Source reconstruction of M/EEG data

Donders Advanced MEG/EEG toolkit 2022

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Outline and objectives

You will learn about **the beamforming source reconstruction technique**: how it works, and what is needed to make it work.

- **Concept of source reconstruction**
  what and why?
- **Forward models (short recap)**
  the ingredients for source reconstruction.
- **Inverse models (focus: beamforming)**
  source estimation at work.

Beamformer source reconstruction of M/EEG data

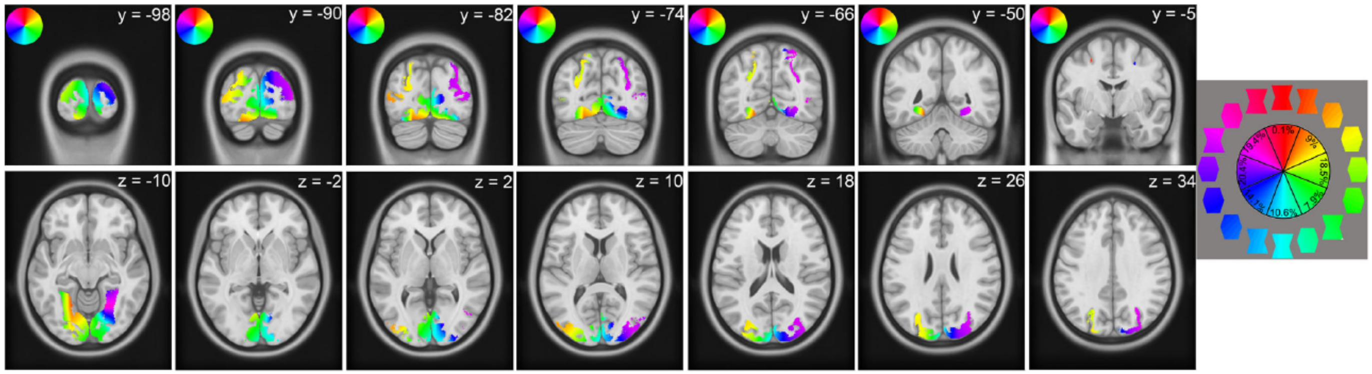
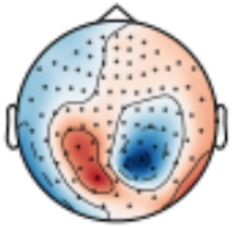
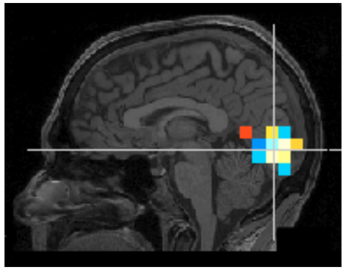


Fig. 1: Popov et al., 2018, Fig. 2: Compumedics NeuroScan

Source reconstruction of M/EEG data

Goal: We want to estimate the source activity underlying our sensor-level measurements.



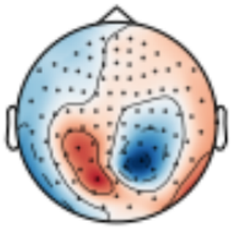


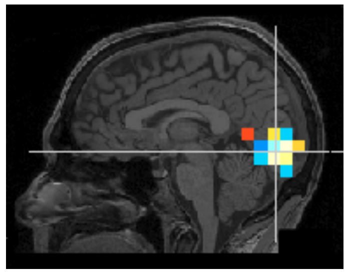
But why?

- Increase spatial resolution of MEEG data.
- Disentangle measured source activity.

Forward and inverse solution

forward solution





inverse solution

Ingredients for a forward model

To compute a forward model, you need:

- source model
  - how do we model the sources (activity) mathematically?
- volume conductor model
  - geometry of the conductor
  - conductivities
- knowledge about sensors
  - where are the sensors relative to the volume conductor?
  - how do we model the sensors?

Coregistration

Unifying all elements in **one coordinate system**.

Example: MEG
Volume conductor model: **MRI space** $\longleftrightarrow$ sensors: **MEG head space**.

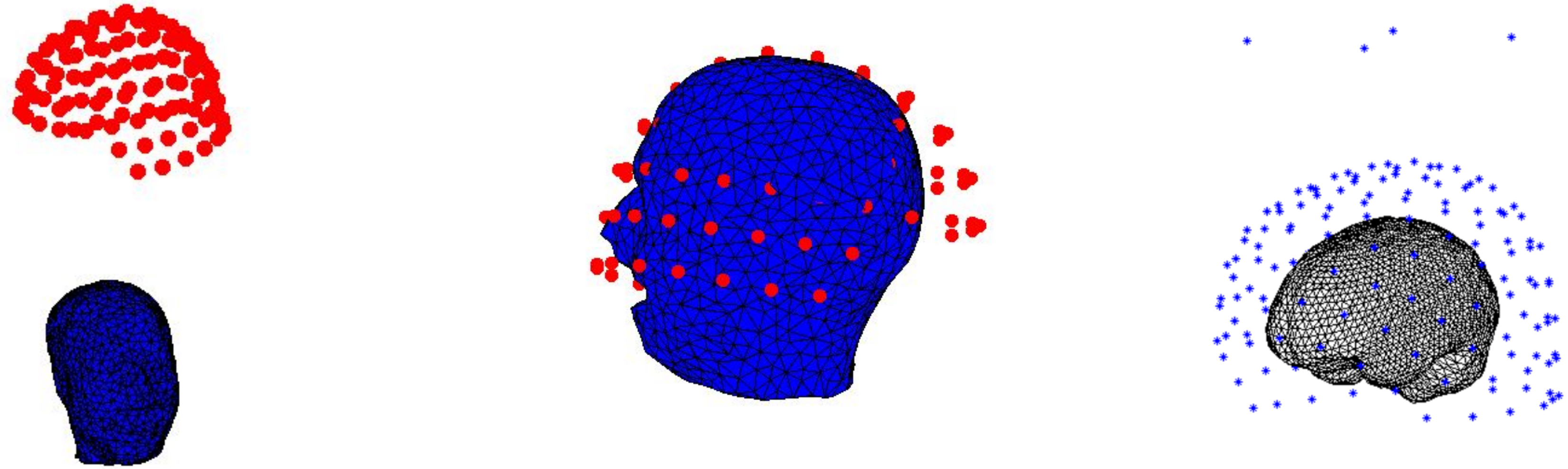


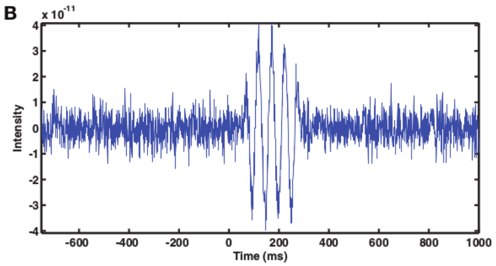
Fig. 3: FieldTrip Toolbox

Coregistration: does it matter?

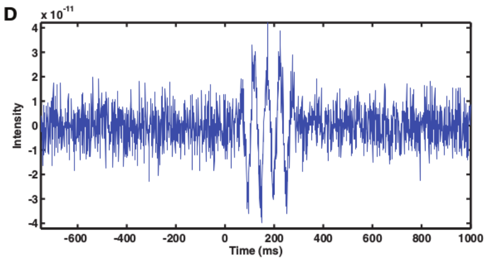
Effects of **faulty coregistration** on source reconstruction in EEG

Dalal et al., 2014

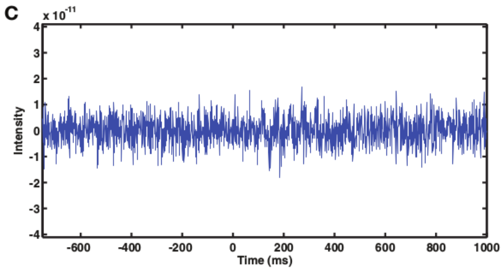
simulated source
in hippocampus:



reconstruction:
coreg. error of **1.5 mm**

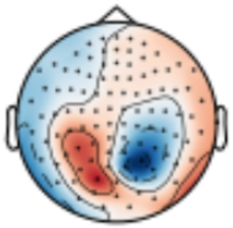


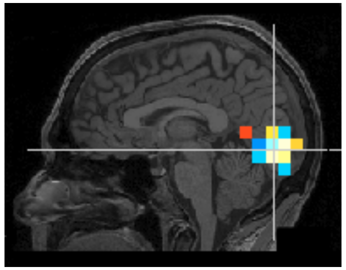
reconstruction:
coreg. error of **6.8 mm**



Forward and inverse solution

forward solution





inverse solution

Inverse models

Aim: estimated source activity from sensor data.

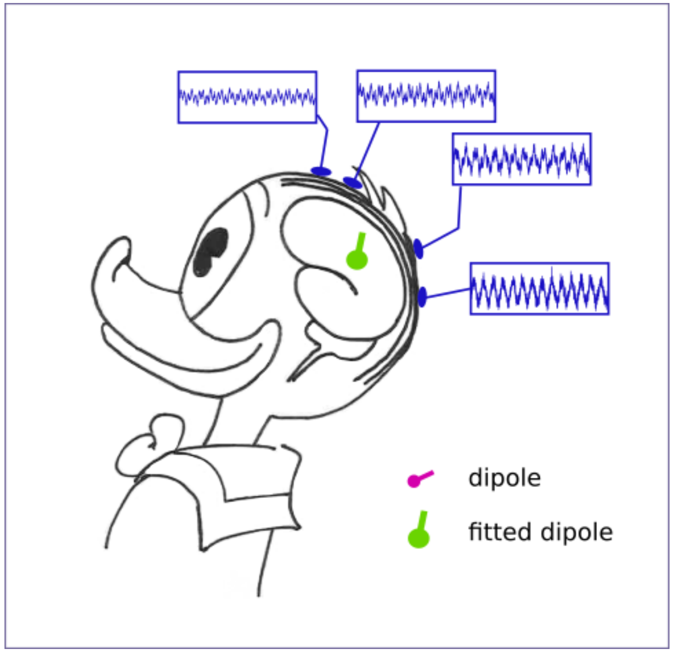
$$\hat{\mathrm{S}} = \mathbf{W}\mathbf{m}$$

(cartoon math)

$\hat{\mathrm{S}}$ = estimated source activity
$\mathbf{W}$ = inverse model
$\mathbf{m}$ = measured sensor data

Single dipole models

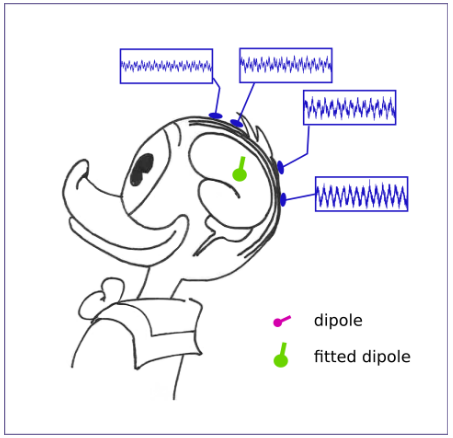
Idea: Find one dipole that explains the measured data best.

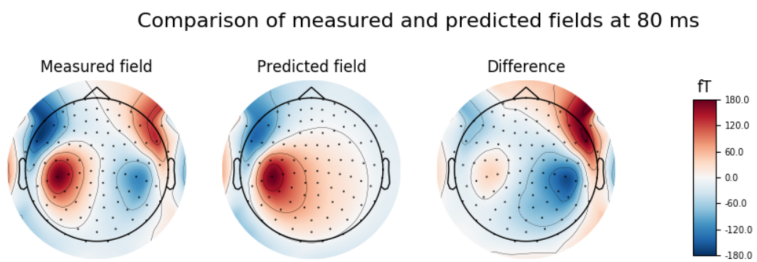


Manipulate the following **parameter** until fit is best:

- location of dipole
- orientation of dipole
- strength of dipole

Dipole fitting: results





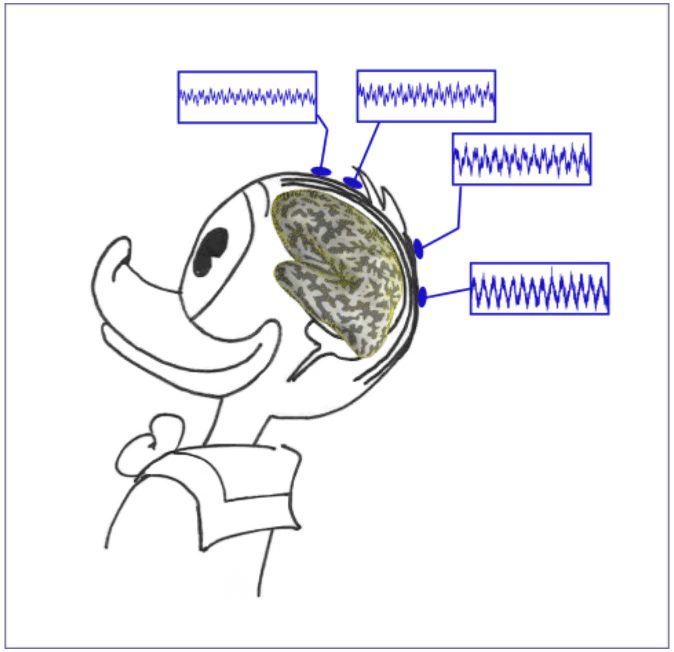
Pros and Cons:

- **sparse model** with goodness of fit measure
- assumption of single activitation probably wrong
- no "brain imaging"

Figure parts: MNE-Python

Distributed source models

Idea: Estimate **source strength** at predefined positions.



Set up a source space **grid** on cortical surface

- strength gets estimated at each grid point (dipole)
- orientation of dipoles fixed or allowed to vary

Figure: MNE-Python

The inverse problem: a closer look

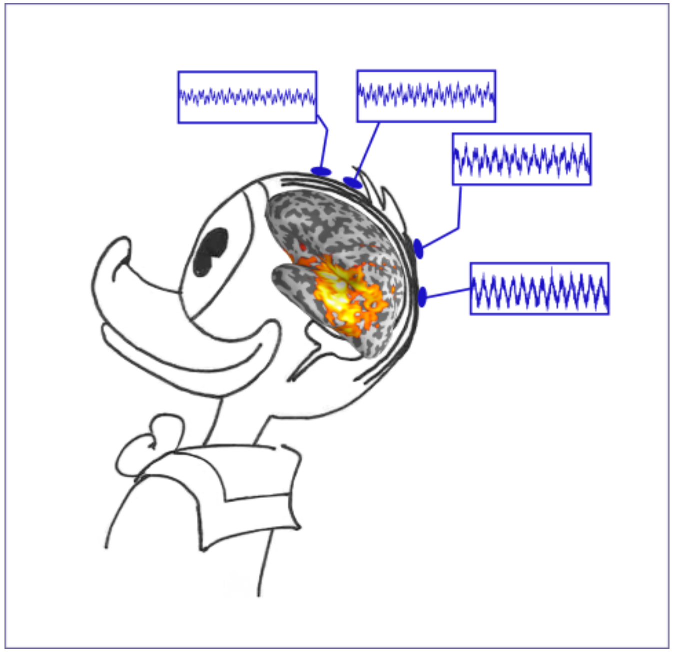
Ill-posed problem: many more grid points (thousands) than sensors (hundreds).

- infinite number of solutions
- use **constraints** to make solvable
- e.g., smoothness or source strength

Figure: Tim Noble & Sue Webster, 1998

Distributed source models: results

Minimum norm estimation / LORETA / dSPM / . . .



Pros and Cons:

- activity gets estimated over **whole brain**
- all measured activity (+ noise) lands in source space

Figure parts: MNE-Python

Beamforming or spatial filtering

- Originally developed for sonar and radar applications.
- Use cases:
  e.g., advanced WiFi routers or 5G networks
- Adapted for EEG and MEG in the 1990s
- Also used to visualize the shadow of the black hole!

Figure: Wikipedia, by Goodtiming8871

Spatial filtering

Spatial **filtering**?
Let's think of filtering data for frequencies:

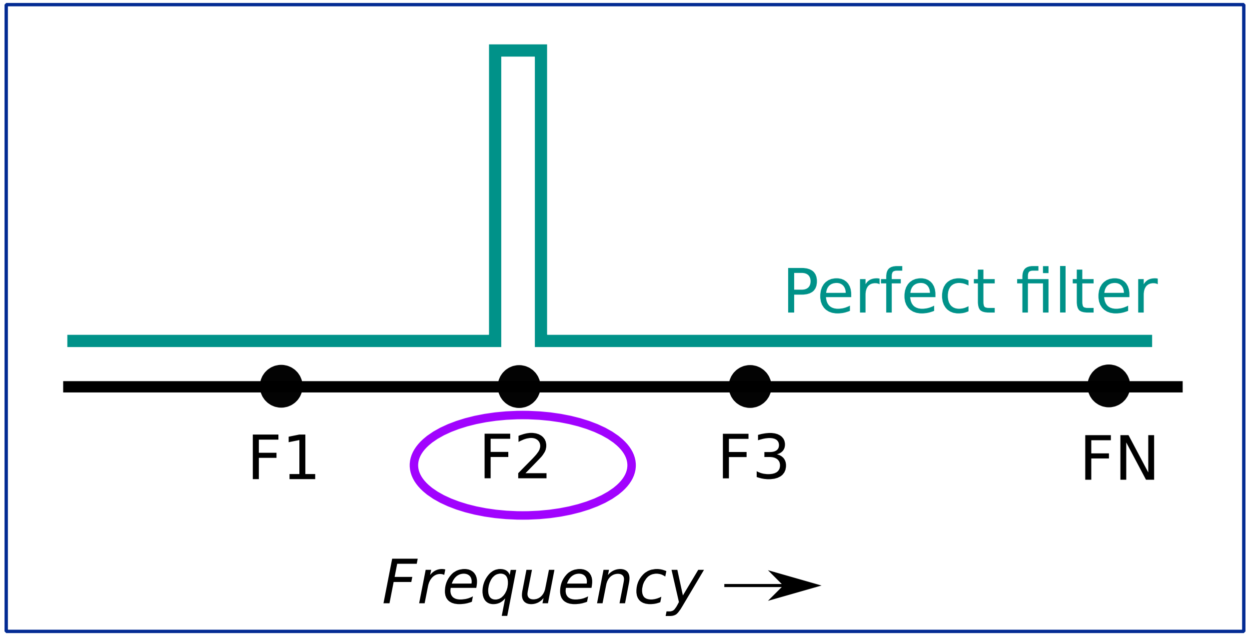


Figure: adapted from FieldTrip

Spatial filtering

Spatial **filtering**?

Let's think of filtering data for frequencies:

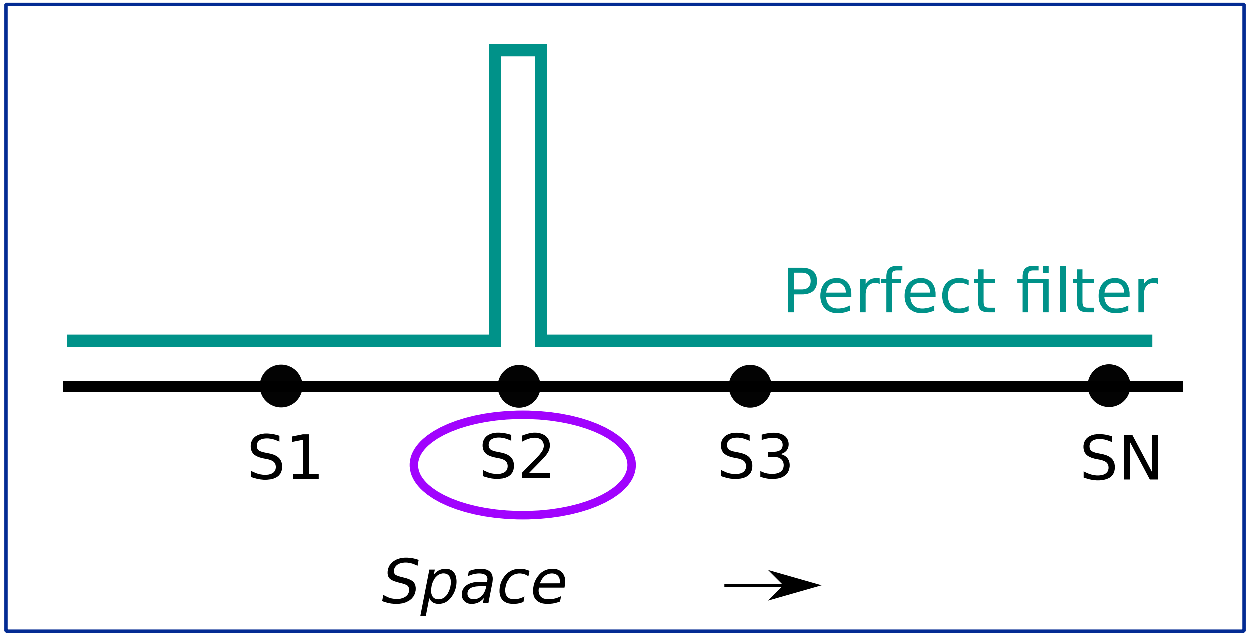
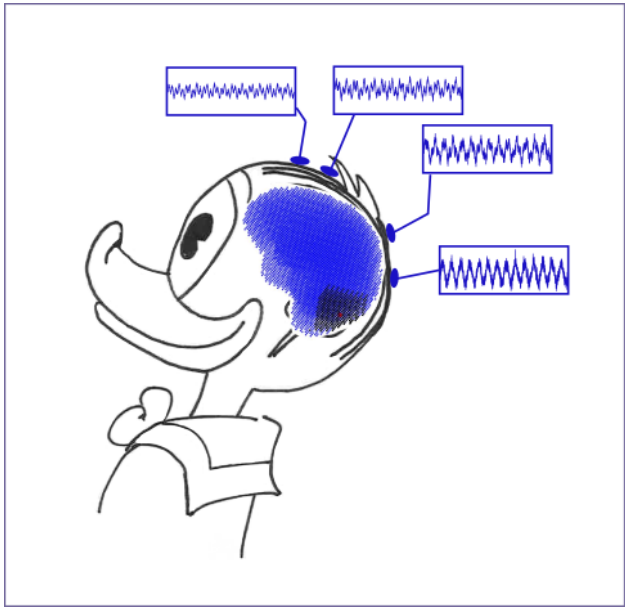


Figure: adapted from FieldTrip

Spatial filtering

Idea: Estimate **activity** for every position independently.



Set up a source space **grid**

- for every point: get a spatial filter
- project measured data through filter

Spatial filtering: a closer look

How does a spatial filter work?

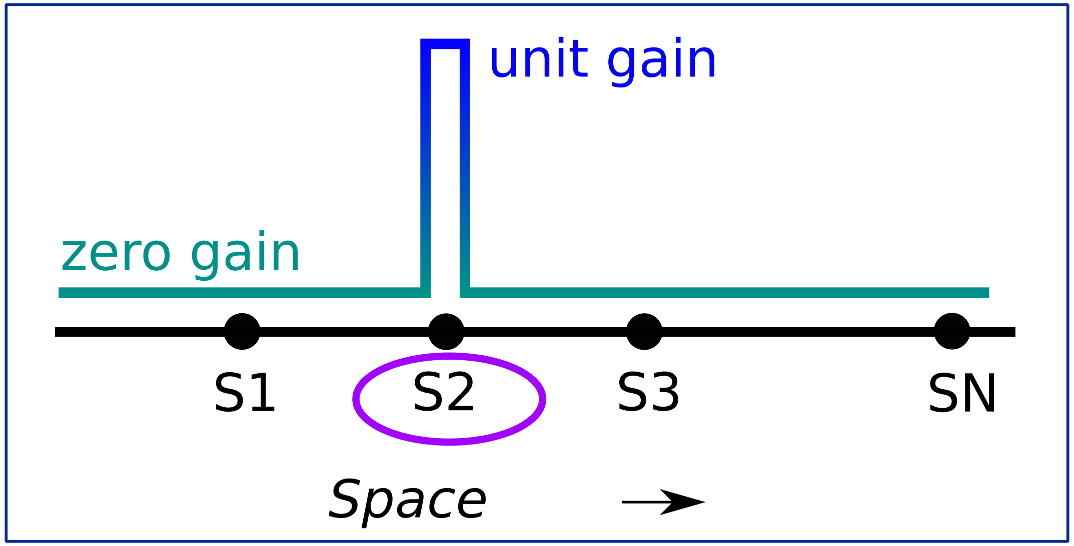
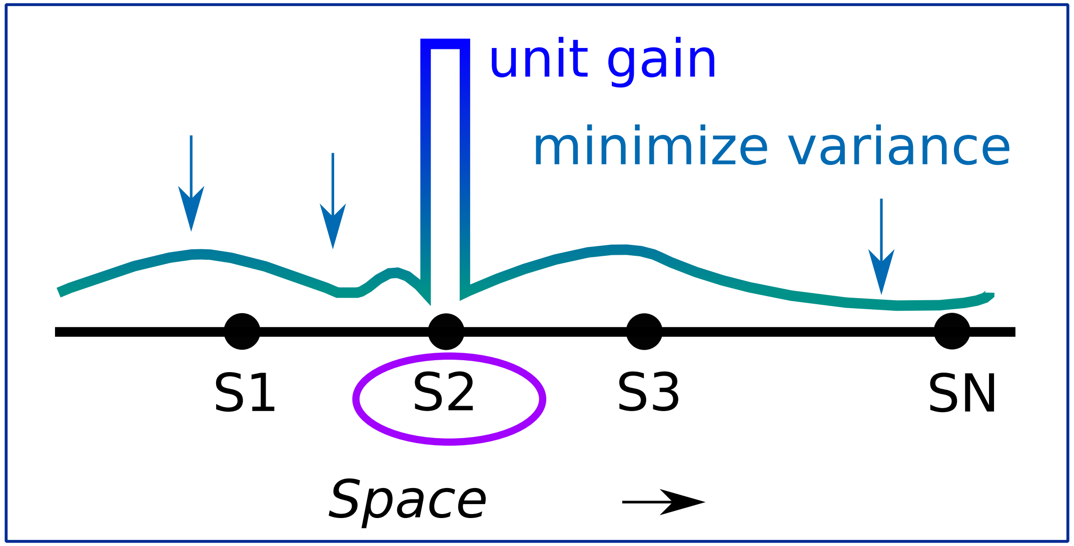


Figure: adapted from FieldTrip

Spatial filtering: a closer look

How does a spatial filter work?

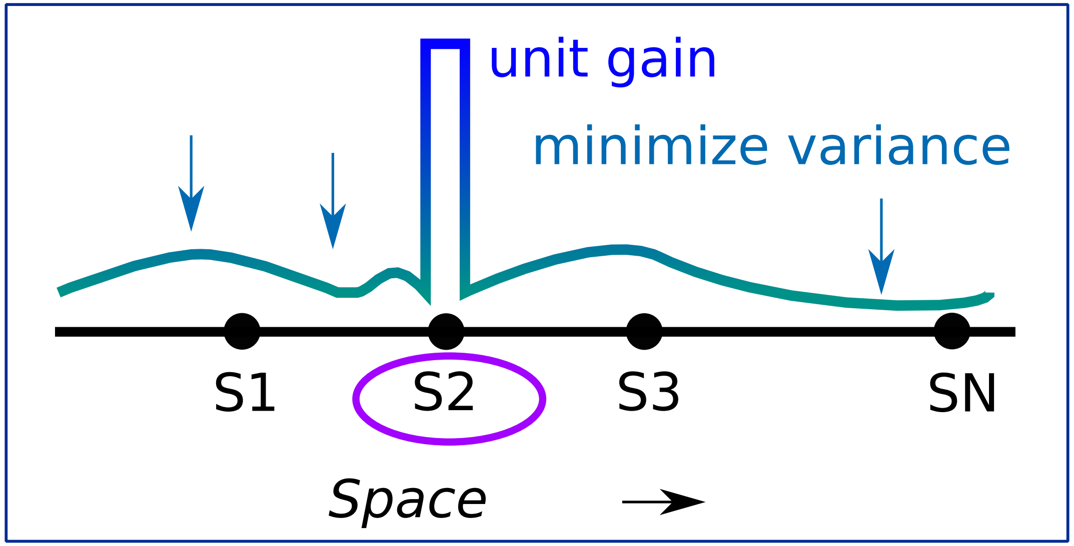


This works great when source activity is **uncorrelated**.

Figure: adapted from FieldTrip

Spatial filtering: a closer look

How does a spatial filter work?

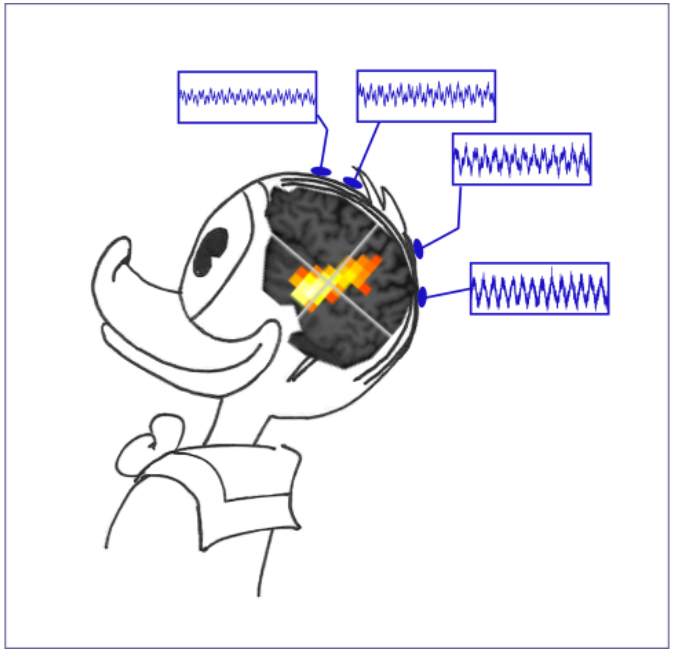


The result is a spatial filter **per grid point**
that describes the **contribution of each sensor** to this source.

Figure: adapted from FieldTrip

Spatial filtering: results

Beamforming



Pros and Cons:

- activity gets estimated over **whole brain**
- beamformer is **selective** to activity
- needs a **precise forward model**
- can be tricky with **correlated sources**

Figure: MNE-Python

Spatial filtering: the maths

Source reconstruction:

$\hat{\mathbf{S}}(r,t) = \mathbf{W}^\top(r)\mathbf{m}(t)$

$\hat{\mathbf{S}}$ = source estimate at location r and time point t
$\mathbf{W}$ = filter weights, $M \times 3$
$\mathbf{m}$ = measurement (data of M channels), $M \times 1$

Beamformer formula:

$\mathbf{W}^\top(r) = [\mathbf{L}^\top(r)\mathbf{C}^{-1}\mathbf{L}(r)]^{-1}\mathbf{L}^\top(r)\mathbf{C}^{-1}$

$\mathbf{L}$ = forward model, $M \times 3$
$\mathbf{C}$ = data covariance matrix, $M \times M$

Data covariance matrix:

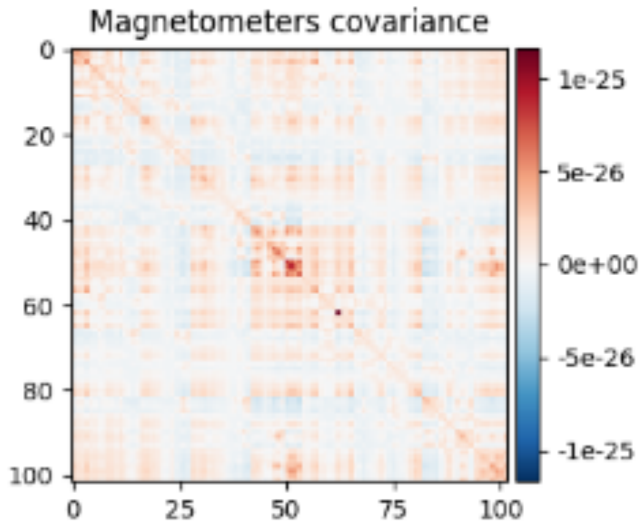


Figure: MNE-Python

Beamformers in FieldTrip

FieldTrip

```
cfg = [];
cfg.method = 'lcmv';
⋮
source = ft_sourceanalysis(cfg, tlk)
```

Vector vs scalar beamformers

- The forward model gives us three orientations.
- The forward model can be constrained: results in **scalar beamformer**.
- Also possible - and widely used - : compute **optimal orientation** based on data.
  `cfg.lcmv.fixedori = 'yes'`

Beamformer types

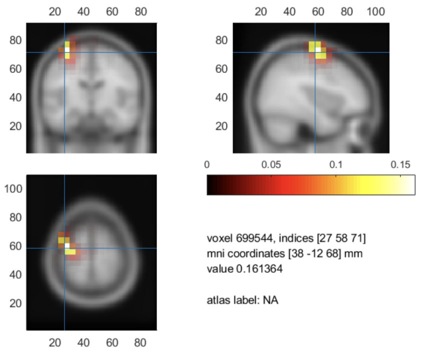


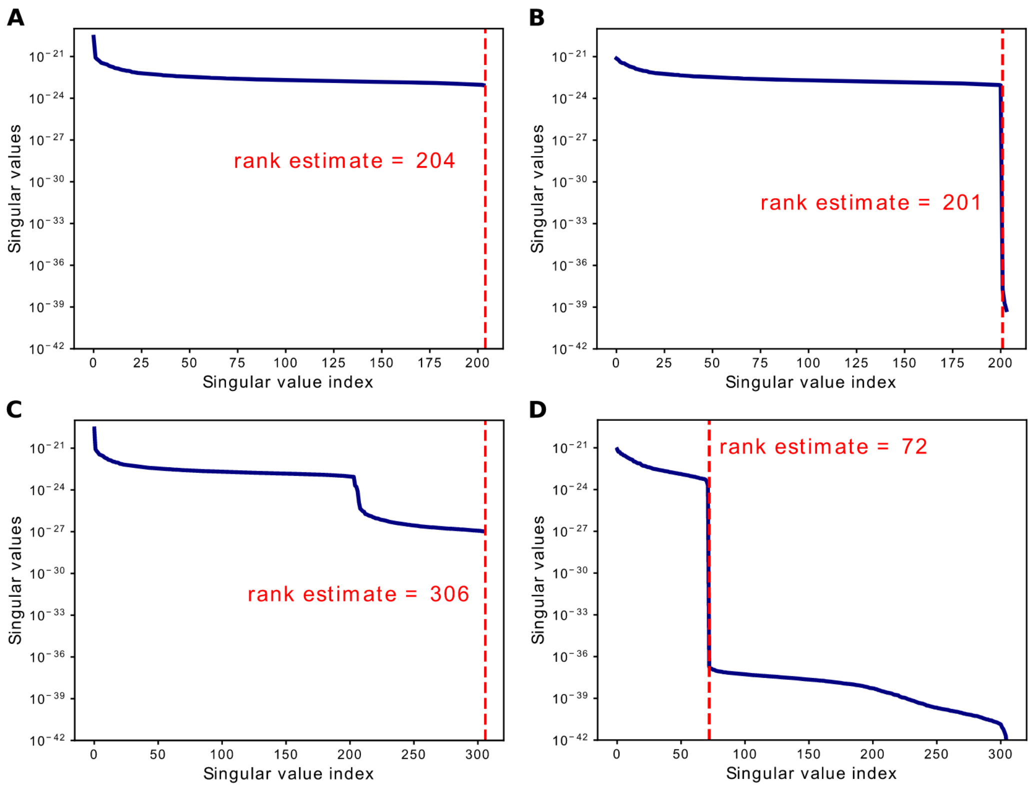
Figure: The neuronal source showing maximum coherence with the left EMG at 20 Hz.

Figure: FieldTrip tutorial

- Linearly-constrained minimum variance beamformer (**LCMV**): **time**-resolved data
- Dynamic Imaging of Coherent Sources (**DICS**): **frequency**-resolved data
- `cfg.method = 'lcmv'` or `cfg.method = 'dics'`

Beamforming: to keep in mind

Covariance matrix estimation and rank deficiency

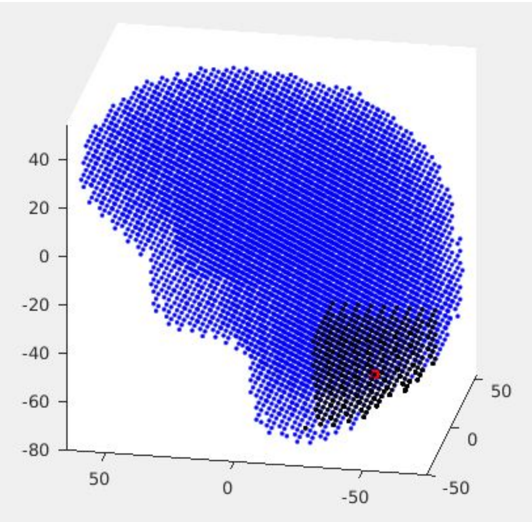


- e.g. through: sampling, ICA, SSS, ...
- rank-deficient covariance matrix can pose problems during **inversion**
- **regularization**: `cfg.lcmv.lambda = '1%'`
- whitening, truncated pseudo-inverse

Figure: Westner et al., 2022

Beamforming: to keep in mind

Depth bias (center of head bias)

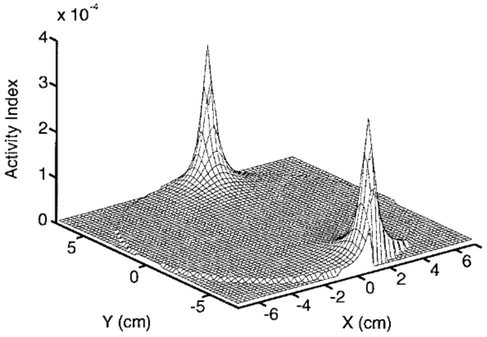


- deep sources have lower forward field coefficients
- this leads to *bigger* beamformer weights
- spatial normalization can mitigate this bias
- **array-gain beamformer** (leadfield normalization)
  `cfg.lcmv.weightnorm = 'arraygain'`
- **unit-noise-gain beamfomrmer** (weight normalization)
  `cfg.lcmv.weightnorm = 'unitnoisegain'`

Beamforming: to keep in mind

Correlated sources

- beamforming assumes sources to be uncorrelated in time

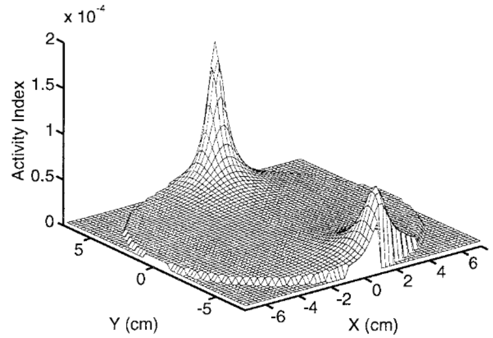


Figures: Van Veen et al., 1997; FieldTrip

Beamforming: to keep in mind

Correlated sources

- beamforming assumes sources to be uncorrelated in time
- correlated sources cannot be resolved properly

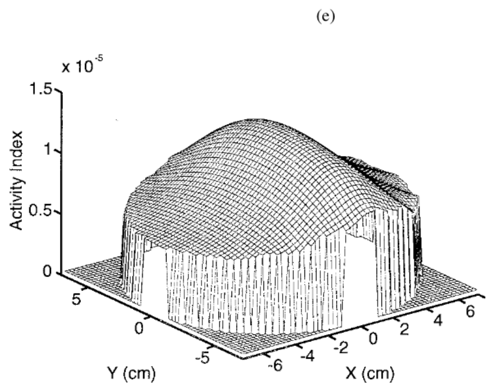


Figures: Van Veen et al., 1997; FieldTrip

Beamforming: to keep in mind

Correlated sources

- beamforming assumes sources to be uncorrelated in time
- correlated sources cannot be resolved properly

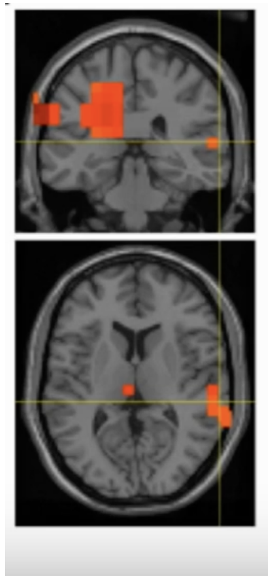


Figures: Van Veen et al., 1997; FieldTrip

Beamforming: to keep in mind

Correlated sources

- beamforming assumes sources to be uncorrelated in time
- correlated sources cannot be resolved properly
- make use of noise in your data



Figures: Van Veen et al., 1997; FieldTrip

Recap: inverse models

Aim: estimated source activity from sensor data.

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

(cartoon math)

$\hat{\mathbf{S}}$ = estimated source activity
$\mathbf{W}$ = inverse model
$\mathbf{m}$ = measured sensor data

$\hat{\mathbf{S}}$

- one or very few sources
- distributed sources
- independent sources

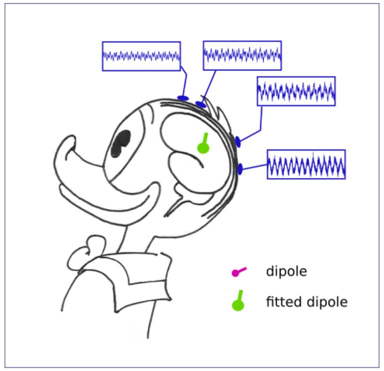
$\mathbf{W}$

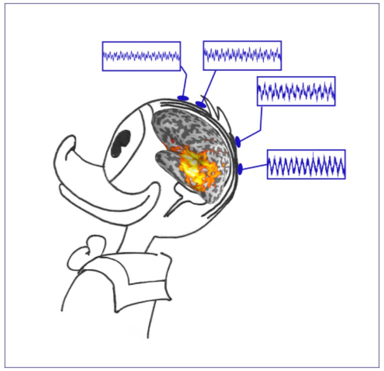
- dipole fitting
- distributed models
- spatial filtering

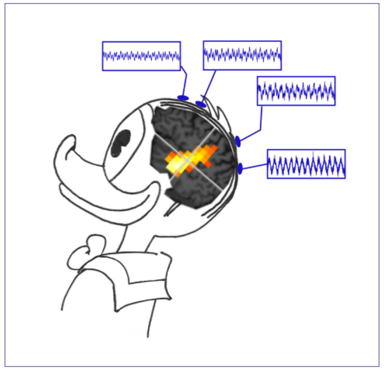
constraints

- limit sources
- minimize residuals and noise
- unit gain and minimize variance

Which inverse method for what?







Dipole fitting:

- single and focal source assumed

MNE:

- distributed activity assumed
- imprecise forward model

Beamforming:

- focal activity
- can deal with external noise

Further reading

Concepts, maths, and best practices:

NeuroImage 246 (2022) 118789

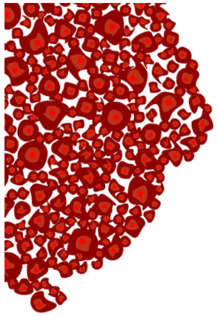
Contents lists available at ScienceDirect

NeuroImage

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

A unified view on beamformers for M/EEG source reconstruction

Britta U. Westner[a,b,*], Sarang S. Dalal[b], Alexandre Gramfort[c], Vladimir Litvak[d], John C. Mosher[e], Robert Oostenveld[a,f], Jan-Mathijs Schoffelen[a]



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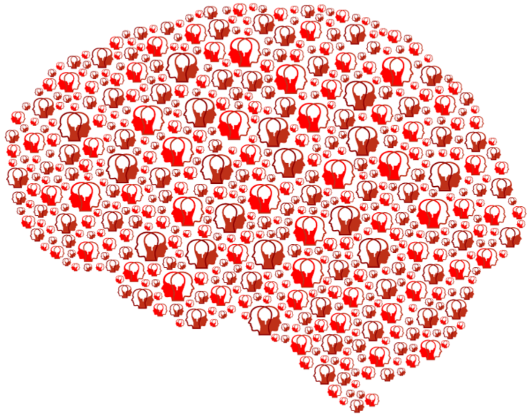
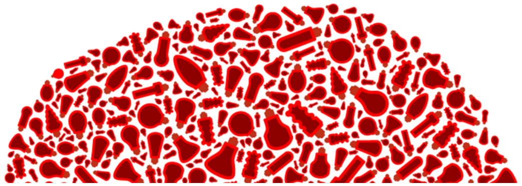
Questions?



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