









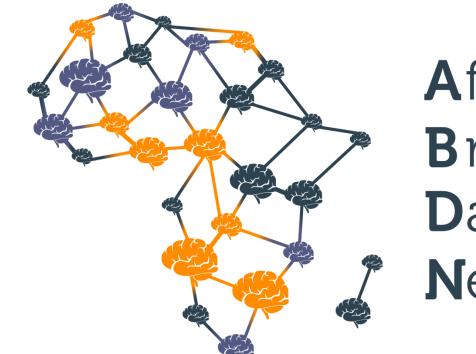


Localizing the sources of ERP topographies

Robert Oostenveld

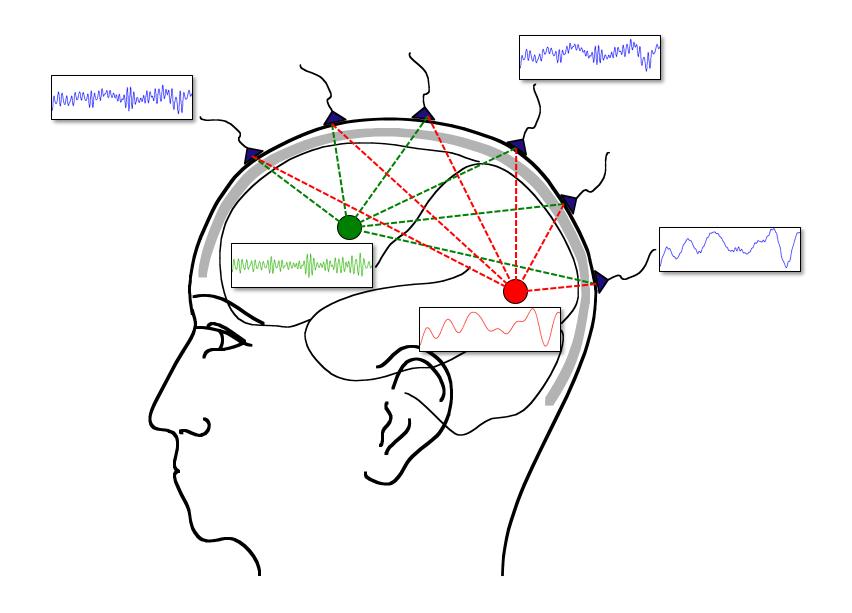
Mikkel C. Vinding

9-14 June 2025 Port Harcourt, Nigeria



African
Brain
Data
Network

Superposition of source activity



Overview

Motivation and background

Forward modeling

Source model

Volume conductor model

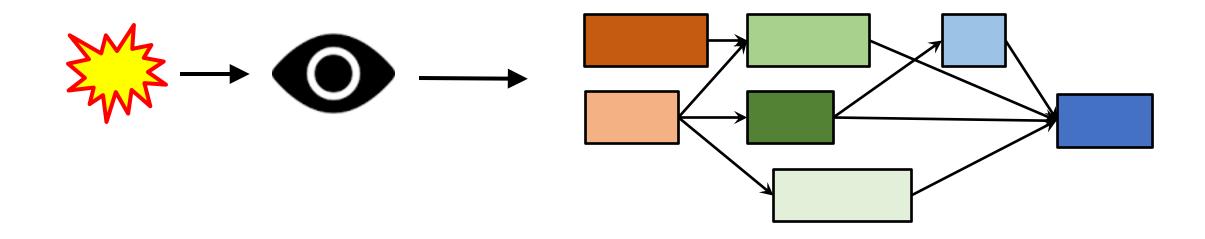
Inverse modeling - biophysical models

Single and multiple dipole fitting

Distributed source models

Beamforming

ERP components reveal the when and where



Different functions in different brain areas.

The brain is a hierarchical functional network.

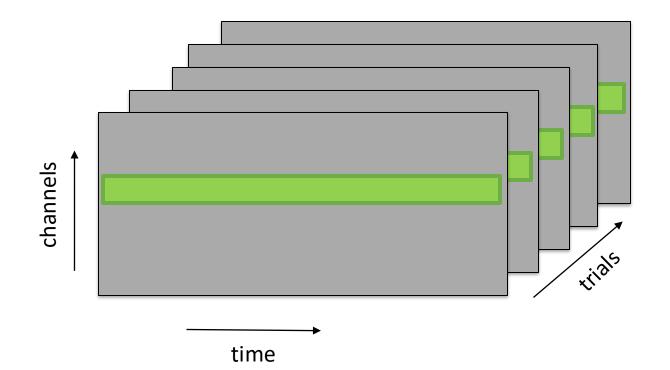
Serial/sequential and parallel processing at different times/latencies in different areas.

Identifying the latency and topography of ERP components helps to disentangle functional networks.

One channel, all time points

When does specific brain activity start (in one condition)?

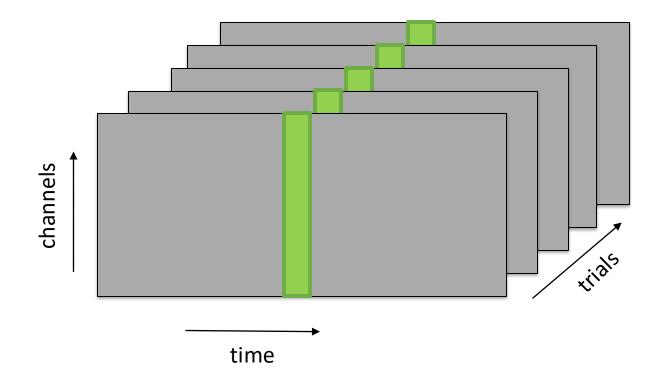
When is the activity different between conditions?



All channels, one time point

What is the topographic distribution (in one condition) at latency t?

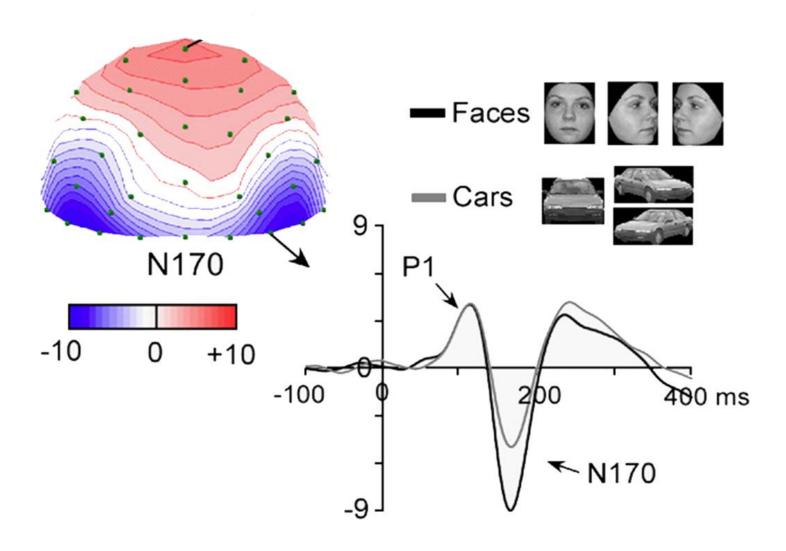
What is the topographic distribution of the difference at latency t?



ERP difference waves to localize face-selective brain areas

The N170 is an ERP response specific for faces, when contrasted to other visual stimuli.

The N170 originates from the fusiform face area (FFA) which is located on the ventral surface of the brain.



Localizing and understanding the ERP

If you find a ERP component, you want to characterize it in physiological terms

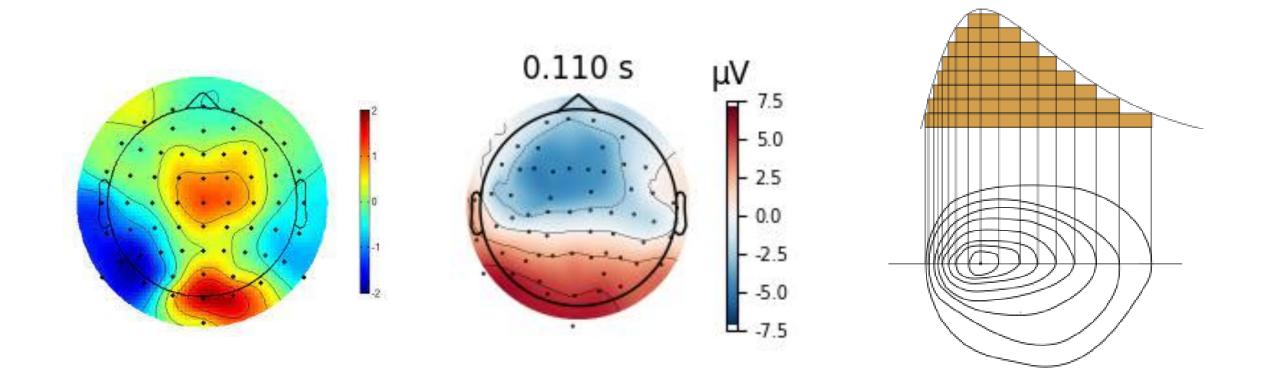
Time or frequency are the "natural" characteristics

"Location" requires interpretation of the scalp topography

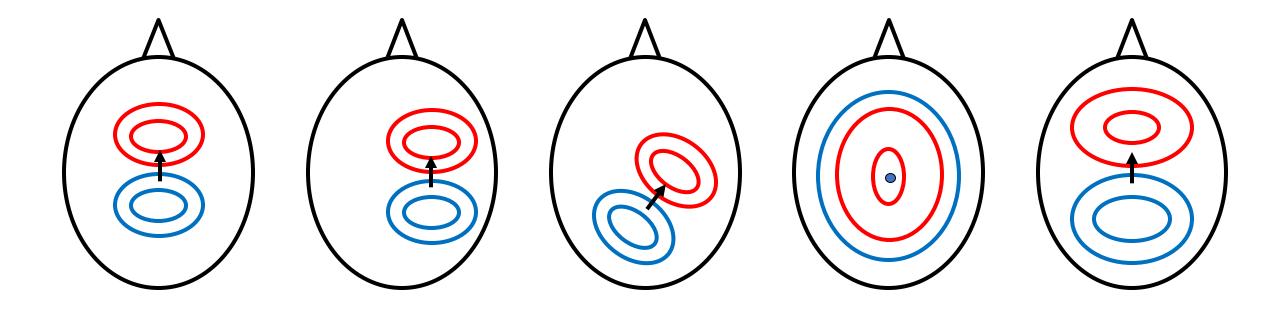
Forward and inverse modeling helps to interpret the topography

Forward and inverse modeling helps to disentangle overlapping source timeseries

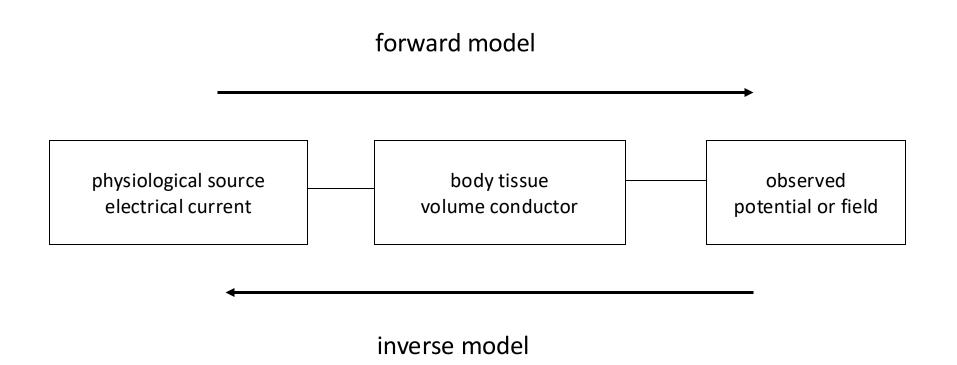
ERP topographies – colors and contour lines



Forward models and ERP topograpies



Biophysical source modelling: overview



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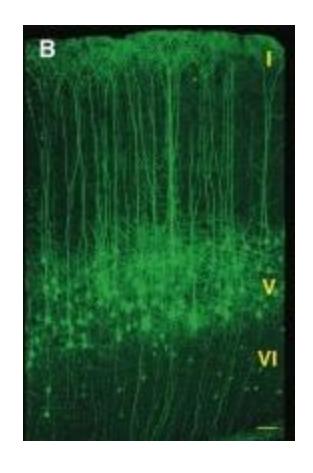
Inverse modeling - biophysical models

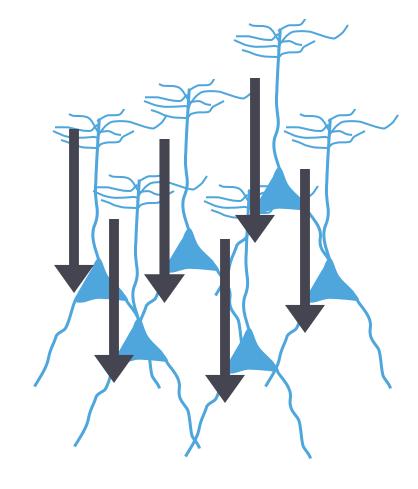
Single and multiple dipole fitting

Distributed source models

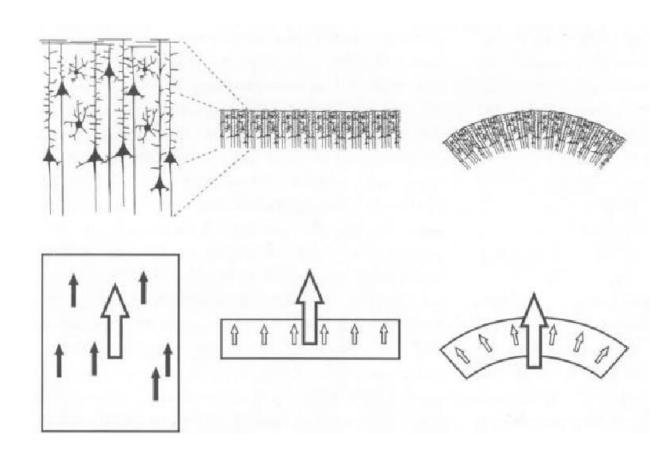
Beamforming

What produces the electric current





Equivalent current dipoles



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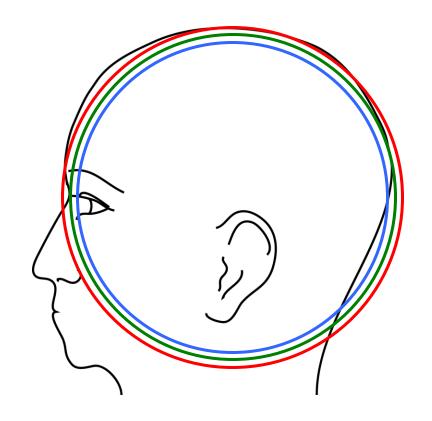
Volume conductor

described electrical properties of tissue

describes geometrical model of the head

describes how the currents flow, not where they originate from

same volume conductor for EEG as for MEG, but also for tDCS, tACS, TMS, ...



Volume conductor

Analytic computational methods for volume conduction problem for simple geometries, like a sphere.

Numerical computational methods for volume conduction problem allow for realistic geometries.

BEM = Boundary Element Method

FEM = Finite Element Method

Volume conductor: Boundary Element Method

Each compartment is

homogenous isotropic

Important tissues

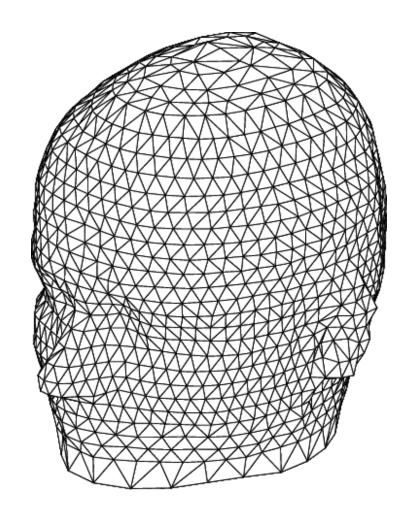
skin

skull

brain

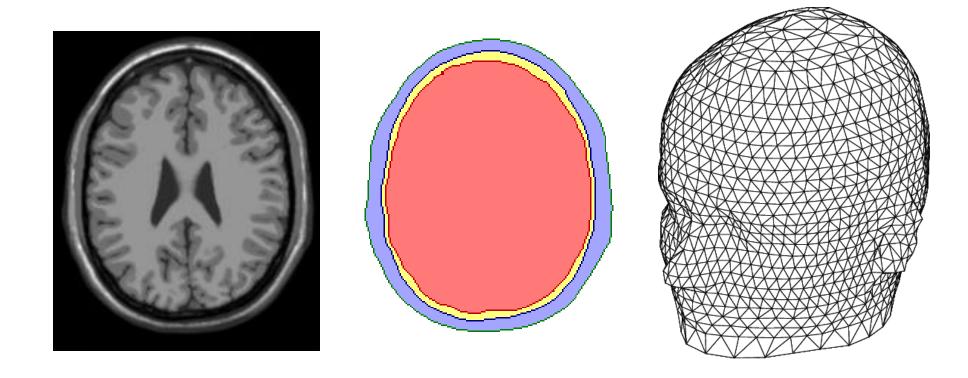
(CSF)

Triangulated surfaces describe boundaries



Volume conductor: Boundary Element Method

Construction of geometry
segmentation in different tissue types
extract surface description
downsample to reasonable number of triangles



Volume conductor: Boundary Element Method

Construction of geometry

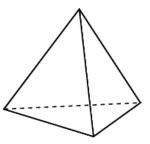
segmentation in different tissue types
extract surface description
downsample to reasonable number of triangles

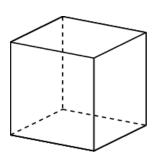
BEM computation of the volume conduction model independent of source model

Volume conductor: Finite Element Method

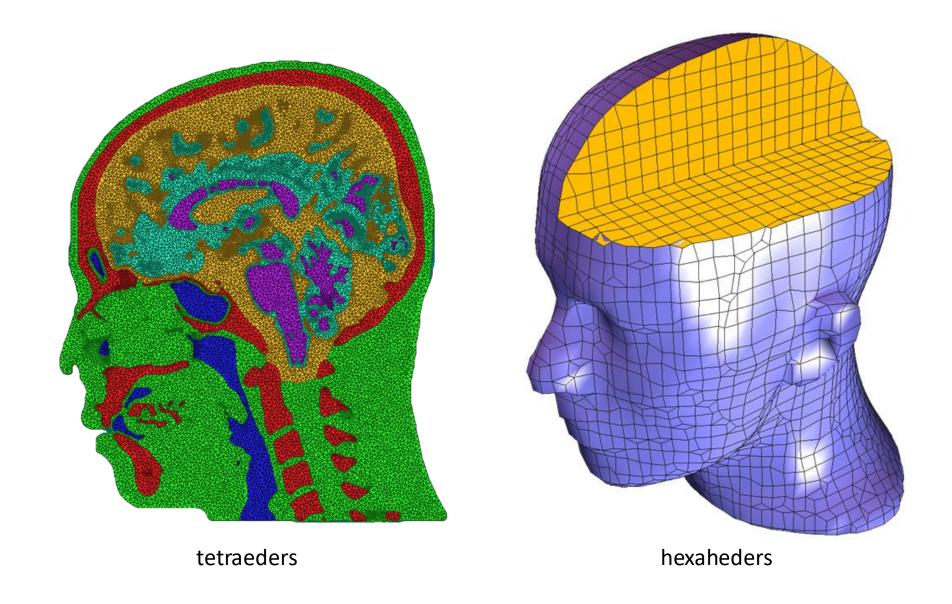
Tesselation of 3D volume in tetraeders or hexaheders





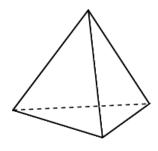


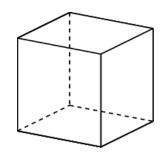
Volume conductor: Finite Element Method



Volume conductor: Finite Element Method

Tesselation of 3D volume in tetraeders or hexaheders





Each element can have its own conductivity

FEM is the most accurate numerical method but computationally quite expensive

Geometrical processing not as simple as BEM

EEG volume conduction

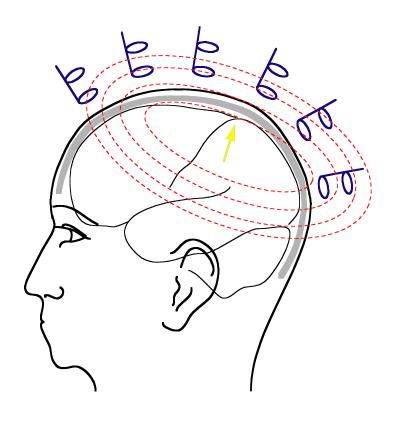
Potential difference between electrodes corresponds to current flowing through skin

Only tiny fraction of current passes through skull

Therefore the model should describe the skull and skin as accurately as possible

Magnetoencephalography (MEG)





MEG volume conduction

MEG measures magnetic field over the scalp

Magnetic field itself is not distorted by skull

Only tiny fraction of current passes through skull, therefore the model can ignore the skull and skin

Magnetic field from ECDs but also from the volume currents

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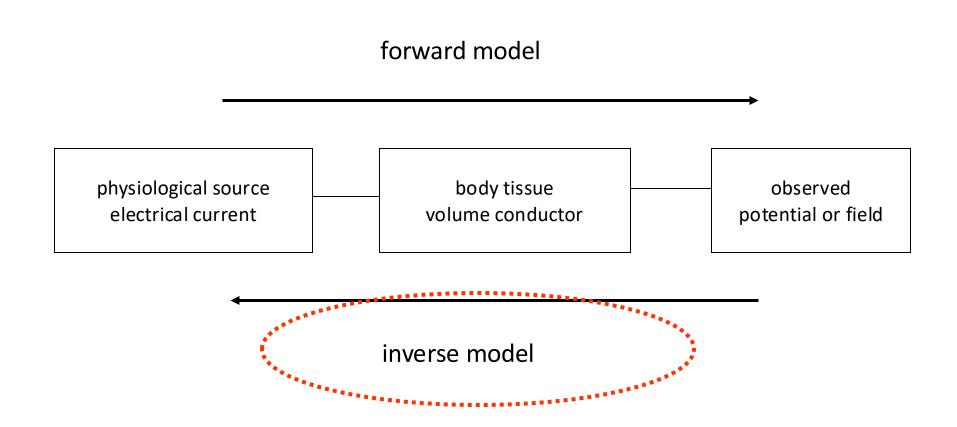
Inverse modeling - biophysical models

Single and multiple dipole fitting

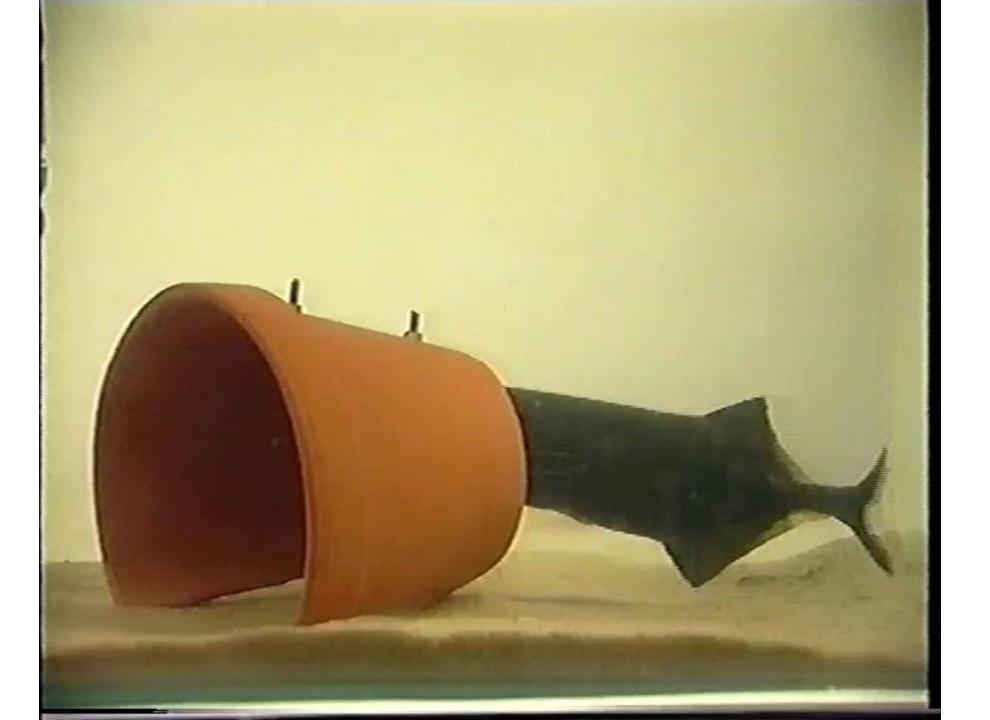
Distributed source models

Beamforming

Biophysical source modelling: overview



Inverse localization: demo



Inverse methods

Single and multiple dipole models

Minimize error between model and measured potential/field

Distributed source models

Perfect fit of model to the measured potential/field

Additional constraint on source smoothness, power or amplitude

Spatial filtering

Scan the whole brain with a single dipole and compute the filter output at every location

Beamforming (e.g. LCMV, SAM, DICS)

Multiple Signal Classification (MUSIC)

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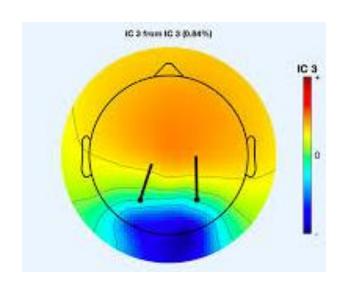
Inverse modeling - biophysical models

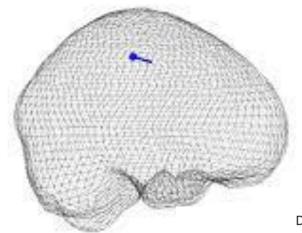
Single and multiple dipole fitting

Distributed source models

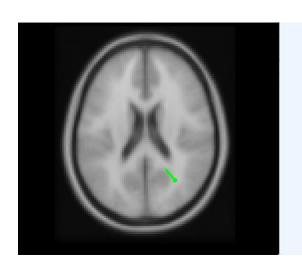
Beamforming

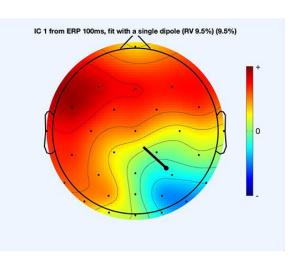
Dipole fitting

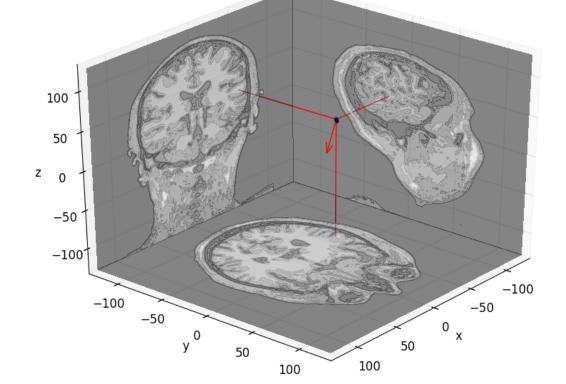




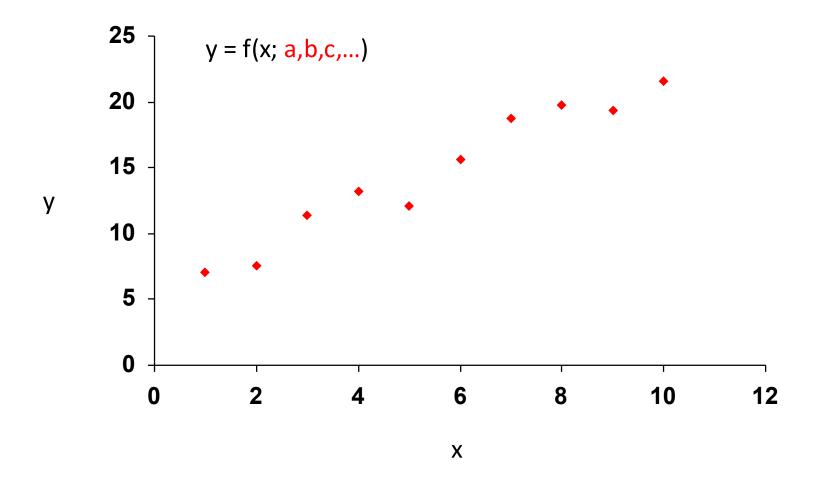
Dipole 6, Time: 0.080s, GOF: 56.9, Amplitude: 39.6nAm (-56.9, -19.7, 26.1) mm







Single or multiple dipole models - Parameter estimation

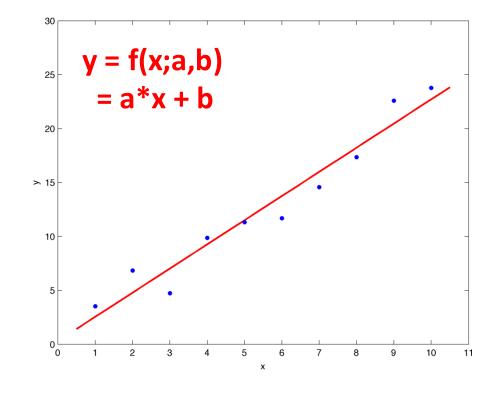


Parameter estimation: dipole parameters

source model with few parameters position orientation strength

compute the model data

minimize difference between actual and model data



Dipole model: linear estimation

$$Y = L_1X_1 + L_2X_2 + ... + L_nX_n + noise$$

$$Y = LX + noise$$

Y is the data, for example 64x500 samples
L is the leadfield matrix, for example 64x3

X is the strength of the source, for example 3x500

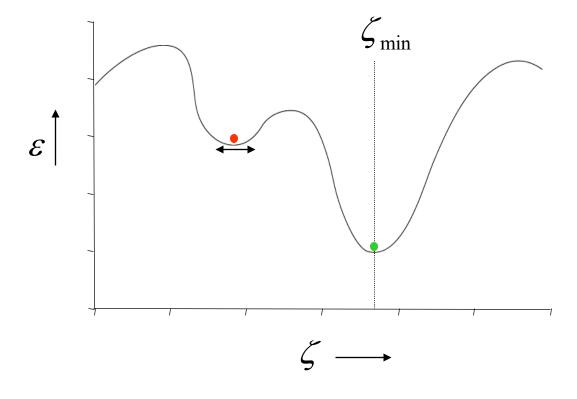
The noise is the same size as the data

The leadfield L depends on the position of the source We compare the model data Y with the measured data

Non-linear parameters

$$\varepsilon rror(\zeta) = \prod_{i=1}^{N} (Y_i(\zeta) - V_i)^2 \implies \min_{\zeta} (\varepsilon rror(\zeta))$$

$$\zeta = a, b, c, \dots$$



Non-linear parameters: grid search

One dimension, e.g. location along medial-lateral 100 possible locations

Two dimensions, e.g. med-lat + inf-sup 100x100=10.000

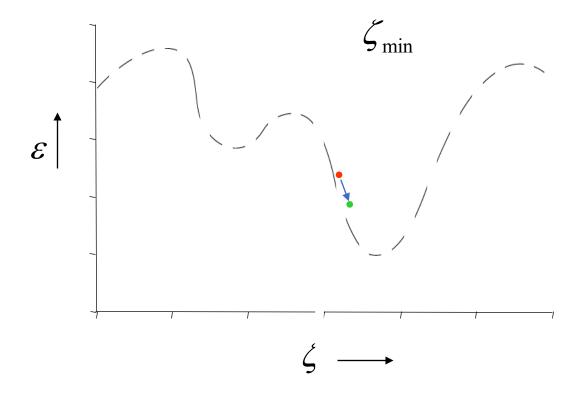
Three dimensions $100x100x100 = 1.000.000 = 10^6$

Two dipoles, each with three dimensions $100x100x100x100x100x100x100 = 10^{12}$

Non-linear parameters: gradient descent optimization

$$\varepsilon rror(\zeta) = \prod_{i=1}^{N} (Y_i(\zeta) - V_i)^2 \implies \min_{\zeta} (\varepsilon rror(\zeta))$$

$$\zeta = a, b, c, \dots$$



Single or multiple dipole models - Strategies

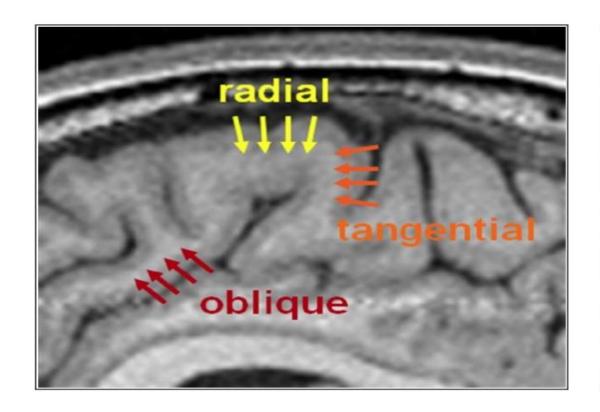
Single dipole:

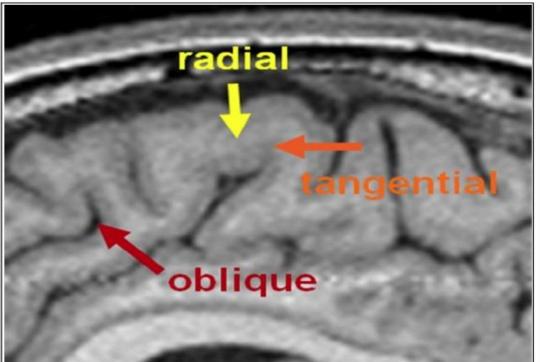
scan the whole brain, followed by iterative optimization

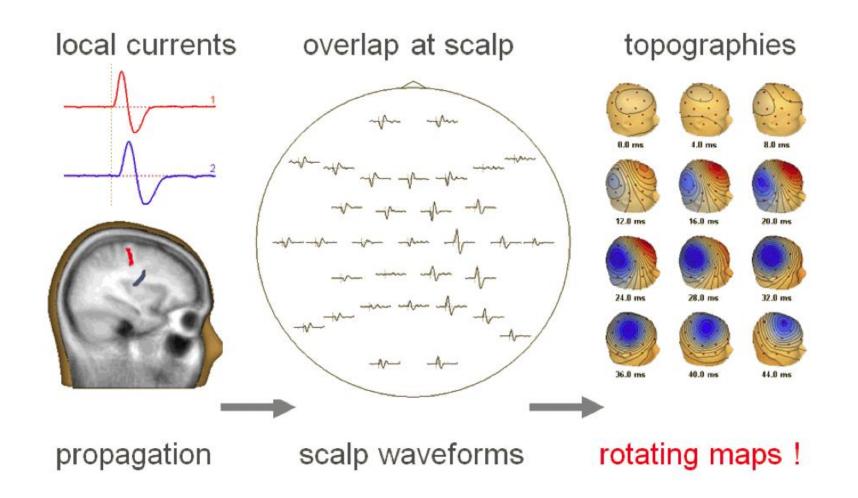
Two dipoles:

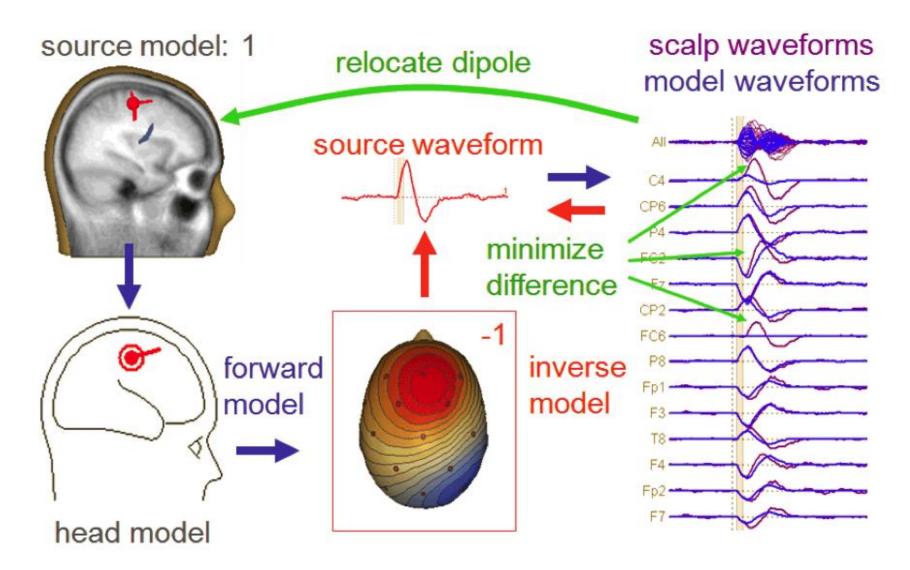
scan with symmetric pair, use that as starting point for iterative optimization

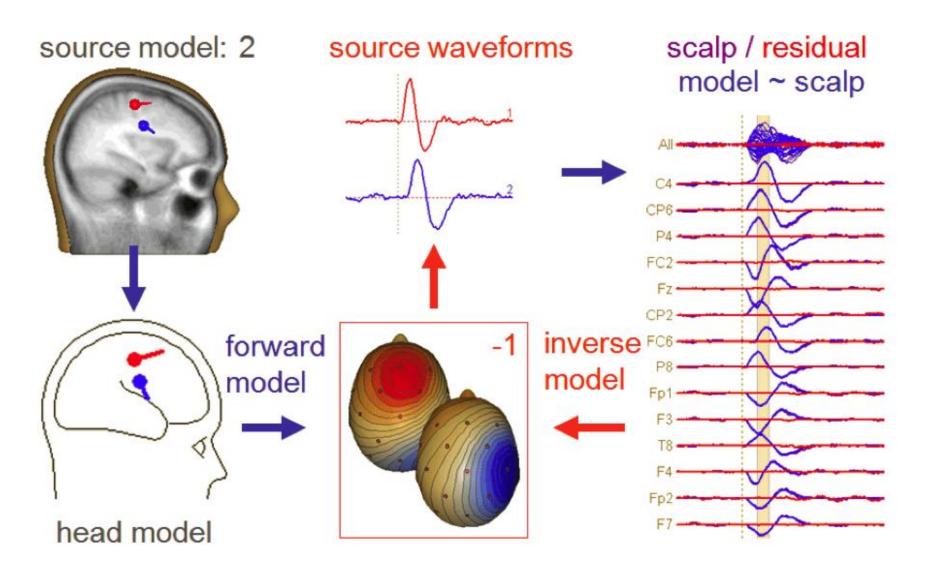
More dipoles:











Sequential dipole fitting to explain spread of activity

Assume that activity starts "small" explain earliest ERP component with single equivalent current dipole

Assume later activity to be more widespread add ECDs to explain later ERP components estimate position of new dipoles re-estimate the activity of all dipoles

Iterative and interactive (hence subjective) process

Overview

Motivation and background

Forward modeling

Source model

Volume conductor model

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Single and multiple dipole fitting

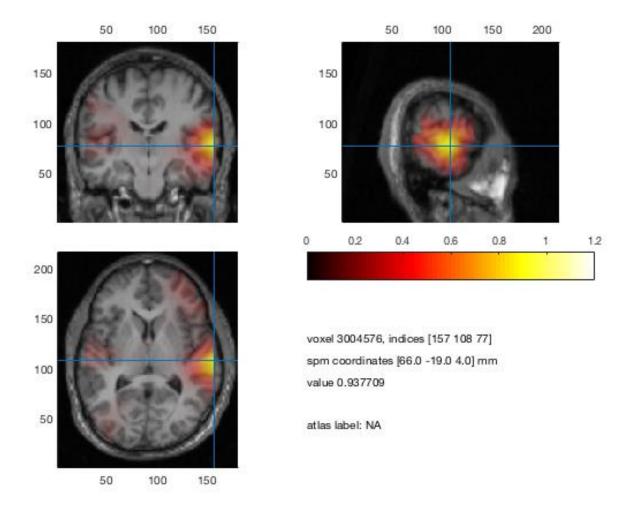
Distributed source models and beamforming

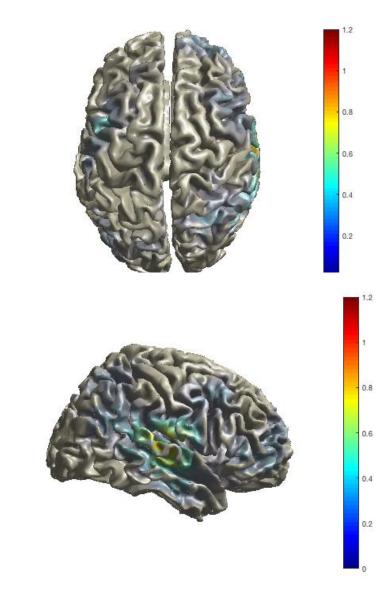
Distributed source models and beamforming

With dipole fitting we assume a single or a few point like sources (ECDs)

But what if we assume that there can be activity distributed over the whole brain?

Distributed source models and beamforming





Distributed source models and beamforming

Position of the source is not estimated as such

We can assume a pre-defined grid (3D volume or on cortical sheet)

We can estimate the strength at every location

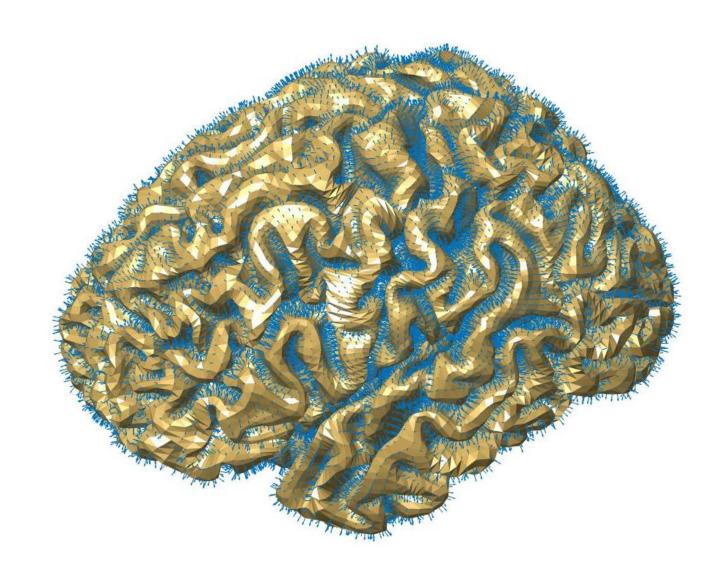
In principle easy to solve, however...

More "unknowns" than "knowns"

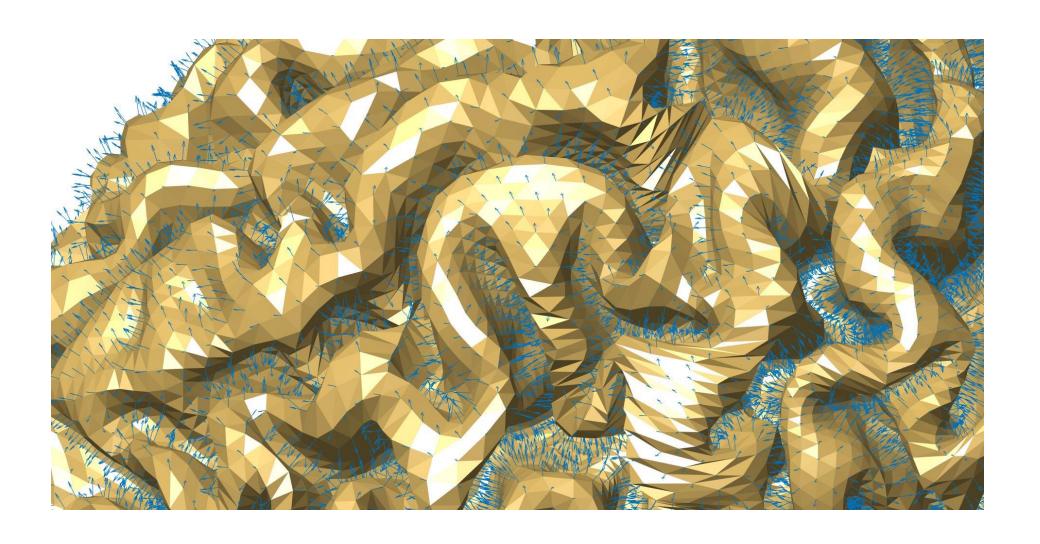
Infinite number of solutions can explain the data perfectly

Additional constraints or assumptions are required

Distributed source model



Distributed source model



Distributed source model: linear estimation

$$Y = L_1X_1 + L_2X_2 + ... + ... + ... + ... + ... + ... + ... + L_nX_n + noise$$

$$Y = LX + noise$$

Y is the data, for example 64x500 samples

L is the leadfield matrix, for example 64x8000

X is the strength of the source, for example 8000x500

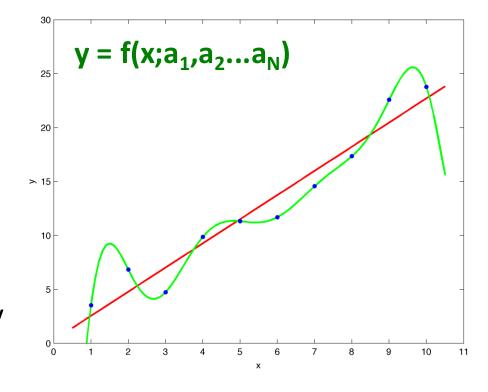
We now have to estimate 8000x500 parameters, from 64x500 data points. This is an overdetermined linear system

Distributed source model: linear estimation

distributed source model with many dipoles throughout the whole brain

estimate the strength of all dipoles

data and noise can be perfectly explained



Distributed source estimation

To find a unique solution to the overdetermined problem we make additional assumptions.

The general assumption is that we want to have the "simplest" solution, so the solution with the minimal overall "norm".

The "norm" expresses the overall amplitude or power of all the sources distributed in the brain.

We compute the Minimum Norm Estimate (MNE).

We can use additional assumptions about the noise and distribution.

Beamforming

With beamforming we also assume that there can be activity everywhere in the brain.

Rather than computing the activity at all locations simultaneously, we compute it for each location seperately.

We scan the whole brain, and for each location we compute a "spatial filter".

This also requires extra assumptions: that the sources are uncorrelated, which is not always the case in reality.

Which source localization method to use

Dipole fitting

Distributed source estimation using MNE

Distributed source estimation using beamforming

Each of them has different assumptions on the actual sources.

Your data is different from others' data, so the method that is best for you might be different as well.

Let's discuss some practical guidelines for selecting a method...

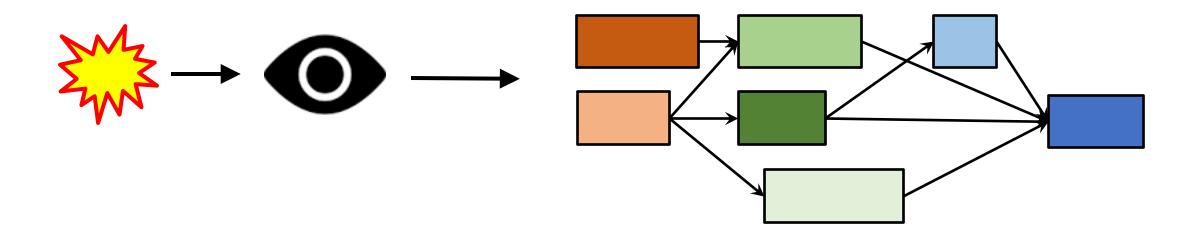
Localizing and understanding the ERP

If you find a ERP component, you want to characterize it in physiological terms

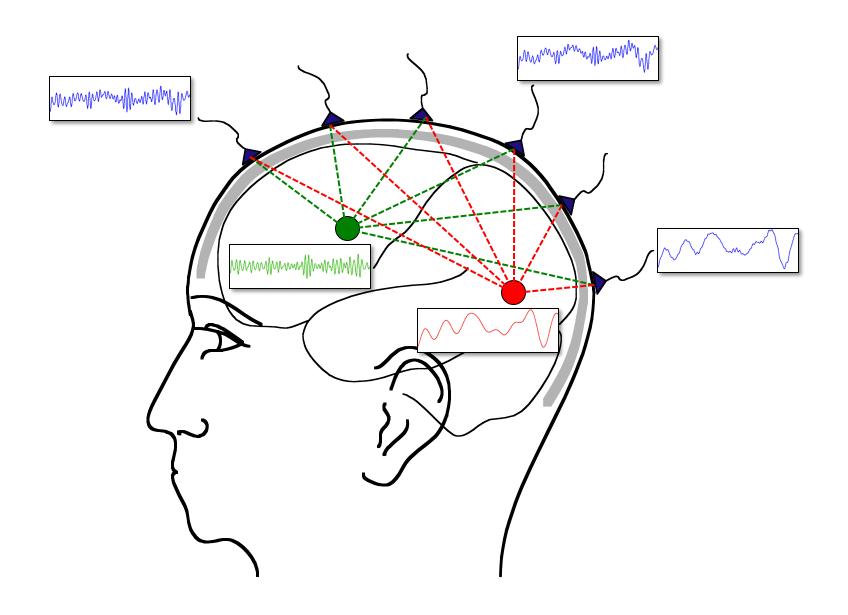
Time is the "natural" characteristic of the ERP

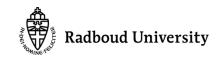
"Location" requires interpretation of the scalp topography

Forward and inverse modeling helps to interpret the **spatial distribution**Forward and inverse modeling helps to disentangle overlapping source **timeseries**



Localize and disentangle the source activity















Localizing the sources of ERP topographies

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