EEG/MEG source reconstruction using beamformers

Amit Jaiswal, *DSc (Tech.)*

Senior Clinical Scientist & Application Lead

MEGIN Oy, Espoo, Finland

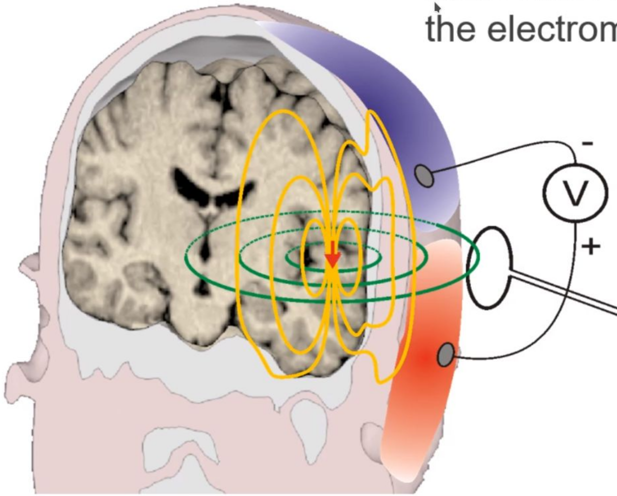
July 25, 2025

IIT Mandi, Mandi, HP, India

MEGIN

MEG/EEG signals measurement

MEG and EEG track electric brain activity by measuring the electromagnetic fields generated by neurons



EEG = measuring the potential differences on the scalp

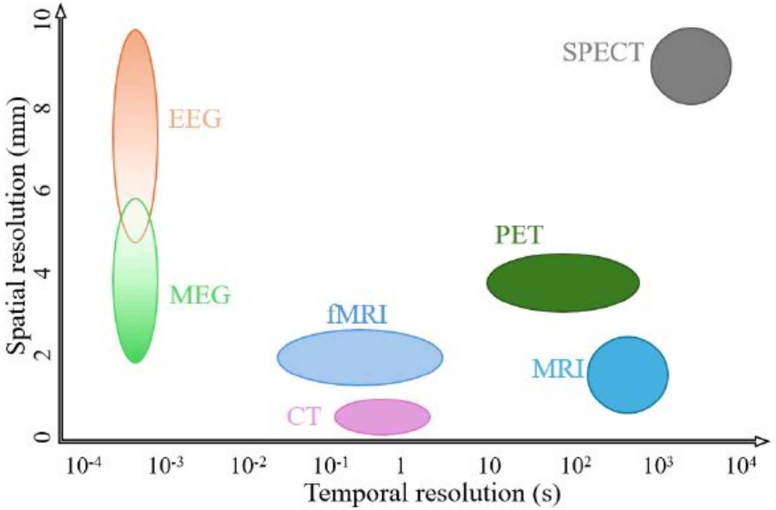
MEG = measuring neuromagnetic fields outside of the head

EEG

MEG + EEG

Source-level analysis: should we do with EEG?

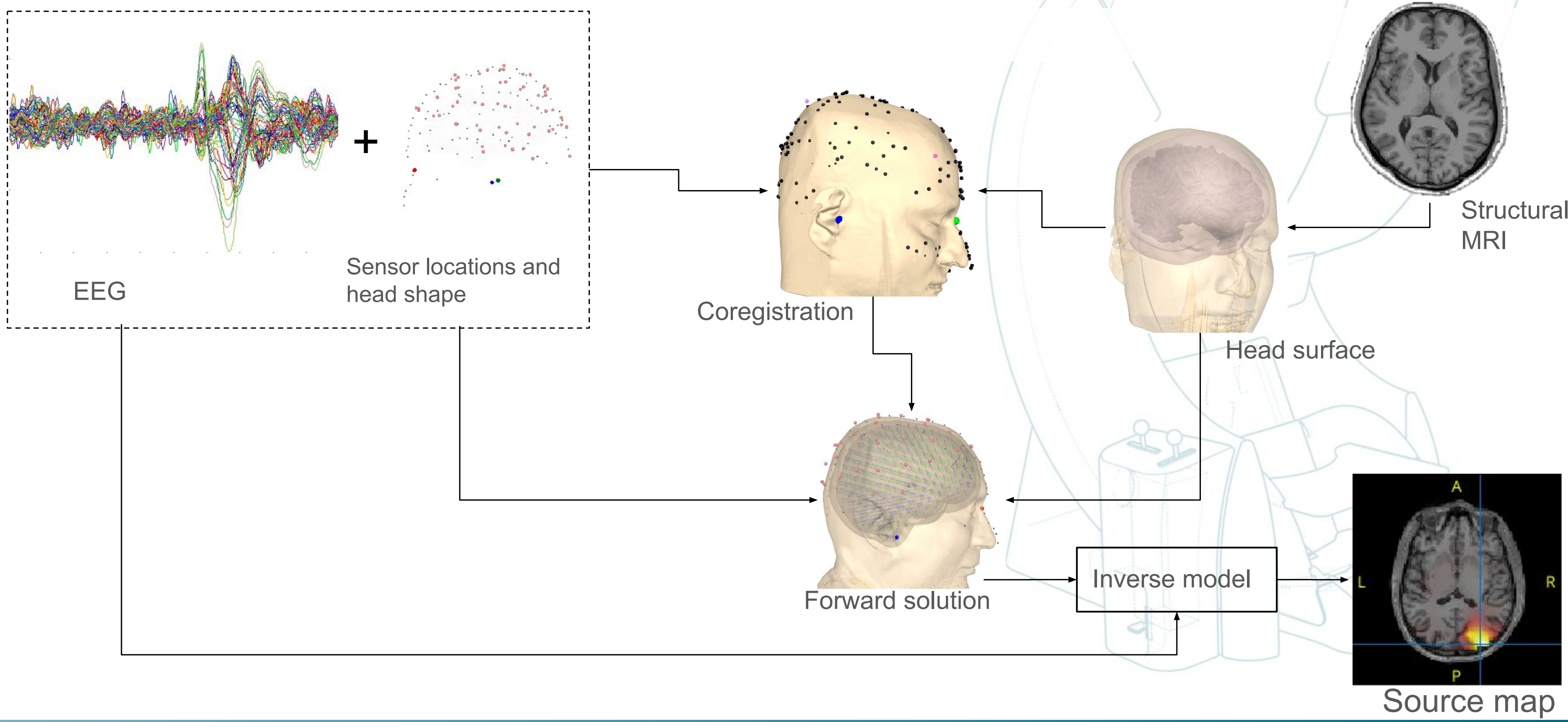
- Due to high spatial resolution MEG source imaging is advantageous in accurately localizing underlying sources.
- Source-level analysis is more common in MEG.
- EEG channels are comparable over participants (within a study) and spatially quite blurry, hence often sensor-level analysis is used.
- EEG source imaging is advantageous if accurate conductor model is provided.



Jaiswal A., 2024

MEGIN

A typical workflow for EEG source imaging



MEGIN

Common source analysis methods

- **Minimum norm estimation (MNE)**
  - estimates the source distribution with the smallest overall power that explains the EEG data.
- **LORETA / sLORETA / eLORETA**
  - methods estimate smooth, distributed source activity.
- **Equivalent current dipole (ECD) fitting**
  - models one or a few discrete dipoles with specific location and orientation.
  - is best for focal sources, such as in epilepsy.
- **Beamforming (e.g., LCMV)**
  - is spatial filtering approach that estimate activity from specific brain regions while suppressing others.
  - Good for analyzing oscillatory activity or task-specific sources.

Beamformers

- Beamforming is scanning method of inverse modeling.
- They scan one source at a time while suppressing activity from other sources (either they are inside brain or noise sources).
- Beamforming is a spatial filtering method, that assumes time courses from difference sources are uncorrelated.
- What it means —
  - The correlated source activity are suppressed.
- Beamformers are adaptive and data-driven, as the filter weights are computed using data covariance.

Sekihara et al., 2001; Spencer et al., 1992; Van Veen et al., 1997, Jaiswal et al., 2020

Common beamformer types

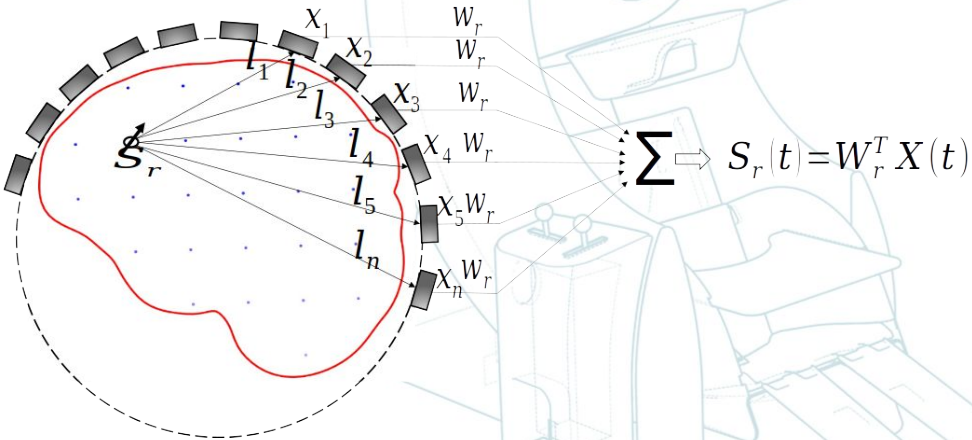
- **LCMV (linearly constrained minimum variance)**
  - Time domain beamformer that minimizes signal power from all directions except the target location.
- **DICS (dynamic imaging of coherent sources)**
  - A frequency-domain beamformer that localizes sources of oscillatory activity.
- **MUSIC (multiple signal classification)**
  - A dipole scanning method that matches observed EEG/MEG signals to theoretical patterns using signal and noise subspaces.

Beamformers in action

Given the sensor-level signal X(t), estimate the activity at source *S* at location *r.*

Available ingredient:

- Sensor-level data
- Forward model (lead field)
    - Conductor model
    - Source model
    - Sensor location



Beamformer (LCMV) formulation

Let, x be a M × 1 signal vector of MEG (or EEG) data measured with M sensors, and N be the number of grid points in the source model with grid locations r_j , (j = 1, ... , N).

Then the source $y(r_j)$ at any location r_j can be estimated as weighted combination of the measurement x as

$$y(r_j) = W^T(r_j)x$$

where the M × 3 matrix $W(r_j)$ is known as a ***spatial filter*** for a source at location r_j.

Vector-type beamformer

Here, $W(r_j)$ is defined as $W(r_j) = \left(L^T(r_j)C^{-1}L(r_j)\right)^{-1} L^T(r_j)C^{-1}$

where $L(r_j)$ is local leadfield matrix, and C is the covariance matrix computed from the measured data samples.

Beamformer formulation (contd…)

- Since 'noise' typically infects the measured signal, the estimated signal variance is generally normalized using projected noise variance C_n . Such normalized estimates are known as the *Neural Activity Index* (NAI; van Veen et al., 1997) and can be written as

$$NAI(r_j) = Trace\left\{\left[L^T(r_j)C^{-1}L(r_j)\right]^{-1}\right\} / Trace\left\{\left[L^T(r_j)C_n^{-1}L(r_j)\right]^{-1}\right\}$$

- Further, orientation optimization is often used to convert the vector type to a *scalar type beamformer*, turning the spatial filter *W(r_j)* to M x 1 vector, and computed as

$$w(r_j) = \left(l_{\eta_{opt}}^T(r_j)C^{-1}l_{\eta_{opt}}(r_j)\right)^{-1} l_{\eta_{opt}}^T(r_j)C^{-1}$$

Jaiswal et al., 2020

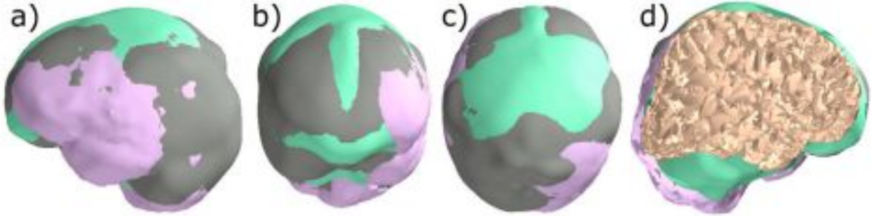
Best applicability of beamformers

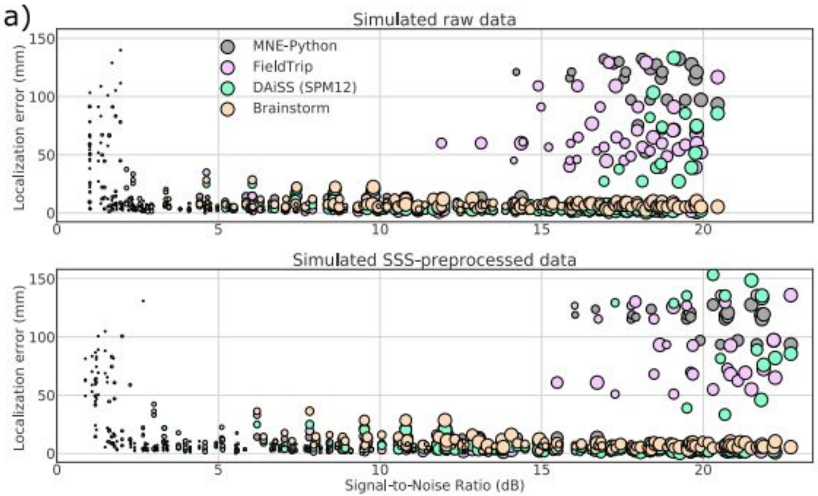
- **Event-related source analysis**
  - Useful for studying task-related brain dynamics by comparing conditions (e.g., rest vs. task).
- **Oscillatory source localization**
  - Ideal for detecting narrow-band neural oscillations (e.g., alpha, beta, gamma) in both MEG and EEG.
- **Exploratory whole-brain scans**
  - Can localize sources without needing prior assumptions about number or location of sources.
- **Good spatial resolution (in MEG)**
  - Particularly effective in MEG due to lower sensitivity to skull conductivity variation compared to EEG.

Limitation of beamformers

- **Poor for highly correlated sources**
  - Beamformers struggle when two or more sources are strongly correlated, often suppressing one or mislocalizing both.
- **Sensitive to head modeling errors**
  - Requires accurate lead field and head model; errors can degrade localization accuracy.
- **Limited for deep sources (especially in EEG)**
  - Deep brain sources are harder to detect, particularly in EEG due to lower sensitivity.
- **Assumes stationarity**
  - Standard beamformers assume that source activity is stationary during the analysis window—limiting for rapidly changing dynamics.

Implementation in open-source s/w and comparison





Jaiswal, A., Nenonen, J., Stenroos, M., Gramfort, A., Dalal, S. S., Westner, B. U., ... & Parkkonen, L. (2020). Comparison of beamformer implementations for MEG source localization. *NeuroImage*, *216*, 116797.

Frequency-domain beamformer

- Frequency-domain beamformers localize sources of oscillatory brain activity by applying spatial filters to the cross-spectral density (CSD) of EEG/MEG signals.
- They are ideal for studying frequency-specific activity and functional connectivity in the brain (e.g., alpha, beta rhythms).

Learn more on the method and application on EEG data:

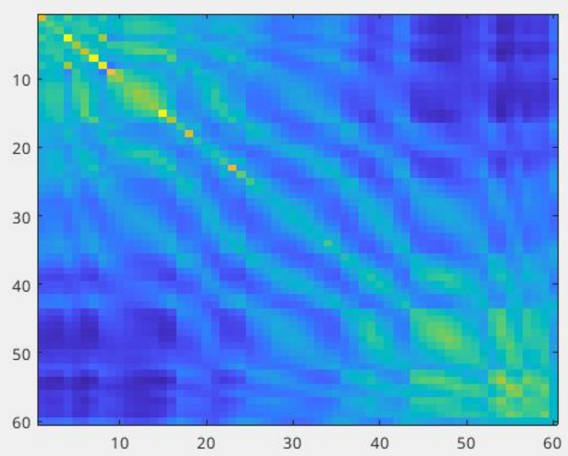
- Groß, J. et al., (2001). Dynamic imaging of coherent sources: studying neural interactions in the human brain. Proceedings of the National Academy of Sciences, 98(2), 694-699.
- Tiwari, A. et al. (2022). Dorsal-Ventral Visual Pathways and Object Characteristics: Beamformer Source Analysis of EEG. *Computers, Materials & Continua*, *70*(2).

Let’s do it in FieldTrip!

Compute data and noise covariance

```
%% Compute noise cov.
cfg = [];
cfg.toilim =[-.5,.05];
epochs_pre = ft_redefinetrial(cfg, epochs);
cfg = [];
cfg.covariance='yes';
evoked_pre = ft_timelockanalysis(cfg,epochs_pre);

%% Compute data cov.
cfg = [];
cfg.toilim  = [.05, .1];
epochs_post = ft_redefinetrial(cfg, epochs_pre);
cfg = [];
cfg.covariance='yes';
evoked_post = ft_timelockanalysis(cfg,epochs);
```



Computing a common spatial filter

```
cfg                   = [];
cfg.method            = 'lcmv';
cfg.grid              = leadfield;
cfg.headmodel         = headmodel;
cfg.lcmv.keepfilter   = 'yes';
cfg.lcmv.fixedori     = 'yes';
cfg.lcmv.reducerank   = 3;
cfg.lcmv.normalize    = 'yes';
cfg.senstype          = 'EEG';
cfg.lcmv.lambda       = '5%';
source_avg            =
ft_sourceanalysis(cfg, evoked);
```

```
disp(source_avg)

      time: [1×601 double]
       cfg: [1×1 struct]
       dim: [17 22 13]
    inside: [4862×1 logical]
       pos: [4862×3 double]
      unit: 'm'
    method: 'average'
       avg: [1×1 struct]
```

MEGIN

Apply it noise (baseline) data

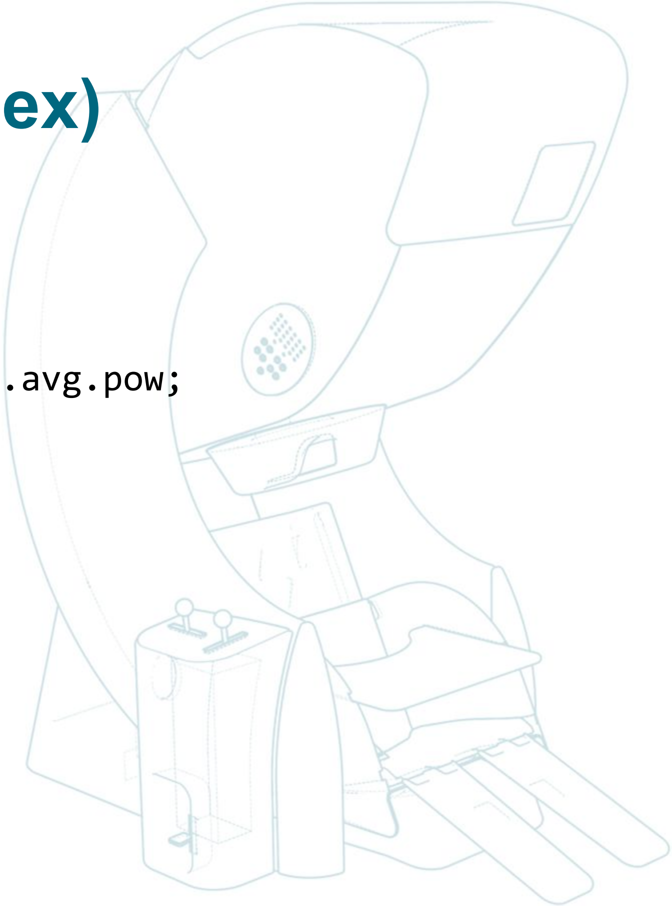
```
cfg                     = [];
cfg.method              = 'lcmv';
cfg.senstype            = 'MEG';
cfg.grid                = leadfield;
cfg.grid.filter         = source_avg.avg.filter;
cfg.headmodel           = headmodel;
source_pre  = ft_sourceanalysis(cfg, evoked_pre); % apply spatial filter on
noise
```

Apply it to data-of-interest (active time window)

```
cfg                     = [];
cfg.method              = 'lcmv';
cfg.senstype            = 'MEG';
cfg.grid                = leadfield;
cfg.grid.filter         = source_avg.avg.filter;
cfg.headmodel           = headmodel;
source_post = ft_sourceanalysis(cfg, evoked_post); % apply spatial filter on data
```

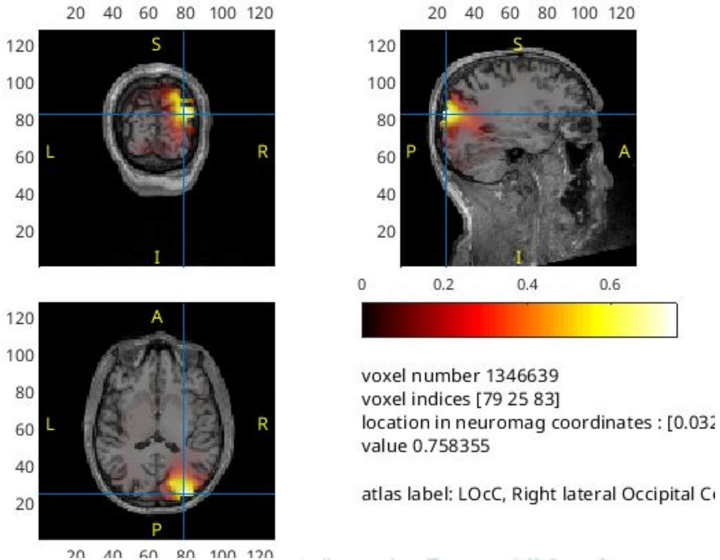
Computing NAI (Neural activity index)

```
%% Calculate Neural Activity Index (NAI)
spatial_map = source_post;
spatial_map.avg.pow =
(source_post.avg.pow-source_pre.avg.pow)./source_pre.avg.pow;
```



Map the source activity on MRI

```
%% Interpolate source map with MRI
cfg            = [];
cfg.downsample = 2;
cfg.parameter  = 'pow';
mapOnMRI = ft_sourceinterpolate(cfg, spatial_map , mri);
%% Plot source map on MRI
maxval = max(mapOnMRI.pow, [], 'all');
cfg = [];
cfg.method        = 'ortho';
cfg.funparameter  = 'pow';
cfg.maskparameter = cfg.funparameter;
cfg.funcolorlim   = [0.0 maxval];
cfg.opacitylim    = [0.0 maxval];
cfg.opacitymap    = 'rampup';
cfg.atlas         = [ft_dir, 'template/atlas/brainnetome/BNA_MPM_thr25_1.25mm.nii'];
ft_sourceplot(cfg, mapOnMRI)
```



MEGIN

Thanks for your attention!

MEGIN