Spatial Filtering Methods in MEG

Part 2: Beamformer Analysis and the BrainWave Toolbox

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A spatial filter is the weighted output of the MEG sensor array that reflects activity at a specific brain location over time.

**Signal Space Projection (SSP)**

\[ W(r) = \sum_{source} strength \times source \]

\[ W(r) = L(r) = \text{lead field of source} \]

**Beamformer**

\[ W(r) = L(r) C_m^{-1} / L(r) C_m^{-1} L(r) \]
Spatial filtering methods

Vector beamformers

Orthogonal current sources at each voxel. Forward model and weights are multidimensional*

e.g., Linearly Constrained Minimum-Variance (LCMV) beamformer (Van Veen et al., 1997)

\[
S(r, t) = W(r)^T m(t)
\]

Scalar beamformers

Estimates a single optimal current direction at each voxel. Forward model and weights are one-dimensional

e.g., Synthetic Aperture Magnetometry (SAM) (Robinson & Vrba, 1999)

\[
s(r, t) = w(r)^T m(t)
\]

*for EEG # directions = 3, for MEG spherical model, # directions = 2
Introduction of Beamformers in EEG/MEG

Linearly Constrained Minimum-Variance (LCMV) beamformer (Van Veen et al., 1997)
- first application of beamformer method to EEG/MEG inverse problem, EEG only

Synthetic Aperture Magnetometry (SAM) (Robinson & Vrba, 1999)
- introduction of scalar beamformer and use of unaveraged data, “differential” imaging

Dynamic Imaging of Coherent Sources (DICS) (Gross et al., 2001)
- frequency domain beamformer, coherence analysis

Eigenspace / spatiotemporal beamformer (Sekihara et al., 2001, 2002; Dalal et al., 2004)
- derived time-courses for eigenspace beamformer (averaged data), NutMEG toolbox

Event-related SAM (erSAM) (Cheyne et al., 2004, 2006)
- combined SAM algorithm and spatiotemporal approach to image evoked responses

SAMerf (Robinson, 2004)
- SAM algorithm modified for short time windows (not same algorithm as erSAM!)

Event-related beamformer (ERB) (Cheyne et al., 2008)
- revised erSAM for optimized orientation calculation

5-D beamformer (Dalal et al., 2010)
- computes beamformer over separate frequency bands and time windows
Adaptive (Minimum-variance) Beamforming

For the adaptive beamformer, we select weights that minimize total source power (weights x data \( \rightarrow 0 \)) but don't suppress the source of interest (weights x forward model for location \( r = 1 \)).

This is the minimization problem:

\[
\min_{\{W(r)\}} P = W(r)^T C W(r) \quad \text{subject to} \quad W(r)^T L(r) = I
\]

where \( L(r) = \) lead field for current dipole(s) at location \( r \)

and \( C = M \times M \) channel covariance matrix of the observed data over \( N \) time samples given by

\[
C_{ij} = \frac{1}{N} \sum_{k=1}^{N} m_i(t_k) m_j(t_k)
\]

The following general solution is obtained using method of Lagrange multipliers

\[
W(r) = C^{-1} L(r) \left[ L(r)^T C^{-1} L(r) \right]^{-1}
\]

“Minimum variance beamformer”
Adaptive (Minimum-variance) Beamforming

Problem:

Beamformer filter can only suppress noise sources that are correlated across sensors.

Therefore, uncorrelated noise (e.g., random system noise) will be amplified by the weights in a non-uniform manner, with increasing distortion with increasing distance from the sensors.
Spatial filtering methods – weight normalization

Source location

Non-normalized
(units = nA-m)

Source activity
(peak = 20 nAm)

Virtual sensor at peak (nA-m)

\[ S(r, t) = w(r)^T m(t) \]
Spatial filtering methods – weight normalization

The non-uniform distortion of beamformer images can be removed by normalizing the weight vector \( w(r) \) for each voxel \( w(r) \), to have unit length ("unit-gain" or Borgiatti-Kaplan beamformer)

\[
\mathbf{w}_n(r) = \frac{\mathbf{w}(r)}{\sqrt{\sum_{i=0}^{M} \left(\mathbf{w}_i(r)\right)^2}}
\]

Units of \( w(r) = \text{A-m} / \text{Tesla} \)
(output of beamformer is A-m)

Units of \( w_n(r) \) are arbitrary units
(output of beamformer in arbitrary units)

The “neural activity index” (Van Veen, 1997) and “pseudo-Z” (Robinson and Vrba, 1999) include an additional scaling of the unit-gain beamformer to units of specified noise \( n_w \)

\[
\mathbf{w}_n(r) = \frac{\mathbf{w}(r)}{\sqrt{\sum_{i=0}^{M} \left(\mathbf{w}_i(r) n_w\right)^2}}
\]

Output of beamformer is scaled to units of noise variance. Robinson termed this “pseudo-Z”
Spatial filtering methods – weight normalization

Source location

Non-normalized (units = nA-m)

Source activity (peak= 20 nAm)

Normalized (units = pseudo-Z)

virtual sensor at peak (nA-m)

virtual sensor at peak (pseudo-Z)

\[ s(r,t) = w(r)^T m(t) \]
Adaptive (Minimum-variance) Beamforming

Interpreting the spatial extent of activity peaks in beamformer images

Do bigger blobs mean more (wider) activation?
Effect of SNR on beamformer resolution

Simulated bilateral auditory cortex sources

X = 0.0 cm
Y = 5.5 and -5.5 cm
Z = 6.0 cm

+ Gaussian noise

FWHM of peak is reduced with higher SNR!
Introduction to Beamformers

Do I need to clean my data?

It depends…

Advantages:

• reduces amount of noise sources beamformer has to suppress

Disadvantages:

• weak noise and brain sources might be harder to separate if close
• noise reduction techniques will reduce rank of covariance matrix
Beamformer suppression of eye-movement artifacts

- adult performing self-paced movements (KIT-Macquarie MEG 160)

During fixation

During visual scanning

Sensor data (all channels) (0 – 15 Hz)

Motor cortex activation (t = -75 ms)

Motor cortex time-course

Scanning

Fixating
ERB method suppresses ferromagnetic artifacts

Motor Field (MF) localization in subject with metal retainer

Average (frontal sensors)

ERB source image (2 mm)

Right index finger movement
Introduction to Beamformers

Beamformer solutions depend on how well we can estimate the inverse of the covariance matrix (C⁻¹)


Depends on:

• condition number of covariance matrix (ratio of max / min eigenvalues)
• number of channels (less is better?)
• bandwidth of data (smaller bandwidth increases covariance error)
• number of time samples in data (about 30 s recommended)
Decrease in FWHM of beamformer peaks / increase in pseudo-Z power with increasing amount of data used to compute covariance matrix (from Brookes et al., 2008)
Covariance Matrix Regularization:

In cases where data covariance is rank deficient (e.g., PCA or SSS has been applied to the raw data) or ill-conditioned (e.g., too few samples, averaged data) regularization of covariance matrix may be required.

\[
W_\theta = [C + \mu \Sigma]^{-1} L_\theta \left[ L_\theta^T (C + \mu \Sigma)^{-1} L_\theta \right]^{-1}
\]

Diagonal regularization

As \( \mu \to \infty \)
\[
W_\theta = L_\theta \left[ L_\theta^T L_\theta \right]^{-1}
\]

(minimum noise sensitivity)

As \( \mu \to 0 \)
\[
W_\theta = C^{-1} L_\theta \left[ L_\theta^T C^{-1} L_\theta \right]^{-1}
\]

(maximum spatial resolution)

\( L_\theta \) = forward solution for target location
\( C \) = data covariance matrix
\( \mu \) = regularization parameter
\( \Sigma \) = diagonal matrix of sensor noise
Introduction to Beamformers

Increase in FWHM of beamformer peaks with covariance matrix regularization (from Brookes et al., 2008)
Introduction to Beamformers

Is it true beamformers can’t image correlated sources?
Spatial filtering methods – effects of source correlation

Simulation (3 sources)

Source activity

Source power

Source power

Source power

Source power

+ Gaussian noise (200 trials)
Spatial filtering methods – effects of source correlation

Simulation (auditory evoked fields)

Source 1 (0, 5.5, 6.0)
Source 2 (0, -5.5, 6.0)
Gaussian noise (10 - 20 fT / Hz^{1/2})
150 trials

Beamformer source reconstruction

Right hemisphere source jittered trial-by-trial by 6 ms

Average (all sensors)

Trial-by-trial latency jitter of 6 ms reduces effect of correlation
Correcting for correlations in beamformer solutions

• “Coherent Source Region Suppression” method (Dalal et al., 2006)

• identify region where correlated source is known to exist

• can be done iteratively to image (e.g., left and right hemisphere sources)

Image 1 (RH suppression)  Image 2 (RH suppression)  “corrected” image = \text{max}(\text{image1},\text{image2})
Spatial filtering methods – effects of source correlation

from Beal et al., 2010

Used Dalal’s correlation suppression method to image left and right hemispheres separately
(a) Whole-Array Beamforming

(b) Half-Array Beamforming

(c) Left Hemisphere

Right Hemisphere

MEG - Analysis Methods

Source reconstruction algorithms

Source waveforms

Time-frequency analysis of oscillatory activity

Spatiotemporal movies

Evoked responses

3D source images

Source waveforms

Evoked responses

Time-frequency analysis of oscillatory activity

Spatiotemporal movies
Differential imaging using the “SAM” beamformer

1. Single trial data
2. Compute beamformer
3. Compute Source Power

- N samples
- T trials
- M channels
- M x M Active Covariance matrix (C_A)
- M x M Baseline Covariance matrix (C_B)
- Bandpass filter and segment into active and control windows

Forward solution (B) for source r

compute beamformer weights W(r) = C_A^{-1}B/B^T C_A^{-1}B

Pseudo-T = W(r)^T C_A W(r) - W(r)^T C_B W(r)

SAM = Synthetic Aperture Magnetometry
(Robinson & Vrba, 1999)

Alternatively, compute pseudo-F

\[ F = \begin{cases} 
F - 1 & \text{if } F > 1.0 \\
1 - 1/F & \text{if } F < 1.0 
\end{cases} \]

where \( F = W(r)^T C_A W(r) / W(r)^T C_B W(r) \)
Differential (dual-state) SAM imaging

Beta rebound somatotopy

Differential SAM images - rebound period (0.5 - 1 s) minus baseline
Event-related (spatiotemporal) beamformer

Single trial data

M channels

N samples

T trials

\[ M \times M \]

Covariance matrix (C)

Forward solution (B) for source \( j \)

\[ W(j) = C^{-1}B/B^TC^{-1}B \]

Compute beamformer

Source activity for voxel \( j \)

\[ S(j,t) = W(j) \times m(t) \]

Take absolute value

and repeat for all voxels

Bandpass filter

Map power at latency of evoked response

\[ t = 20 \text{ ms} \]

\[ \text{pseudo-Z} \]

\[ 3.0 \]

\[ 1.0 \]
Beamformer localization of premovement motor field (MF)

ERB image in MRIViewer (t = -40 ms, threshold = FWHM)

Time course at peak (virtual sensor)

Self-paced right index finger movement
Recording time ≈ 10 min (100-130 movements)

DC-15 Hz
**BrainWave** (a Matlab-based GUI for beamformer analysis)

- requires MATLAB, runs on Linux, Mac OS X or Windows
- optimized using multi-threaded C-mex functions
- import and epoch raw data with support for CTF, Yokogawa, Neuromag, 4D (under development)
- import and co-register DICOM MRI, generate surfaces and spherical head models
- computes “event-related” or differential (SAM) beamformer images
- normalization of images to MNI template (requires SPM8)
- normalization to template MRI (if MRI not available)
- built-in 4D image viewer (“glass brain”)
- computes source activity time course (“virtual sensors”) – average or time-frequency plots
- group images with contrasts and permutation tests
- group averaging of source activity waveforms or their time-frequency transformations

Available for download at [http://cheynelab.utoronto.ca](http://cheynelab.utoronto.ca)

(* Beamformer Reconstruction And INteractive WAviform Visualization Environment)
Suggested Readings

**Beamforming Methods:**


