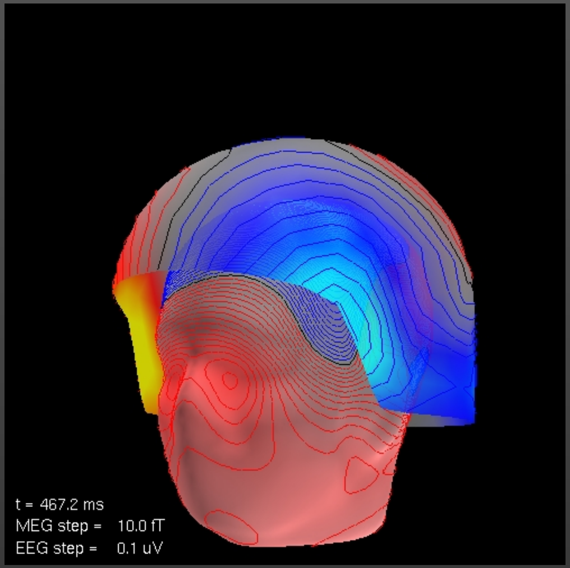
front view

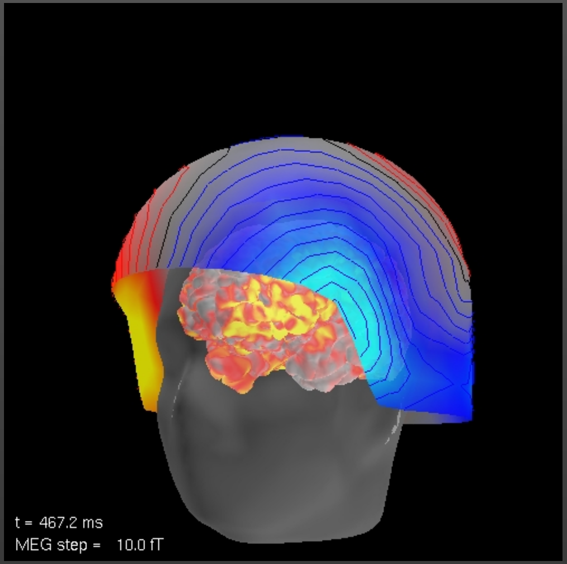
left view

right view

Artefacts in EEG and MEG (Can) End Up in Source Space

Example: Eye Blink





This is a problem with 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 Separation

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 noise topography **N**

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 **T** 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

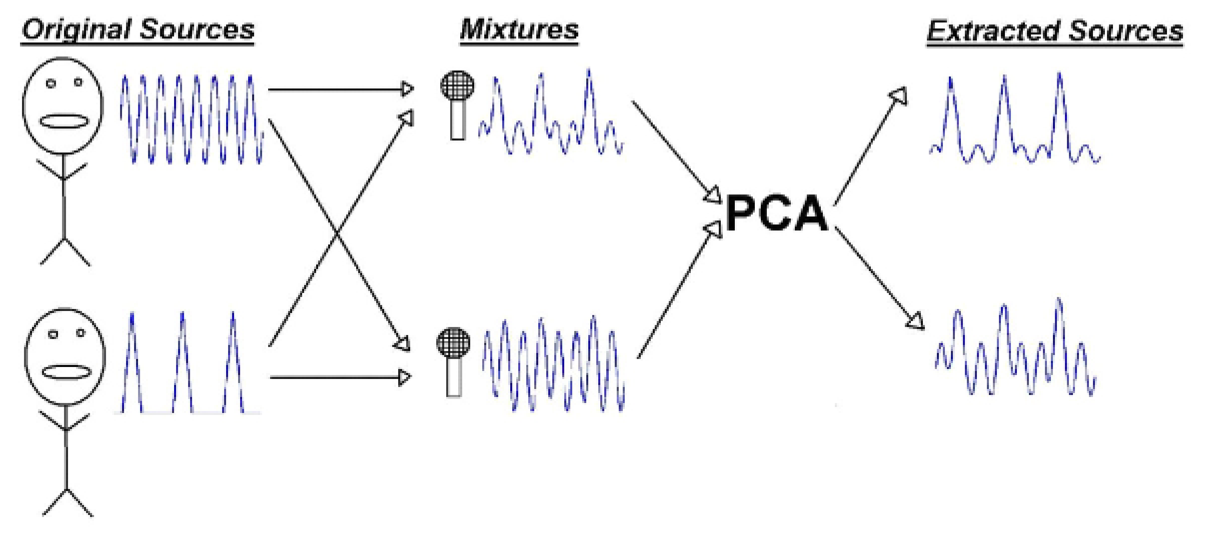
Also:

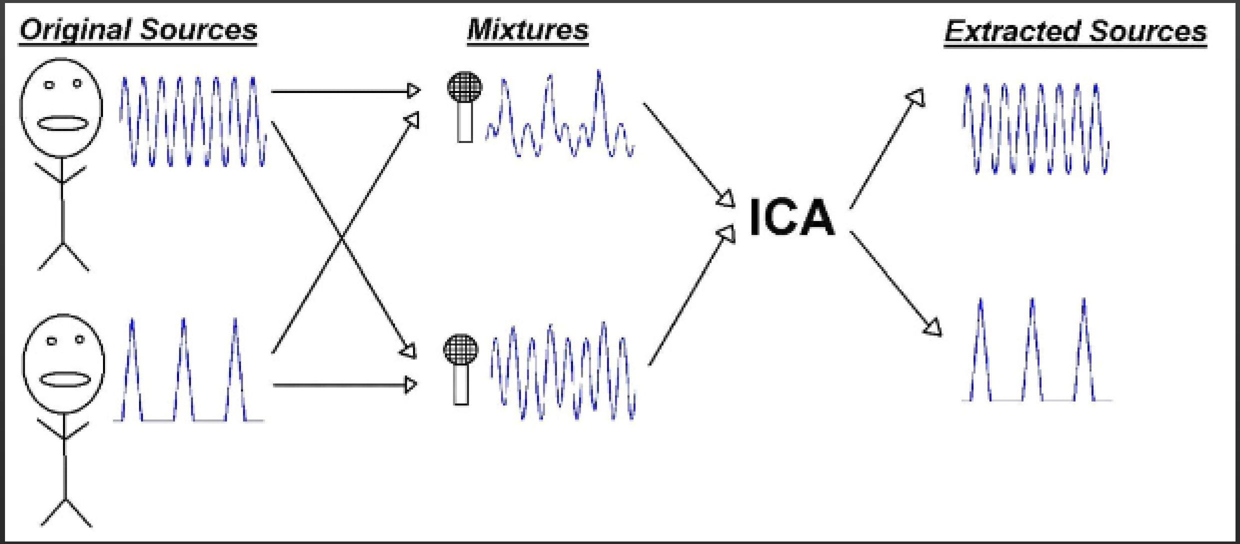
- Components have an order according to the variance they explain (e.g. $\mathrm{var}(\mathbf{T}_1)>\mathrm{var}(\mathbf{T}_2)>\ldots$)
- Can be used to determine the number of independent components (according to specified criteria)
- Relatively fast (try svd() or princomp() in Matlab)

•**Unfortunately: Orthogonality and variance ordering 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

Independent Component Analysis

Instead, ICA uses other measures of “independence” among sources, e.g. based on “mutual information”, “non-Gaussianity”, “kurtosis”, “negentropy” (note: there is not “the ICA”).

There is no theoretical proof that ICA’s assumptions are more physiological – the proof of the pudding is in the eating (i.e. check your data).

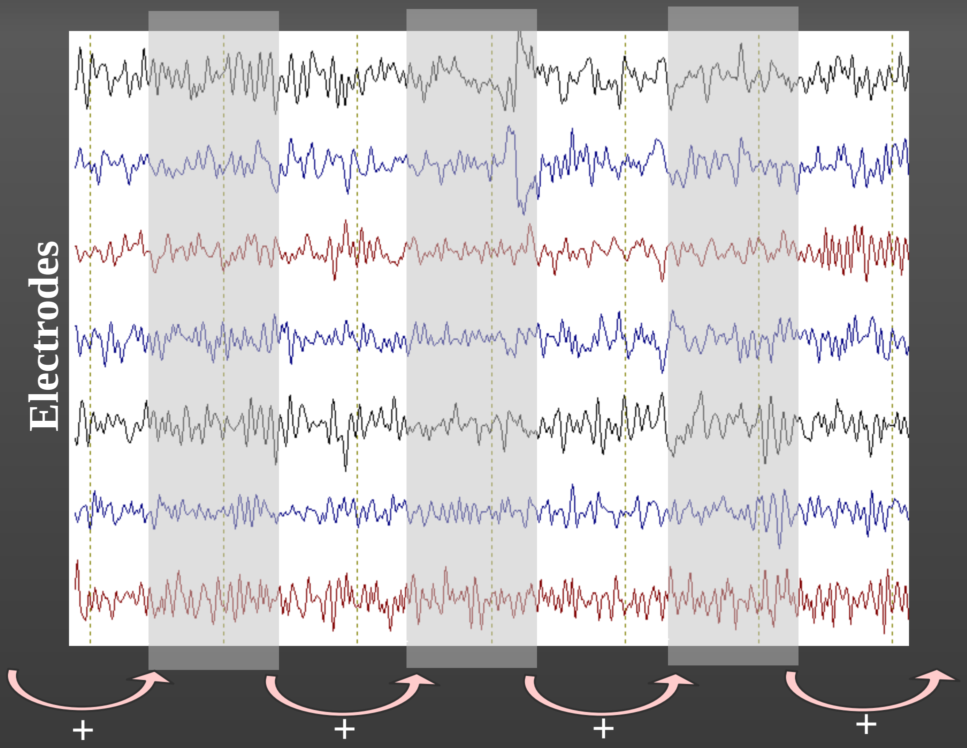
ICA has been successful in detecting non-random noise sources such as ECG and eye blinks.

ICA needs an estimate of the number of sources, and does not order the sources.

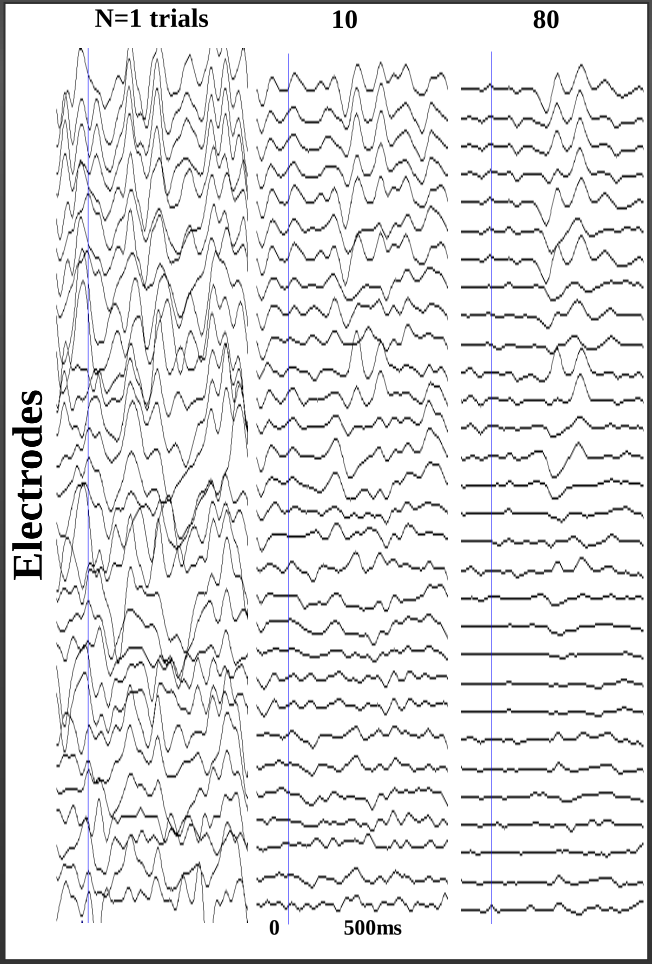
ICA can take a while (fast algorithms available).

Data Averaging

Continuous “raw” data:



Averaged data:



http://imaging.mrc-cbu.cam.ac.uk/meg/IntroEEGMEG

Data Averaging

The necessary number of trials depends on effect size, noise, variability across participants, your stats etc. –
the more the better

For random noise, variance goes down with n, and standard deviation with sqrt(n)

For “one-off” artefacts, amplitude in the average goes down with n

“Robust Averaging” procedures exist (e.g. in SPM) that weigh epochs with an estimate of their reliability (e.g. distance to mean)

Artefact Rejection

Usually, epochs are excluded from averaging when they exceed some maximum-minimum criterion

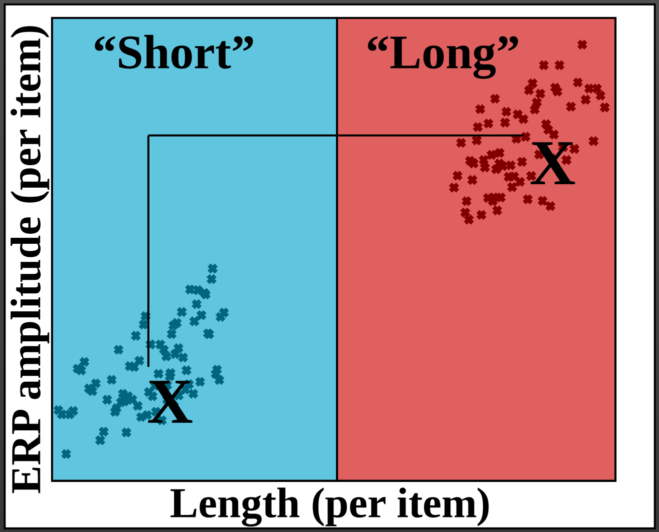
Make sure “chronically bad channels” are excluded from this procedure
(or there won’t be any data left to average)

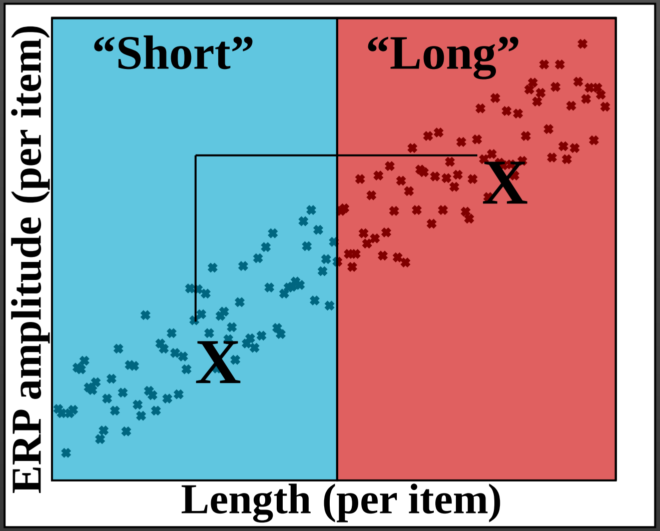
Prior to any procedure that combines signals across channels, such as average reference, SSP or ICA, bad channels should be removed
(or signals from bad channels may be projected into the good ones)

Appropriate filtering and artefact correction (e.g. ICA) should be applied beforehand
(but don’t feel too safe: artefacts may slip through)

Parametric vs Factorial Designs

Consider parametric analysis if stimulus variables are continuous
(still less common in EEG/MEG than in fMRI analysis)



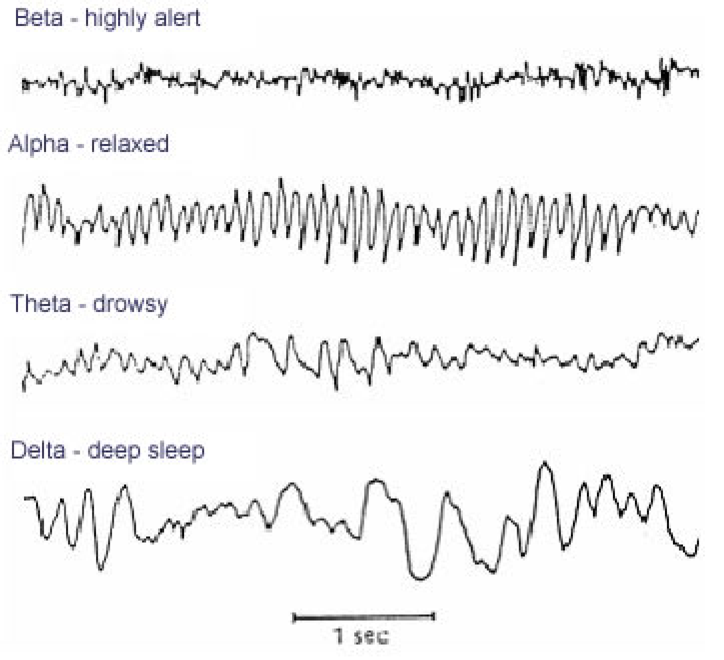


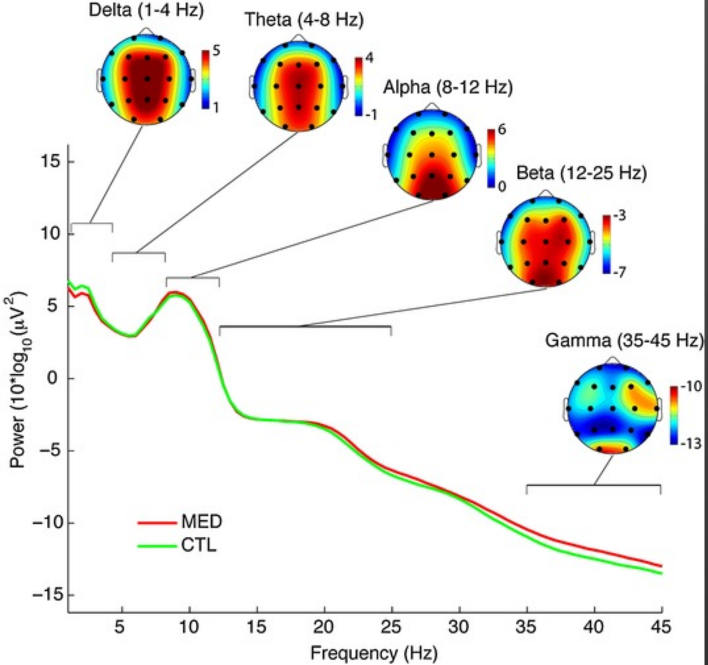
Smith&Kutas, Psychophysiol 2015a
Hauk et al., Neuroimage 2006

“Brain Rhythms” and “Oscillations”

Time course and topography may differ among different frequency bands

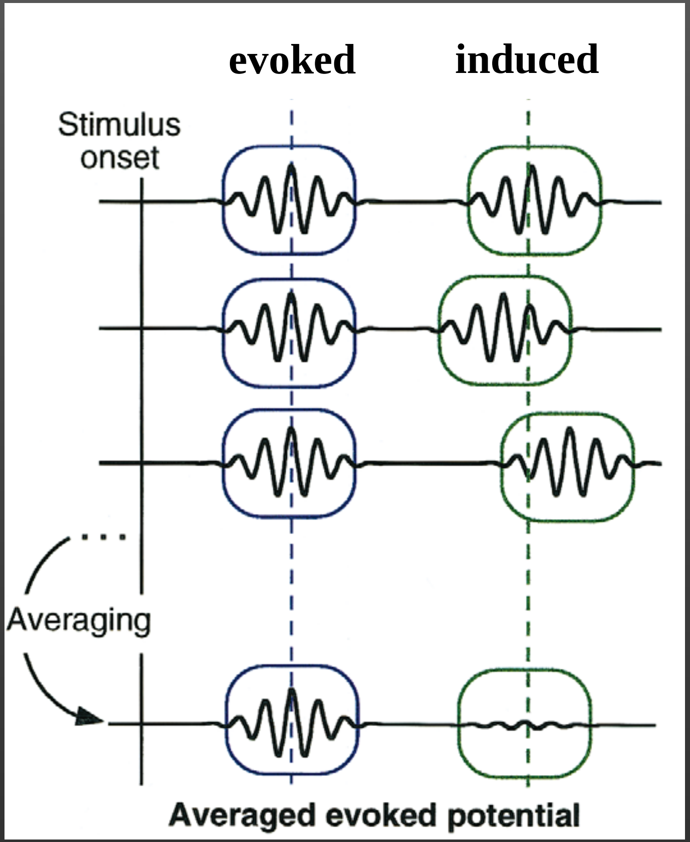
(and may depend on task, environment, subject group etc.)





http://link.springer.com/article/10.1007%2Fs10339-009-0352-1/

Evoked and Induced Activity



Tallon-Baudry & Bertrand, TICS 1999