An overview of beamformer approaches:

Basic principles, underlying assumptions, and major causes of errors

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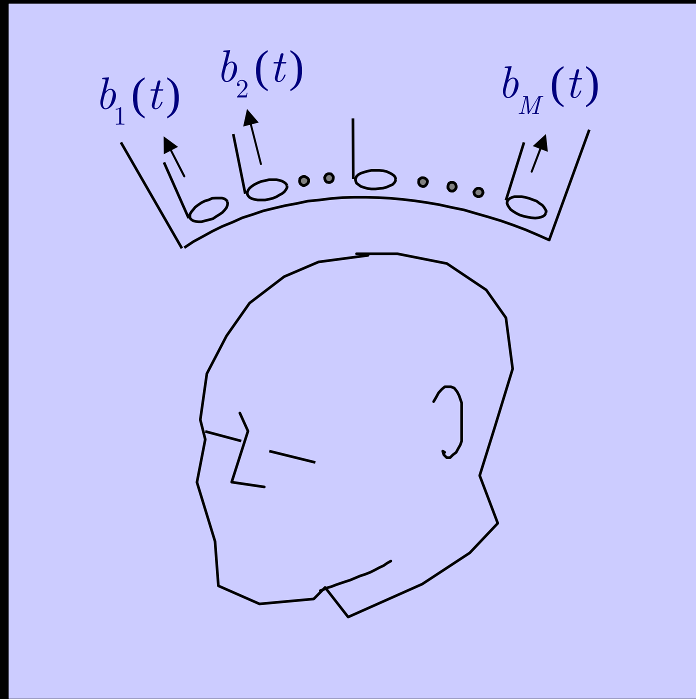
Definitions



- array measurements: $\boldsymbol{b}(\mathrm{t}) = \begin{bmatrix} b_1(t) \\ b_2(t) \\ \vdots \\ b_M(t) \end{bmatrix}$

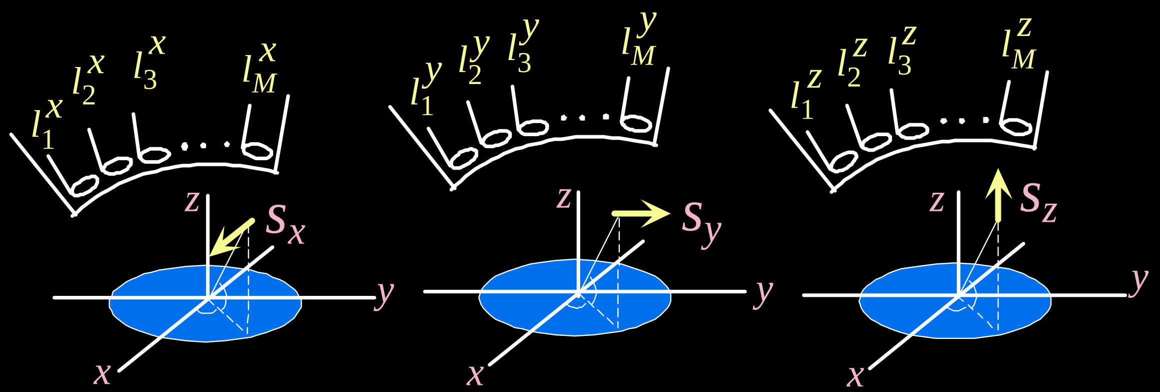
- data covariance matrix: $\boldsymbol{R} = \left\langle \boldsymbol{b}(t)\boldsymbol{b}^T(t) \right\rangle$

- source magnitude: $s(\boldsymbol{r},t)$

- source orientation: $\boldsymbol{\eta}(\boldsymbol{r},t) = [\eta_x(\boldsymbol{r},t), \eta_y(\boldsymbol{r},t), \eta_z(\boldsymbol{r},t)]$

Sensor lead field

$$\boldsymbol{L}(\boldsymbol{r}) = \begin{bmatrix} l_1^x(\boldsymbol{r}) & l_1^y(\boldsymbol{r}) & l_1^z(\boldsymbol{r}) \\ l_2^x(\boldsymbol{r}) & l_2^y(\boldsymbol{r}) & l_2^z(\boldsymbol{r}) \\ \vdots & \vdots & \vdots \\ l_M^x(\boldsymbol{r}) & l_M^y(\boldsymbol{r}) & l_M^z(\boldsymbol{r}) \end{bmatrix}, \quad \boldsymbol{l}(\boldsymbol{r}) = \boldsymbol{L}(\boldsymbol{r}) \begin{bmatrix} \eta_x(\boldsymbol{r}) \\ \eta_y(\boldsymbol{r}) \\ \eta_z(\boldsymbol{r}) \end{bmatrix}$$



$|s_x| = |s_y| = |s_z| = 1$

Spatial filter

$$\hat{s}(\boldsymbol{r},t)=\boldsymbol{w}^T(\boldsymbol{r})\boldsymbol{b}(t)=\underbrace{[w_1(\boldsymbol{r}),\ldots,w_M(\boldsymbol{r})]}_{\Uparrow\ \text{weight vector}}\begin{bmatrix} b_1(t)\\ \vdots \\ b_M(t)\end{bmatrix}=\sum_{m=1}^{M} w_m(r)b_m(t)$$

Minimum-variance spatial filter

$$\min_{\boldsymbol{w}} \boldsymbol{w}^T\boldsymbol{R}\boldsymbol{w} \text{ subject to } \boldsymbol{w}^T\boldsymbol{l}(\boldsymbol{r})=1 \Rightarrow \quad \boldsymbol{w}^T(\boldsymbol{r})=\frac{\boldsymbol{l}^T(\boldsymbol{r})\boldsymbol{R}^{-1}}{\boldsymbol{l}^T(\boldsymbol{r})\boldsymbol{R}^{-1}\boldsymbol{l}(\boldsymbol{r})}$$

Assume Q sources are located at $\boldsymbol{r}_1,\ \boldsymbol{r}_2,\ \ldots,\ \boldsymbol{r}_Q$

Outputs of spatial filter pointing at $\boldsymbol{r}_p$ (with $\boldsymbol{w}^T(\boldsymbol{r}_p)\boldsymbol{l}(\boldsymbol{r}_p) = 1$)

$$\Downarrow$$

$$\min \boldsymbol{w}^T(\boldsymbol{r}_p)\boldsymbol{R}\boldsymbol{w}(\boldsymbol{r}_p) = \left\langle s(\boldsymbol{r}_p, t)^2 \right\rangle + \sum_{q \neq p} \left\langle s(\boldsymbol{r}_q, t)^2 \right\rangle \left\| \boldsymbol{w}^T(\boldsymbol{r}_p)\boldsymbol{l}(\boldsymbol{r}_q) \right\|$$

$$\Uparrow \qquad\qquad\qquad\qquad \Downarrow$$

$$\left\langle s(\boldsymbol{r}_p, t) s(\boldsymbol{r}_q, t) \right\rangle = 0 \qquad\qquad \text{zero}$$

Therefore, this minimization gives the weight satisfying

$$\boldsymbol{w}^T(\boldsymbol{r}_p)\boldsymbol{l}(\boldsymbol{r}_q) = 1 \quad \text{for } p = q$$

$$= 0 \quad \text{for } p \neq q$$

Vital assumption: $\left\langle s(\boldsymbol{r}_p, t) s(\boldsymbol{r}_q, t) \right\rangle = 0$ for $p \neq q$

Low-rank signal assumption

Consider a simplest case where we know locations and orientations of all Q sources

weight $\boldsymbol{w}(\boldsymbol{r}_1)$ (containing M unknowns) can be obtained by solving a set of Q linear equations:

$$\boldsymbol{w}^T(\boldsymbol{r}_1)\boldsymbol{l}(\boldsymbol{r}_1) = w_1(\boldsymbol{r}_1)l_1(\boldsymbol{r}_1) + \ldots + w_M(\boldsymbol{r}_1)l_M(\boldsymbol{r}_1) = 1$$

$$\boldsymbol{w}^T(\boldsymbol{r}_1)\boldsymbol{l}(\boldsymbol{r}_2) = w_1(\boldsymbol{r}_1)l_1(\boldsymbol{r}_2) + \ldots + w_M(\boldsymbol{r}_1)l_M(\boldsymbol{r}_2) = 0$$

$$\vdots$$

$$\boldsymbol{w}^T(\boldsymbol{r}_1)\boldsymbol{l}(\boldsymbol{r}_Q) = w_1(\boldsymbol{r}_1)l_1(\boldsymbol{r}_Q) + \ldots + w_M(\boldsymbol{r}_1)l_M(\boldsymbol{r}_Q) = 0$$

If $Q > M$, there is no solution for $\boldsymbol{w}^T(\boldsymbol{r}_1)$

$$\boxed{Q < M}$$

Fundamental assumptions for adaptive beamformer source reconstruction:

- Sources are uncorrelated.
- Signals are low rank.

Vector source detection

The electromagnetic sources are three dimensional vectors.

$$\Downarrow$$

The minimum-variance beamformer should incorporate the vector nature of sources.

Two-types of formulations have been proposed:
(1) Scalar formulation
(2) Vector formulation

Scalar formulation

$$\hat{s}(\boldsymbol{r},t) = \boldsymbol{w}^T(\boldsymbol{r},\boldsymbol{\eta})\boldsymbol{b}(t) \approx \boldsymbol{w}^T(\boldsymbol{r},\boldsymbol{\eta}_{opt})\boldsymbol{b}(t)$$

$$\Uparrow$$

$$\boldsymbol{\eta}_{opt} = \arg\max_{\boldsymbol{\eta}} \left\langle \hat{s}(\boldsymbol{r},t)^2 \right\rangle = \arg\max_{\boldsymbol{\eta}} \boldsymbol{w}^T(\boldsymbol{r},\boldsymbol{\eta})\boldsymbol{R}\boldsymbol{w}(\boldsymbol{r},\boldsymbol{\eta})$$

Scalar MV beamformer

$$\boldsymbol{\eta}_{opt} = \underset{\boldsymbol{\eta}}{\mathrm{argmax}} \left\langle \hat{s}(\boldsymbol{r},t)^2 \right\rangle = \left[\arg\min_{\boldsymbol{\eta}} (\boldsymbol{\eta}^T \boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}^{-1}\boldsymbol{L}(\boldsymbol{r})\boldsymbol{\eta}) \right]^{-1} = \boldsymbol{u}_{min}$$

$$\Uparrow$$

eigenvector corresponding to the minimum eigenvalue of $[\boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}^{-1}\boldsymbol{L}(\boldsymbol{r})]$

$$\boldsymbol{w}^T(\boldsymbol{r},\boldsymbol{\eta}) = \frac{\boldsymbol{u}_{min}^T \boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}^{-1}}{\boldsymbol{u}_{min}^T \boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}^{-1}\boldsymbol{L}(\boldsymbol{r})\boldsymbol{u}_{min}}$$

Robinson and Vrba, 1998, Sekihara et al., 1996

Vector formulation

uses three weight vectors which detect x, y, and z source components.

$$[\hat{s}_x(\boldsymbol{r}), \hat{s}_y(\boldsymbol{r}), \hat{s}_z(\boldsymbol{r})] = [\boldsymbol{w}_x(\boldsymbol{r}), \boldsymbol{w}_y(\boldsymbol{r}), \boldsymbol{w}_z(\boldsymbol{r})]^T \boldsymbol{b}(t)$$

Vector MV beamformer formulation

$$\min_{\boldsymbol{w}_x} \boldsymbol{w}_x^T \boldsymbol{R} \boldsymbol{w}_x \text{ subject to } \boldsymbol{w}_x^T \boldsymbol{l}_x = 1,\ \boldsymbol{w}_x^T \boldsymbol{l}_y = 0,\ \boldsymbol{w}_x^T \boldsymbol{l}_z = 0$$

$$\min_{\boldsymbol{w}_y} \boldsymbol{w}_y^T \boldsymbol{R} \boldsymbol{w}_y \text{ subject to } \boldsymbol{w}_y^T \boldsymbol{l}_x = 0,\ \boldsymbol{w}_y^T \boldsymbol{l}_y = 1,\ \boldsymbol{w}_y^T \boldsymbol{l}_z = 0$$

$$\min_{\boldsymbol{w}_z} \boldsymbol{w}_z^T \boldsymbol{R} \boldsymbol{w}_z \text{ subject to } \boldsymbol{w}_z^T \boldsymbol{l}_x = 0,\ \boldsymbol{w}_z^T \boldsymbol{l}_y = 0,\ \boldsymbol{w}_z^T \boldsymbol{l}_z = 1$$

$$\Downarrow$$

$$[\boldsymbol{w}_x(\boldsymbol{r}), \boldsymbol{w}_y(\boldsymbol{r}), \boldsymbol{w}_z(\boldsymbol{r})]^T = [\boldsymbol{L}^T(\boldsymbol{r}) \boldsymbol{R}^{-1} \boldsymbol{L}(\boldsymbol{r})]^{-1} \boldsymbol{L}^T(\boldsymbol{r}) \boldsymbol{R}^{-1}$$

Spencer et al. 1992, Van Veen, et al. 1996

Equivalence between the two formulations -output power

Scalar formulation:

$$\max_{\boldsymbol{\eta}} \left\langle \hat{s}(\boldsymbol{r},t)^2 \right\rangle = \max_{\boldsymbol{\eta}} \frac{1}{\boldsymbol{\eta}^T \boldsymbol{L}^T(\boldsymbol{r}) \boldsymbol{R}^{-1} \boldsymbol{L}(\boldsymbol{r}) \boldsymbol{\eta}} = \frac{1}{\gamma_{min}}$$

Vector formulation:

$$\max_{\boldsymbol{\eta}} \left\langle \hat{s}(\boldsymbol{r},t)^2 \right\rangle = \max_{\boldsymbol{\eta}} \left\| [\hat{s}_x(\boldsymbol{r}), \hat{s}_y(\boldsymbol{r}), \hat{s}_z(\boldsymbol{r})] \boldsymbol{\eta} \right\|^2 = \frac{1}{\gamma_{min}}$$

γ_{min} : minimum eigenvalue of $[\boldsymbol{L}^T(\boldsymbol{r}) \boldsymbol{R}^{-1} \boldsymbol{L}(\boldsymbol{r})]$

Two formulations give the same output power
if the beamformer is set at the optimum orientation.

Equivalence between the two formulations -output SNR

Scalar beamformer

$$Z_S^{opt}(\boldsymbol{r}) = \max_{\boldsymbol{\eta}} \frac{\left\langle \hat{s}(\boldsymbol{r},\boldsymbol{\eta},t)^2 \right\rangle}{\sigma_0^2 \left\| \boldsymbol{w}(\boldsymbol{r},\boldsymbol{\eta}) \right\|^2} = \frac{1}{\sigma_0^2 \alpha_{min}}$$

Vector beamformer

$$Z_V^{opt}(\boldsymbol{r}) = \max_{\boldsymbol{\eta}} \frac{\left\| [\hat{s}_x(\boldsymbol{r}), \hat{s}_y(\boldsymbol{r}), \hat{s}_z(\boldsymbol{r})]\boldsymbol{\eta} \right\|^2}{\sigma_0^2 \left\| \boldsymbol{W}(\boldsymbol{r})\boldsymbol{\eta} \right\|^2} = \frac{1}{\sigma_0^2 \alpha_{min}}$$

α_{min} : minimum eigenvalue of $\left[\boldsymbol{L}^T(\boldsymbol{r}) \boldsymbol{R}^{-1} \boldsymbol{L}(\boldsymbol{r}) \right]^{-1} \left[\boldsymbol{L}^T(\boldsymbol{r}) \boldsymbol{R}^{-2} \boldsymbol{L}(\boldsymbol{r}) \right]$

Two formulations give the same asymptotic output SNR
if the beamformer is set at the optimum orientation.

Poster F174: K. Sekihara et al., "Asymptotic SNR of Scalar…"

Bias of estimated source locations

Remarkable property of the adaptive beamformer is that the methods do not have a source location bias even in the presence of noise.

This is in contrast to the minimum-norm-based reconstruction methods where the source location bias more or less exists.

Location bias for a single source

A single source at $\boldsymbol{r}_1$

source lead field: $\boldsymbol{f}$, source power: σ_1^2 , noise power: σ_0^2

Condition for no location bias:

$$\underbrace{\sigma_1^2 \left\| \boldsymbol{w}^T(\boldsymbol{r}_1)\boldsymbol{f} \right\|^2 + \sigma_0^2 \left\| \boldsymbol{w}(\boldsymbol{r}_1) \right\|^2}_{\text{total power at source location}} > \underbrace{\sigma_1^2 \left\| \boldsymbol{w}^T(\boldsymbol{r})\boldsymbol{f} \right\|^2 + \sigma_0^2 \left\| \boldsymbol{w}(\boldsymbol{r}) \right\|^2}_{\text{total power at any other locations}}$$

Adaptive spatial filters

Minimum variance

$$\boldsymbol{w}(\boldsymbol{r}) = \boldsymbol{R}^{-1}\,\boldsymbol{l}(\boldsymbol{r}) / [\boldsymbol{l}^T(\boldsymbol{r})\boldsymbol{R}^{-1}\boldsymbol{l}(\boldsymbol{r})] \;\Leftarrow \min_{\boldsymbol{w}} \boldsymbol{w}^T\boldsymbol{R}\boldsymbol{w} \text{ subject to } \boldsymbol{w}^T\boldsymbol{l}(\boldsymbol{r}) = 1$$

Minimum variance with normalized lead field

$$\boldsymbol{w}(\boldsymbol{r}) = \boldsymbol{R}^{-1}\,\tilde{\boldsymbol{l}}(\boldsymbol{r}) / [\tilde{\boldsymbol{l}}^T(\boldsymbol{r})\boldsymbol{R}^{-1}\tilde{\boldsymbol{l}}(\boldsymbol{r})] \;\Leftarrow \min_{\boldsymbol{w}} \boldsymbol{w}^T\boldsymbol{R}\boldsymbol{w} \text{ subject to } \boldsymbol{w}^T\boldsymbol{l}(\boldsymbol{r}) = |\boldsymbol{l}(\boldsymbol{r})|$$

Weight-normalized minimum variance (Borgiotti-Kaplan)

$$\boldsymbol{w}(\boldsymbol{r}) = \boldsymbol{R}^{-1}\,\boldsymbol{l}(\boldsymbol{r}) / \sqrt{\boldsymbol{l}^T(\boldsymbol{r})\boldsymbol{R}^{-2}\boldsymbol{l}(\boldsymbol{r})} \;\Leftarrow \min_{\boldsymbol{w}} \boldsymbol{w}^T\boldsymbol{R}\boldsymbol{w} \text{ subject to } \boldsymbol{w}^T\boldsymbol{w} = 1$$

$$\tilde{\boldsymbol{l}}(\boldsymbol{r}) = \boldsymbol{l}(\boldsymbol{r}) / \|\boldsymbol{l}(\boldsymbol{r})\|$$

Condition for no location bias

$$\boxed{\sigma_1^2 \left\| \boldsymbol{w}^T(\boldsymbol{r}_1)\boldsymbol{f} \right\|^2 + \sigma_0^2 \left\| \boldsymbol{w}(\boldsymbol{r}_1) \right\|^2 > \sigma_1^2 \left\| \boldsymbol{w}^T(\boldsymbol{r})\boldsymbol{f} \right\|^2 + \sigma_0^2 \left\| \boldsymbol{w}(\boldsymbol{r}) \right\|^2}$$

Minimum-variance

$$\frac{\|\boldsymbol{f}\|}{\|\boldsymbol{l}\|} \frac{1}{1+\alpha[1-\cos^2(\boldsymbol{l},\boldsymbol{f})]} < 1$$

Minimum variance with normalized lead field

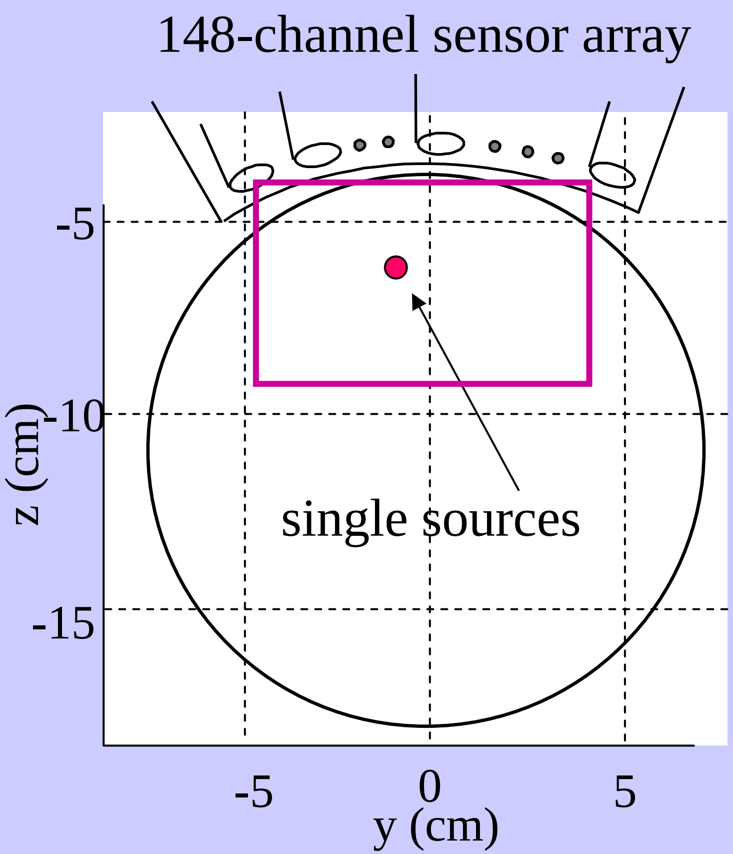
$$\frac{1}{1+\alpha[1-\cos^2(\boldsymbol{l},\boldsymbol{f})]} < 1$$

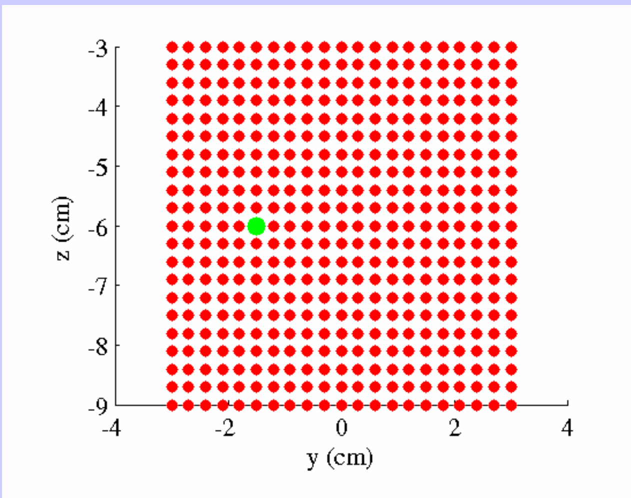
Weight-normalized minimum variance

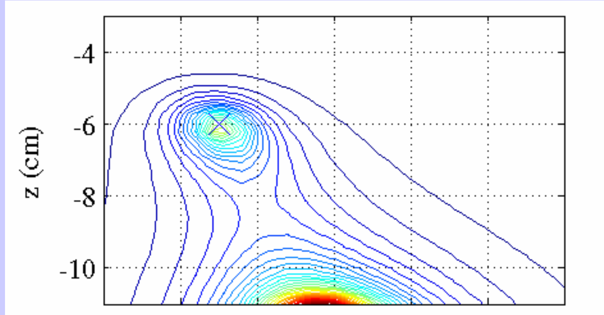
$$\frac{1+\alpha[1-\cos^2(\boldsymbol{l},\boldsymbol{f})]}{1+\alpha[1-\cos^2(\boldsymbol{l},\boldsymbol{f})]+\alpha(\alpha+1)[1-\cos^2(\boldsymbol{l},\boldsymbol{f})]} < 1$$

$$\alpha = (\sigma_1^2/\sigma_0^2)\|\boldsymbol{f}\|^2 \geq M, \quad 0 \leq \cos(\boldsymbol{l},\boldsymbol{f}) = \frac{\left|\boldsymbol{l}^T\boldsymbol{f}\right|}{\|\boldsymbol{f}\|\|\boldsymbol{l}\|} \leq 1$$

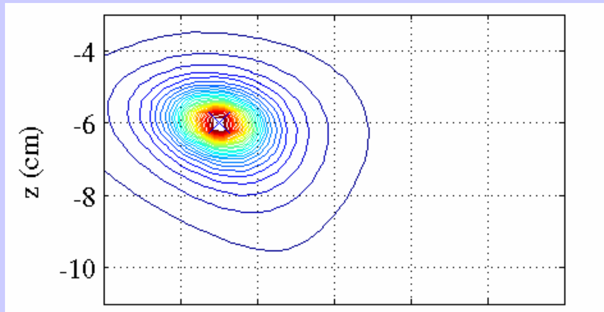
$\alpha = M(148)$



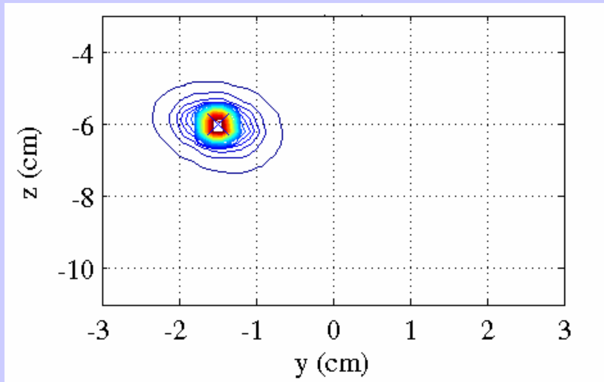




Minimum variance



Minimum variance (normalized lead field)



Weight-normalized minimum variance

(The cross mark indicates the source location.)

Effect of noise on location bias

Input SNR

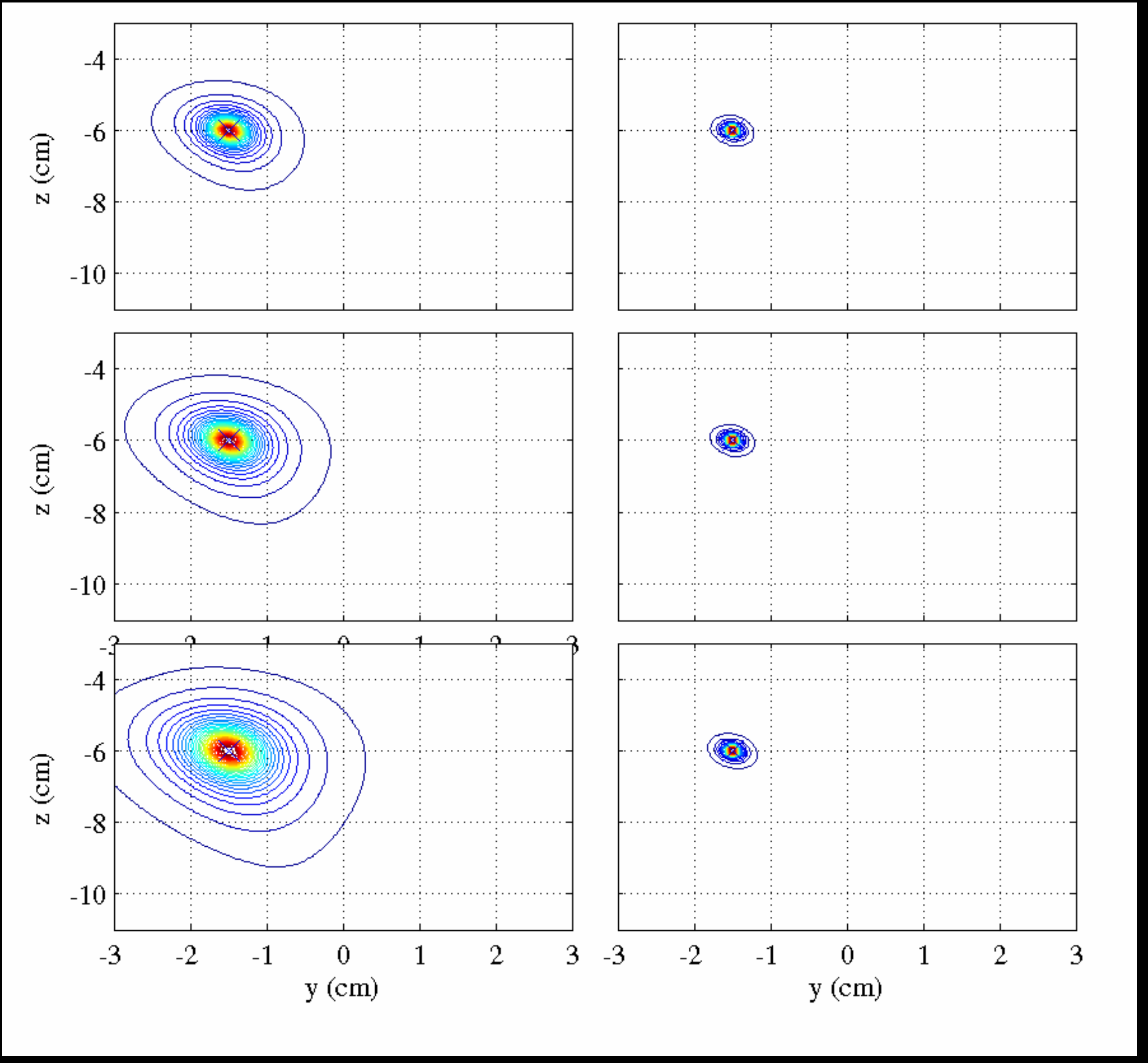
Minimum-variance (normalized lead field)

Weight-normalized minimum-variance

$\alpha = 4M(592)$

$\alpha = 2M(296)$

$\alpha = 1M(148)$



Spatial resolution comparison

Reconstruction profile of a single source: $\phi(\boldsymbol{r}) = \left\| \boldsymbol{w}^T(\boldsymbol{r})\boldsymbol{f} \right\| / \left\| \boldsymbol{w}^T(\boldsymbol{r}_1)\boldsymbol{f} \right\|$

(Point-spread function)

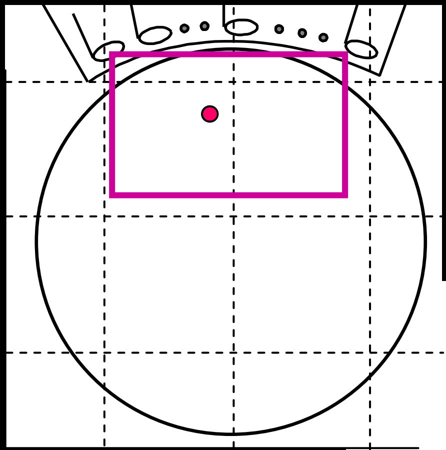
Minimum variance: $\phi(\boldsymbol{r}) = \dfrac{\cos(\boldsymbol{l},\boldsymbol{f})}{1+\alpha[1-\cos^2(\boldsymbol{l},\boldsymbol{f})]}$

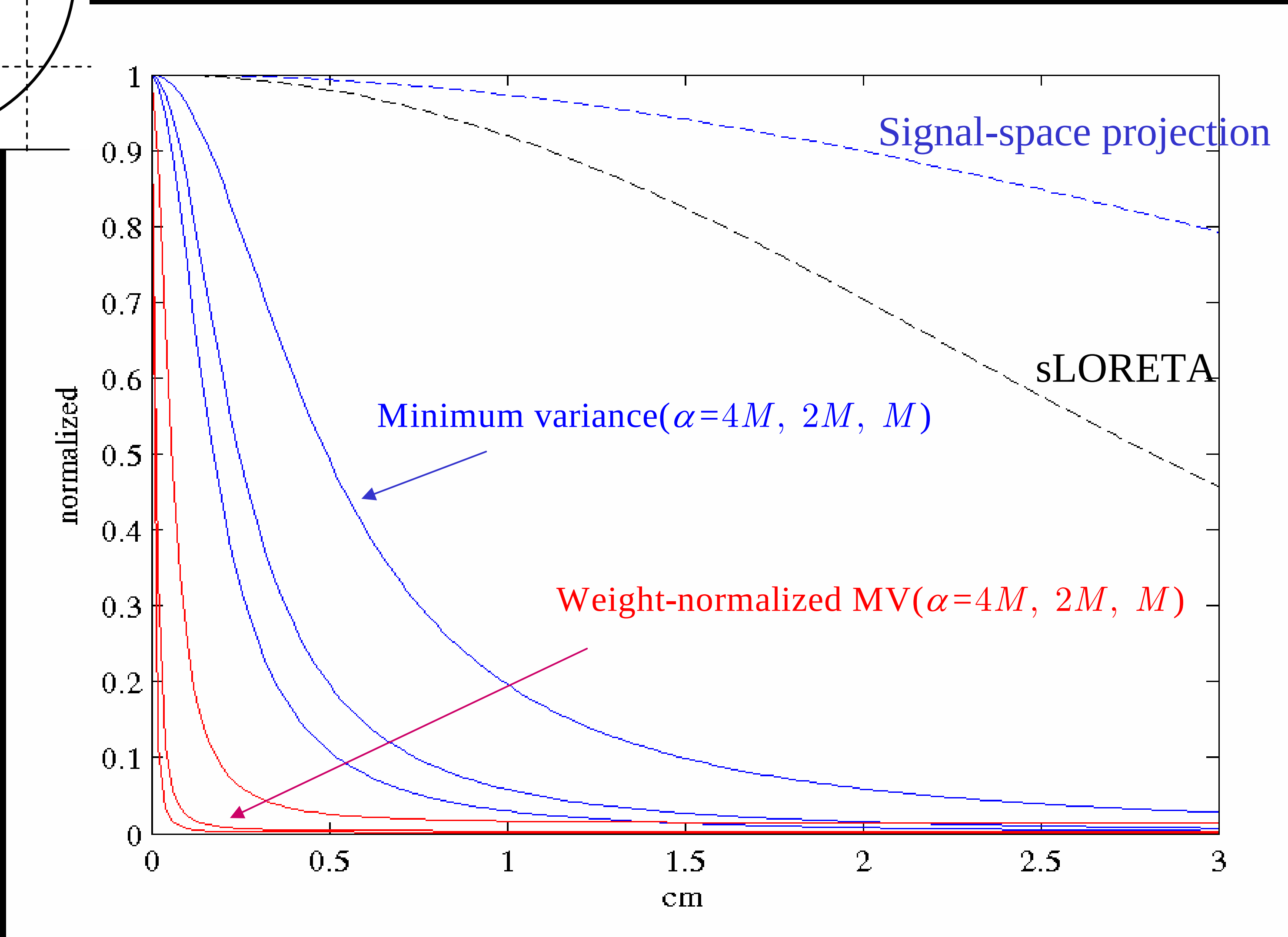
Weight-normalized minimum variance: $\phi(\boldsymbol{r}) \approx \dfrac{1}{1+\alpha^2[1-\cos^2(\boldsymbol{l},\boldsymbol{f})]}$

Signal-space projection: $\phi(\boldsymbol{r}) = \cos(\boldsymbol{l},\boldsymbol{f})$

sLORETA: $\phi(\boldsymbol{r}) = \cos(\boldsymbol{l},\boldsymbol{f} \mid \boldsymbol{G}^{-1})$

Because input SNR $\alpha > M$, these parts causes a rapid decay.




Signal-space projection
sLORETA
Minimum variance(α=4M, 2M, M)
Weight-normalized MV(α=4M, 2M, M)
normalized
cm
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.5
1
1.5
2
2.5
3

What happens if the assumptions that

- sources are uncorrelated,

- signals are low rank,

are not sartisfied.

Source correlation influence for adaptive spatial filters

$$\boldsymbol{w}^T(\boldsymbol{r}_p)\boldsymbol{l}(\boldsymbol{r}_q) = \delta_{pq}$$ (Sources are uncorrelated)

$$\boldsymbol{w}^T(\boldsymbol{r}_p)\boldsymbol{l}(\boldsymbol{r}_q) = \frac{[\boldsymbol{R}_S^{-1}]_{pq}}{[\boldsymbol{R}_S^{-1}]_{pp}}$$ (Sources are partially correlated)

When Q sources are correlated with the pth source,

$$\hat{s}(\boldsymbol{r}_p, t) = s(\boldsymbol{r}_p, t) + \sum_{q=1}^{Q} \frac{[\boldsymbol{R}_S^{-1}]_{pq}}{[\boldsymbol{R}_S^{-1}]_{pp}} s(\boldsymbol{r}_q, t)$$

spatial-filter output　　　　leakages from other correlated sources

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$\boldsymbol{R}_S$: source covariance matrix,　$[\boldsymbol{R}_S^{-1}]_{pq}$:the (p, q) element of $\boldsymbol{R}_S^{-1}$

Sekihara et al., IEEE Biomedical Engineering, 2002

Signal cancellation

When two correlated sources exist

$$\hat{s}(\boldsymbol{r}_1, t) = s(\boldsymbol{r}_1, t) - (\frac{\alpha_1 \mu}{\alpha_2}) s(\boldsymbol{r}_2, t)$$

$$\hat{s}(\boldsymbol{r}_2, t) = -(\frac{\alpha_2 \mu}{\alpha_1}) s(\boldsymbol{r}_1, t) + s(\boldsymbol{r}_2, t)$$

$$\Downarrow$$

$$\left\langle \hat{s}(\boldsymbol{r}_1, t)^2 \right\rangle = (1 - \mu^2) \left\langle s(\boldsymbol{r}_1, t)^2 \right\rangle$$

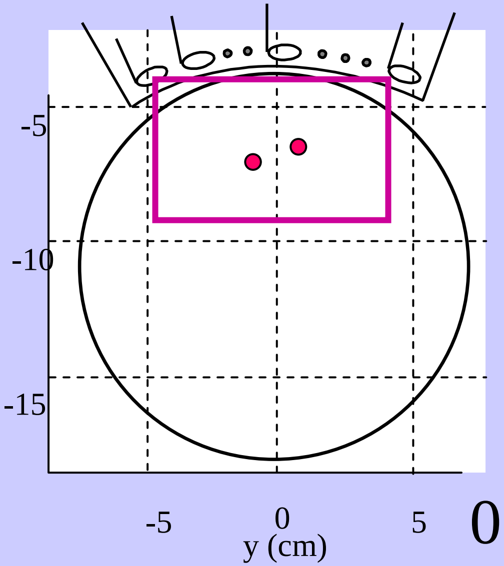
$$\left\langle \hat{s}(\boldsymbol{r}_2, t)^2 \right\rangle = (1 - \mu^2) \left\langle s(\boldsymbol{r}_2, t)^2 \right\rangle$$

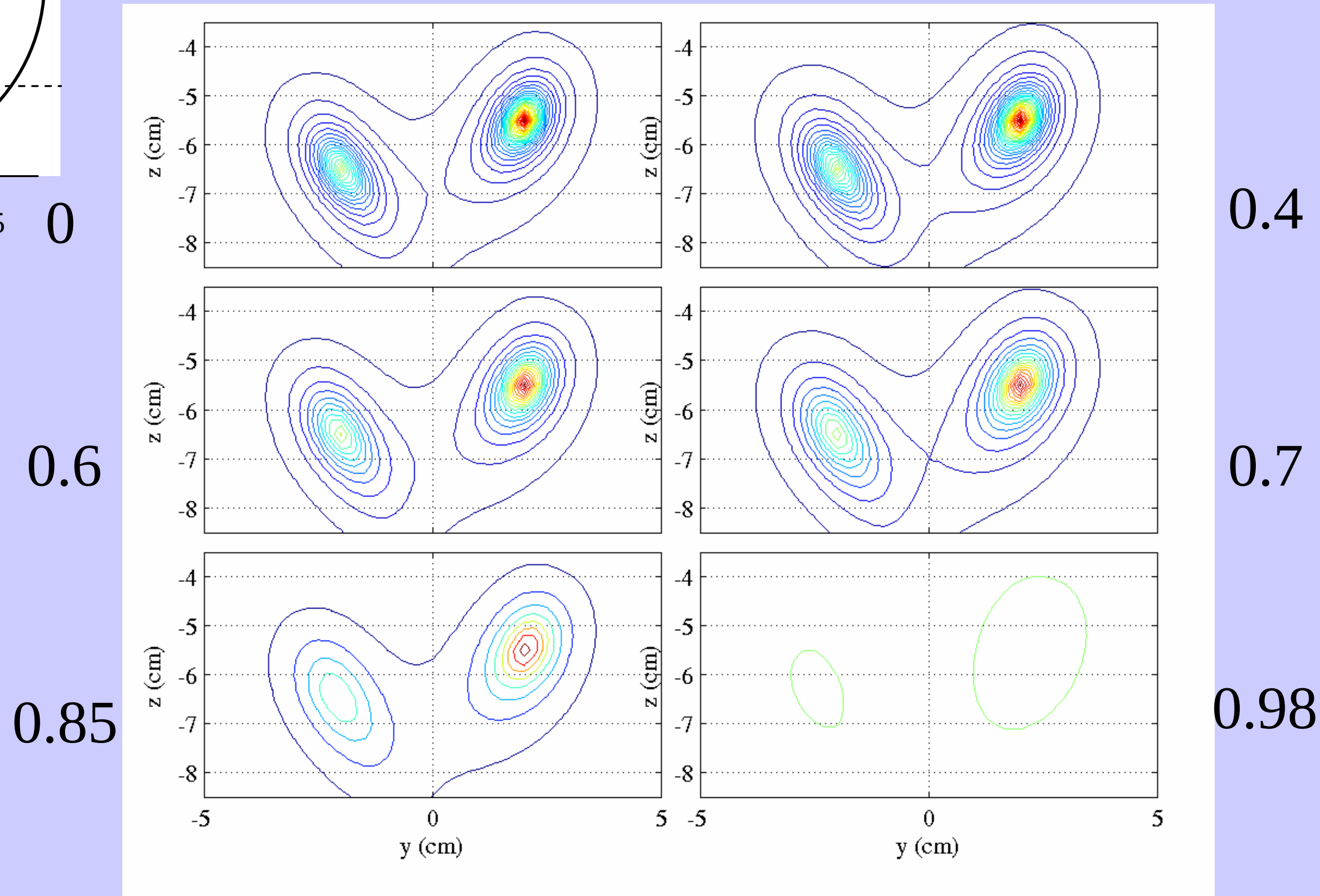
$$\Uparrow$$

Source power decreases by a factor of $(1 - \mu^2)$

source correlation coefficient

Reconstruction experiments when correlated sources exist

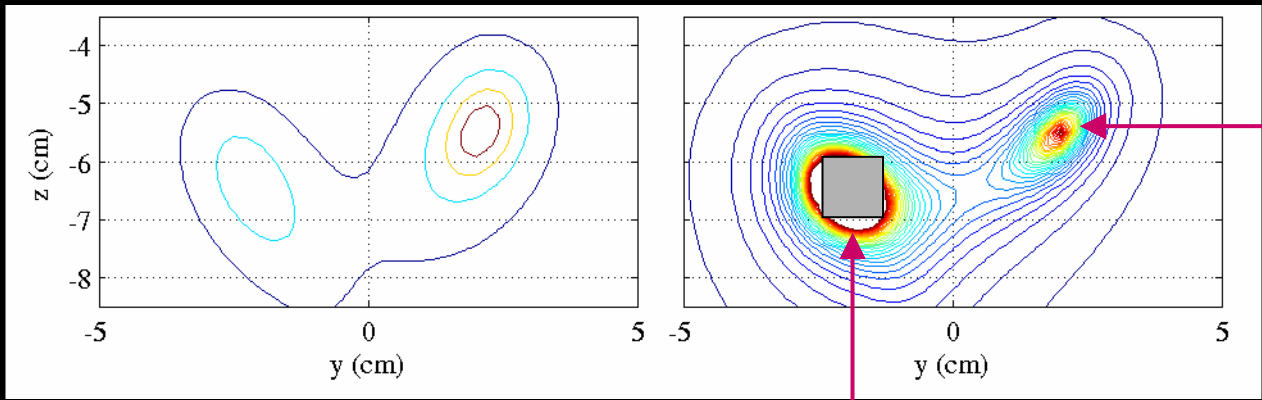




Coherent source suppression:

If locations of coherent interferences are approximately known, its influence can be suppressed.

Correlation coefficient: 0.92

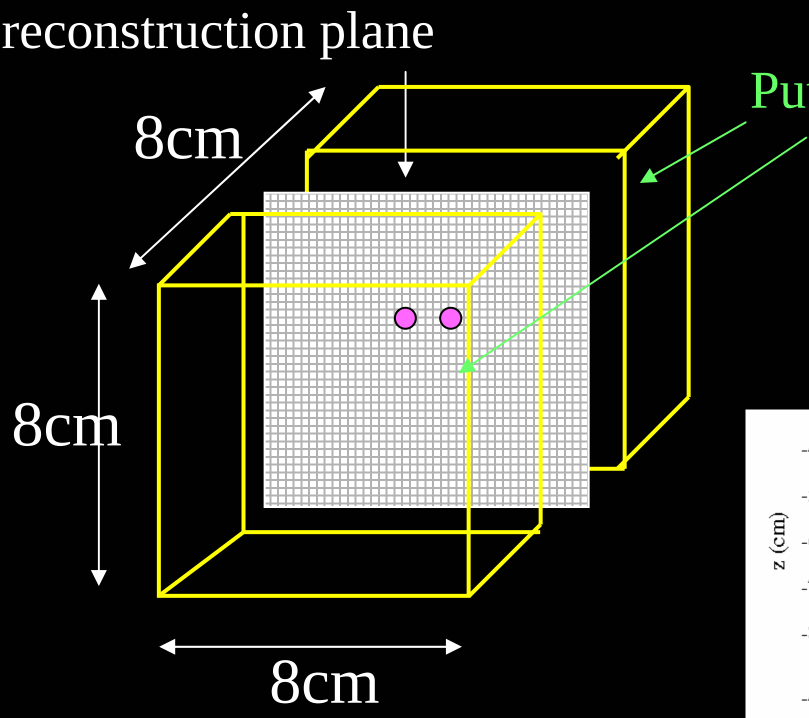


Recover the signal source of interest

Impose the null sensitivity

The detail of this method is described in poster A153:
Sarang et al. “Modified Beamformers for Coherent Source Region Suppression”

Effects of large number of noise sources



No noise source

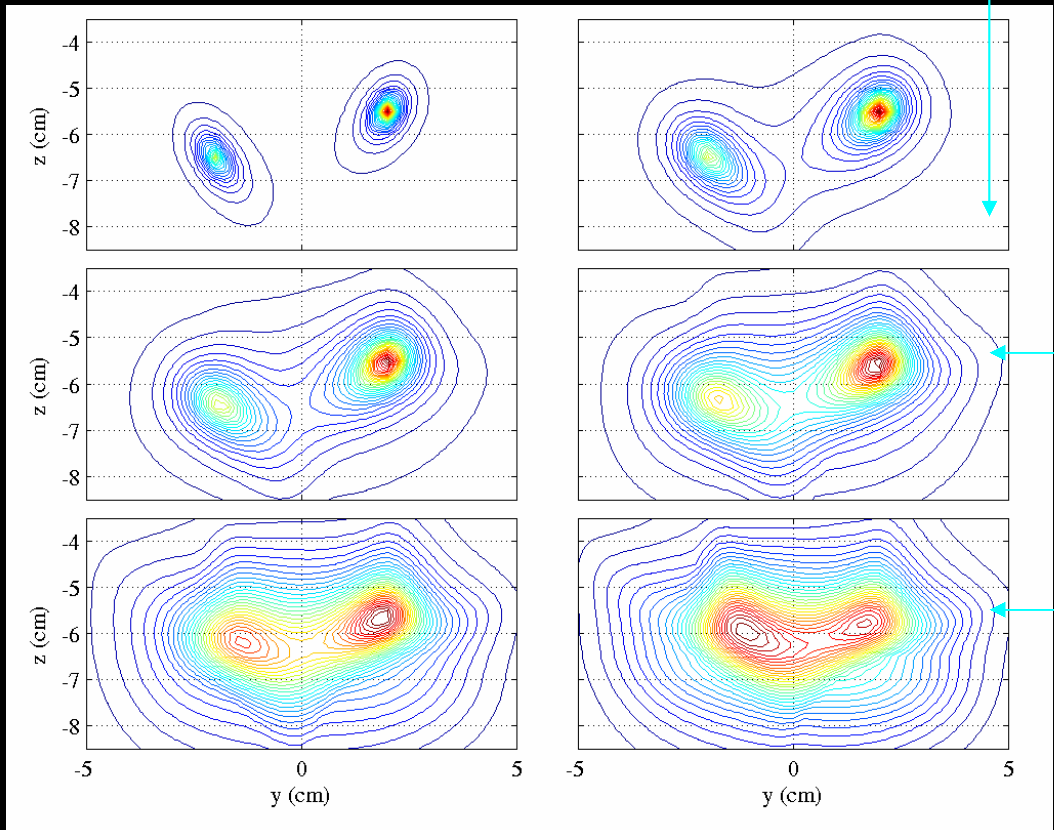
$P_N = 0.1\sigma_2^2$

$P_N = 0.01\sigma_2^2$

$P_N = 0.001\sigma_2^2$

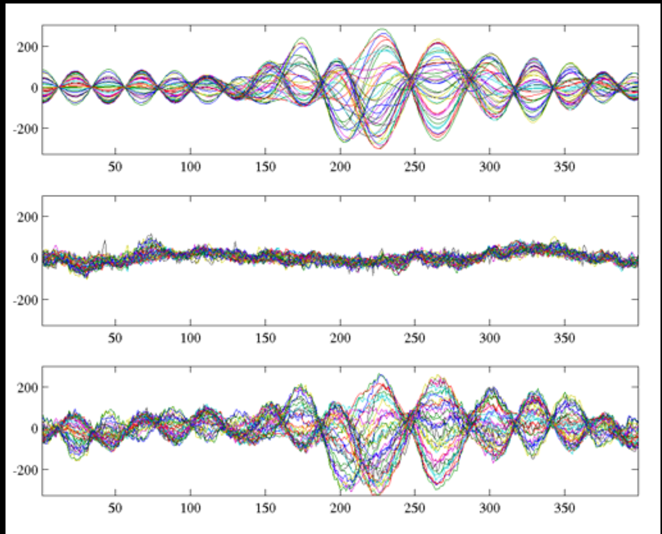
$P_N = 0.003\sigma_2^2$

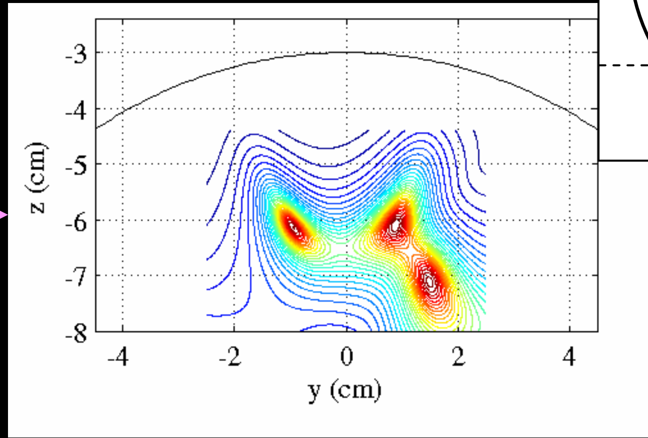
$P_N = 0.03\sigma_2^2$

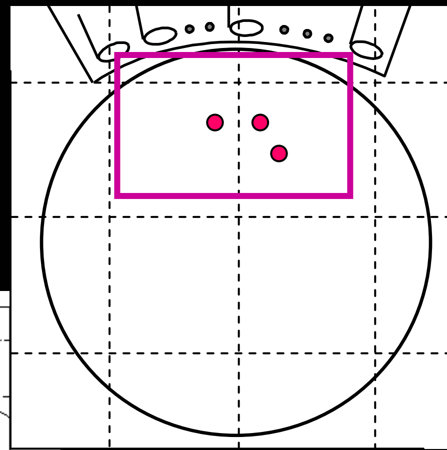


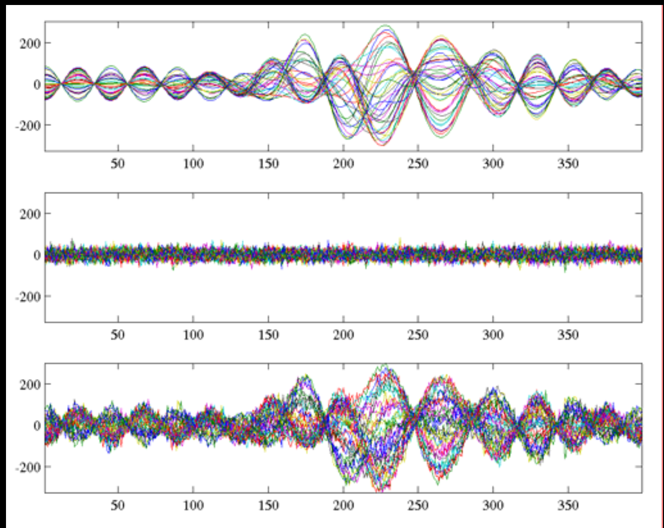
P_N : power of noise sources, σ_2^2 : power of the second source

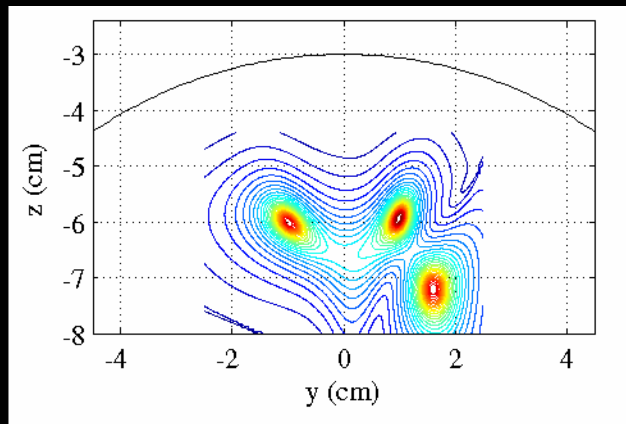
Effect of background brain activity











Reconstruction from brain-noise added data is more blurred.

Implications of these numerical experiment results:

The background brain activity contains many incoherent activities.

$\Downarrow$

Large background brain activity (brain noise) may invalidate the low-rank assumption, and may cause blurred source reconstruction

Other causes of unsatisfactory reconstruction

(1) Forward modeling error

Diagonal loading (Tikhonov regularization))
(Cox. 1974)

Eigenspace projection (Project weight vector onto the signal-subspace of the measurement covariance matrix (Sekihara et al. 2002)

(2) Sample covariance error

Beam space processing (Van Veen)

Summary

- Reviews principles of adaptive beamformer source reconstruction.

- Discusses the equivalence between scalar and vector formulations.

- Describes two underlying assumptions:
  1) Sources are uncorrelated,
  2) Signals are low rank.

- Discusses the influences caused when these assumptions are not satisfied.

- Points out that the forward modeling error and the sample covariance error are also causes of unsatisfactory reconstruction.

Thanks for your attention.

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