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A novel adaptive beamformers for MEG source reconstruction effective when large background brain activities exist

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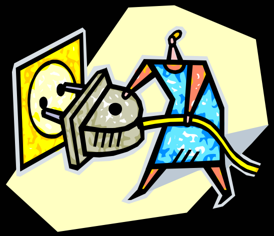
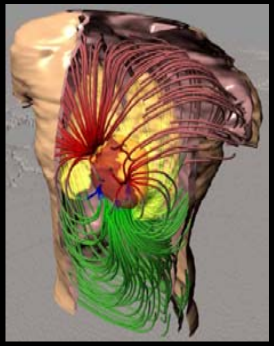
Interferences affecting to MEG sensor data

Low-rank interference

Electronics



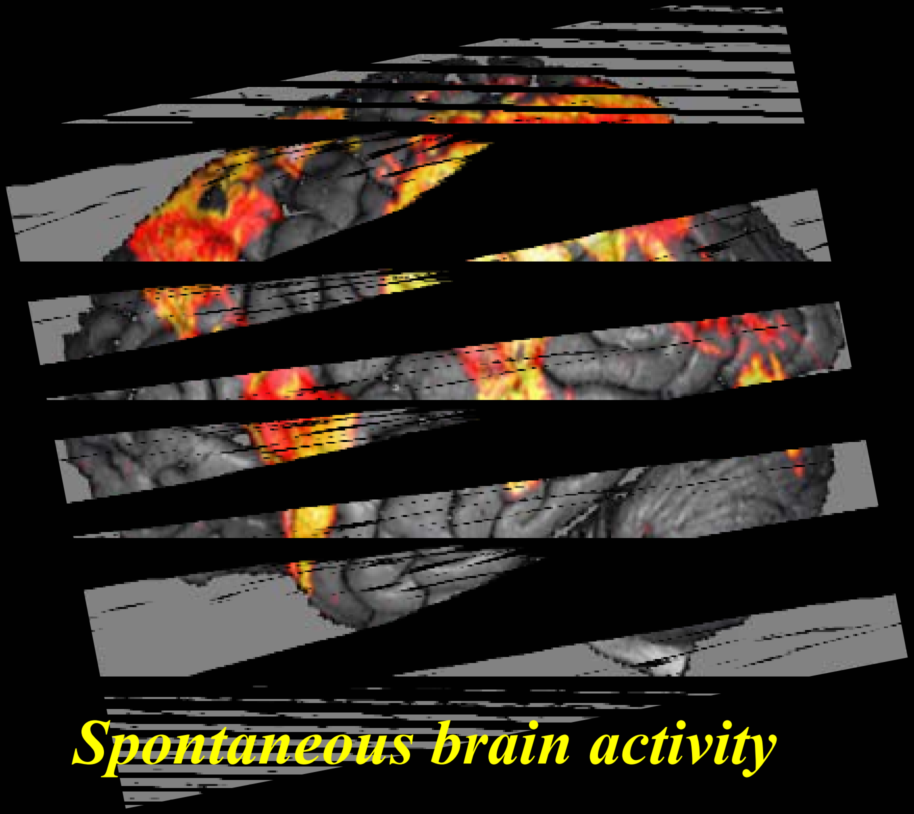
Heartbeat



Eyeblinks

Dental &
Jaw Muscles

High-rank interference



Spontaneous brain activity

no specific spatial, temporal, and frequency patterns

Data model

$$\boldsymbol{b}(t) = \boldsymbol{b}_S(t) + \boldsymbol{b}_I(t) + \boldsymbol{n}(t)$$

Measured magnetic field

Signal magnetic field

Background interference

Sensor noise

$$\boldsymbol{b}(t) = \underbrace{\boldsymbol{b}_S(t) + \boldsymbol{b}_I^{'}(t)}_{\boldsymbol{b}_S(t)} + \boldsymbol{b}_I^{''}(t) + \boldsymbol{n}(t)$$

Definitions

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

Signal covariance: $\boldsymbol{R}_S = \left\langle \boldsymbol{b}_S(t)\boldsymbol{b}_S^T(t) \right\rangle$

Interference plus noise covariance: $\boldsymbol{R}_{i+n} = \left\langle \left(\boldsymbol{b}_I(t) + \boldsymbol{n}(t)\right)\left(\boldsymbol{b}_I(t) + \boldsymbol{n}(t)\right)^T \right\rangle$

Data model

Task: $\boldsymbol{b}(t) = \boldsymbol{b}_S(t) + \boldsymbol{b}_I(t) + \boldsymbol{n}(t)$

Control: $\boldsymbol{b}_C(t) = \boldsymbol{b}_I(t) + \boldsymbol{n}(t)$

Covariance matrix relations

Task: $\boldsymbol{R} = \boldsymbol{R}_S + \boldsymbol{R}_{i+n}$

Control: $\boldsymbol{R}_C = \boldsymbol{R}_{i+n}$

Problem How to obtain source reconstruction free from the influence of $\boldsymbol{b}_I(t)$

We propose:

(1) Prewhitening beamforming

(2) Partitioned factor analysis + adaptive beamforming

Prewhitening estimation of signal covariance

Calculate $\tilde{\boldsymbol{R}} = \boldsymbol{R}_C^{-1/2}\boldsymbol{R}\boldsymbol{R}_C^{-1/2}$

(Tilde is used to indicate the prewhitened version of a matrix)

$$\tilde{\boldsymbol{R}}_S = \sum_{j=1}^{Q} \gamma_j \boldsymbol{u}_j \boldsymbol{u}_j^T \quad \Rightarrow \quad \underline{\tilde{\boldsymbol{R}} = \sum_{j=1}^{Q} (\gamma_j + 1)\boldsymbol{u}_j \boldsymbol{u}_j^T} + \sum_{j=Q+1}^{M} \boldsymbol{u}_j \boldsymbol{u}_j^T .$$

$$\Uparrow$$

$\tilde{\boldsymbol{R}}$ has signal-level eigenvalues greater than 1,
and their eigenvectors are equal to those of $\tilde{\boldsymbol{R}}_S$

Signal covariance estimation

$$\hat{\boldsymbol{R}}_S = \boldsymbol{R}_C^{1/2}\left[\boldsymbol{U}_S \boldsymbol{U}_S^T (\tilde{\boldsymbol{R}} - \boldsymbol{I})\right]\boldsymbol{R}_C^{1/2} = \boldsymbol{R}_C^{1/2}\left[\sum_{j=1}^{Q} (\gamma_j - 1)\boldsymbol{u}_j\right]\boldsymbol{R}_C^{1/2}$$

$$\uparrow$$

$$\boldsymbol{U}_S = [\boldsymbol{u}_1, \ldots, \boldsymbol{u}_Q]$$

For details, poster P-163, (session P4-1) 8/22 3:00—5:00PM

Prewhitening beamforming

Signal covariance estimation

$$\hat{\boldsymbol{R}}_S = \boldsymbol{R}_C^{1/2}\left[\sum_{j=1}^{Q}(\gamma_j - 1)\boldsymbol{u}_j\right]\boldsymbol{R}_C^{1/2}$$

Signal time course estimation

$$\hat{\boldsymbol{b}}_S(t) = \boldsymbol{R}_C^{1/2}\left[\sum_{j=1}^{Q}(\gamma_j - 1)\boldsymbol{u}_j\right]\boldsymbol{R}_C^{-1/2}\boldsymbol{b}_C(t)$$

Prewhitening beamforming

$$\hat{s}_{PW}(\boldsymbol{r},t) = \frac{\boldsymbol{l}^T(\boldsymbol{r})(\hat{\boldsymbol{R}}_S + \mu\boldsymbol{I})^{-1}\hat{\boldsymbol{b}}_S(t)}{\boldsymbol{l}^T(\boldsymbol{r})(\hat{\boldsymbol{R}}_S + \mu\boldsymbol{I})^{-1}\boldsymbol{l}(\boldsymbol{r})}$$

Partitioned factor analysis (PFA)

Variational Bayesian Factor Analysis (VBFA)

Data model:

$$\text{measured data} \rightarrow \boldsymbol{y}_n = \boldsymbol{A}\boldsymbol{x}_n + \boldsymbol{v}_n$$

mixing matrix　factors　sensor noise

Prier probability:

$$p(\boldsymbol{x}_n) = N(\boldsymbol{x}_n \mid 0, \boldsymbol{I}) \qquad p(\boldsymbol{A}) = \prod_{m,l}^{M,L} N(A_{m,l} \mid 0, \lambda_m \alpha_l)$$

$$p(\boldsymbol{v}_n) = N(\boldsymbol{v}_n \mid 0, \boldsymbol{\Lambda})$$

Derivation of posterior probability:

$$p(\boldsymbol{A} \mid \boldsymbol{y}) = \underset{q(\boldsymbol{A}|\boldsymbol{y})}{\arg\max}\, F(q), \quad p(\boldsymbol{x} \mid \boldsymbol{y}) = \underset{q(\boldsymbol{x}|\boldsymbol{y})}{\arg\max}\, F(q)$$

Here $F(q) = \int d\boldsymbol{x}\, d\boldsymbol{A} [\log p(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{A}) - \log q(\boldsymbol{x} \mid \boldsymbol{y}) - \log q(\boldsymbol{A} \mid \boldsymbol{y})]$

Variational Bayes EM algorithm

E step: $p(\boldsymbol{x} \mid \boldsymbol{y}) = \arg\max_{q(\boldsymbol{x}|\boldsymbol{y})} F(q)$

$$\boldsymbol{\Gamma} = \bar{\boldsymbol{A}}^T \boldsymbol{\Lambda} \bar{\boldsymbol{A}} + M\boldsymbol{\Psi}^{-1} + \boldsymbol{I}$$

$$\bar{\boldsymbol{x}}_n = \boldsymbol{\Gamma}^{-1} \bar{\boldsymbol{A}}^T \boldsymbol{\Lambda} \boldsymbol{y}_n$$

for $p(\boldsymbol{x}_n \mid \boldsymbol{y}_n) = N(\boldsymbol{x}_n \mid \bar{\boldsymbol{x}}_n, \boldsymbol{\Gamma})$

M step: $p(\boldsymbol{A} \mid \boldsymbol{y}) = \arg\max_{q(\boldsymbol{A}|\boldsymbol{y})} F(q)$

$$\bar{\boldsymbol{A}} = \boldsymbol{R}_{yx} (\boldsymbol{R}_{xx} + \boldsymbol{\alpha})^{-1}$$

$$\boldsymbol{\Psi} = \boldsymbol{R}_{xx} + \boldsymbol{\alpha}$$

for $p(\boldsymbol{A} \mid \boldsymbol{y}_n) = \prod_{m,l}^{M,L} N(\boldsymbol{a}_m \mid \bar{\boldsymbol{a}}_m, \lambda_m \boldsymbol{\Psi})$

$$\boldsymbol{\alpha} = \arg\min_{\boldsymbol{\alpha}} F(q) \;\Rightarrow\; \boldsymbol{\alpha} = \frac{1}{M} \mathrm{diag}(\bar{\boldsymbol{A}}^T \boldsymbol{\Lambda} \bar{\boldsymbol{A}} + \boldsymbol{\Psi}^{-1})$$

$$\boldsymbol{\Lambda} = \arg\min_{\boldsymbol{\Lambda}} F(q) \Rightarrow \boldsymbol{\Lambda} = \frac{1}{N} \mathrm{diag}(\boldsymbol{R}_{yy} - \bar{\boldsymbol{A}} \boldsymbol{R}_{yx}^T)$$

Partitioned factor analysis (PFA)

Stimulus-Evoked Factor Analysis (SEFA)

Data model

Control: $\boldsymbol{y}_n = \boldsymbol{B}\boldsymbol{u}_n + \boldsymbol{v}_n$

Task: $\boldsymbol{y}_n = \boldsymbol{A}\boldsymbol{x}_n + \boldsymbol{B}\boldsymbol{u}_n + \boldsymbol{v}_n$

(1) Apply VBFA to control data and obtain $\bar{\boldsymbol{B}}$, and the noise precision $\boldsymbol{\Lambda}$.

(2) Apply VBFA to task data, and obtain

$$\hat{\boldsymbol{b}}_S(t) = E_A E_{\boldsymbol{x}}[\boldsymbol{A}\boldsymbol{x}_n] = \bar{\boldsymbol{A}}\bar{\boldsymbol{x}}_n$$

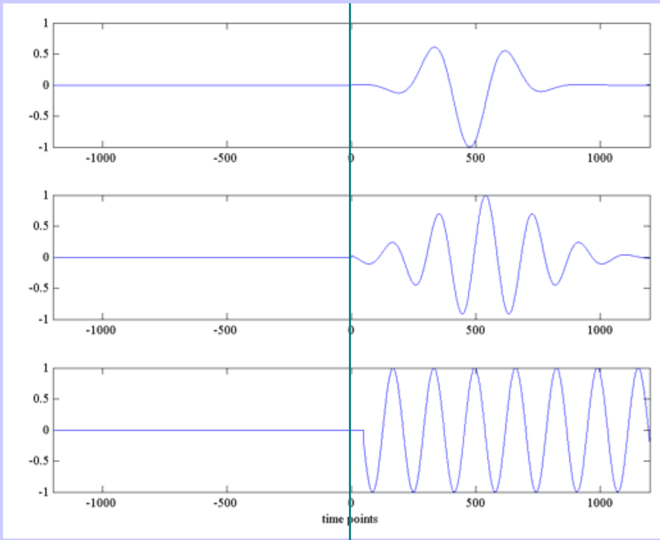
$$\hat{\boldsymbol{R}}_S = E_A E_{\boldsymbol{x}}[(\boldsymbol{A}\boldsymbol{x}_n)(\boldsymbol{A}\boldsymbol{x}_n)^T] = \bar{\boldsymbol{A}}\boldsymbol{R}_{xx}\bar{\boldsymbol{A}}^T + \boldsymbol{\Lambda}^{-1}\mathrm{tr}[\boldsymbol{R}_{xx}(\boldsymbol{R}_{xx} + \boldsymbol{\alpha})^{-1}]$$

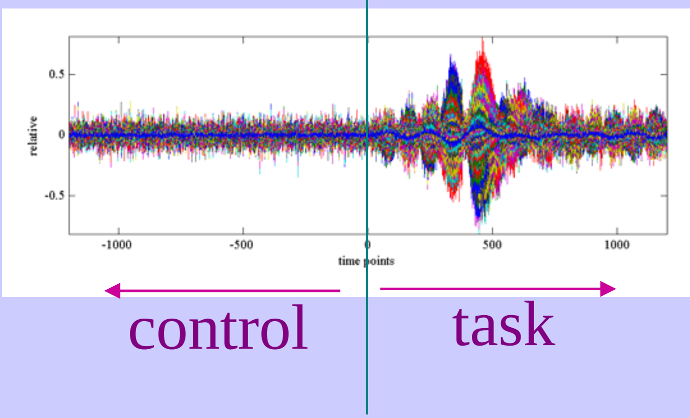
(3) Use these estimated results for adaptive beamforming.

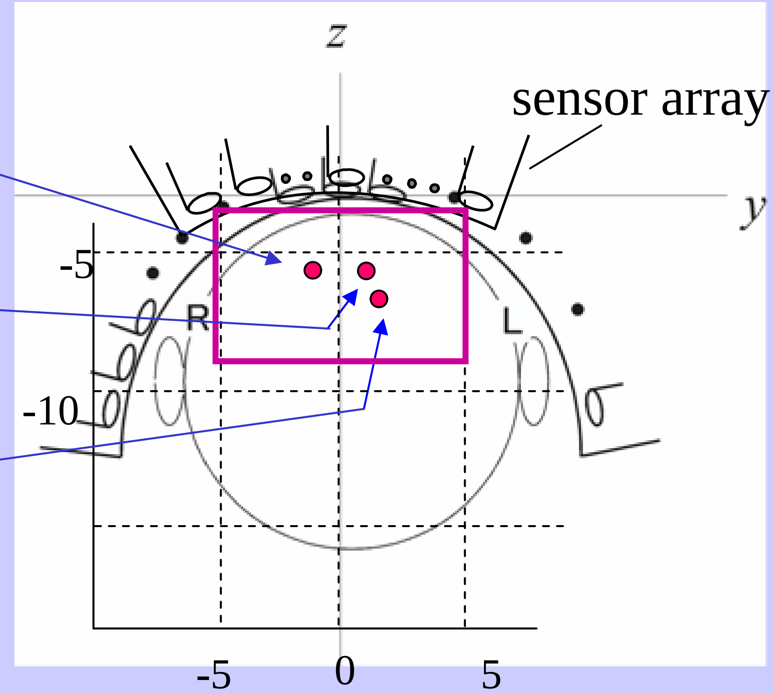
$$\hat{s}_{PFA}(\boldsymbol{r}, t) = \frac{\boldsymbol{l}^T(\boldsymbol{r})\hat{\boldsymbol{R}}_S^{-1}\hat{\boldsymbol{b}}_S(t)}{\boldsymbol{l}^T(\boldsymbol{r})\hat{\boldsymbol{R}}_S^{-1}\boldsymbol{l}(\boldsymbol{r})}$$

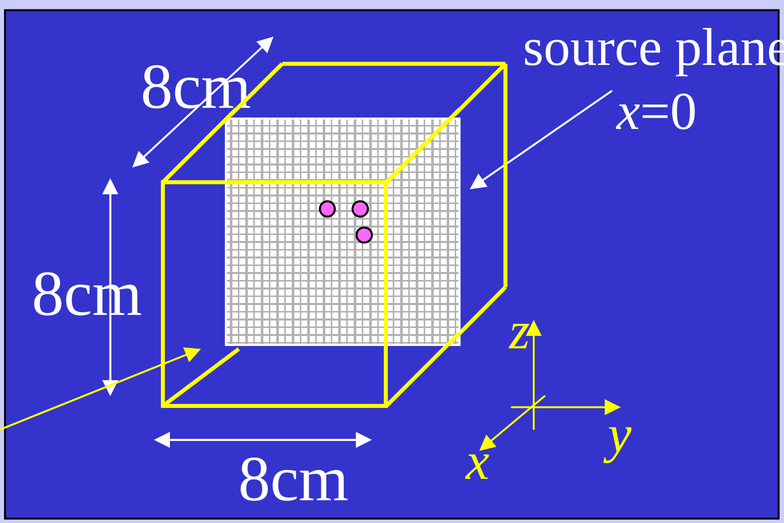
For details, visit poster P-116, (session P3-1) 8/21 10:00—12:00PM

assumed source waveform



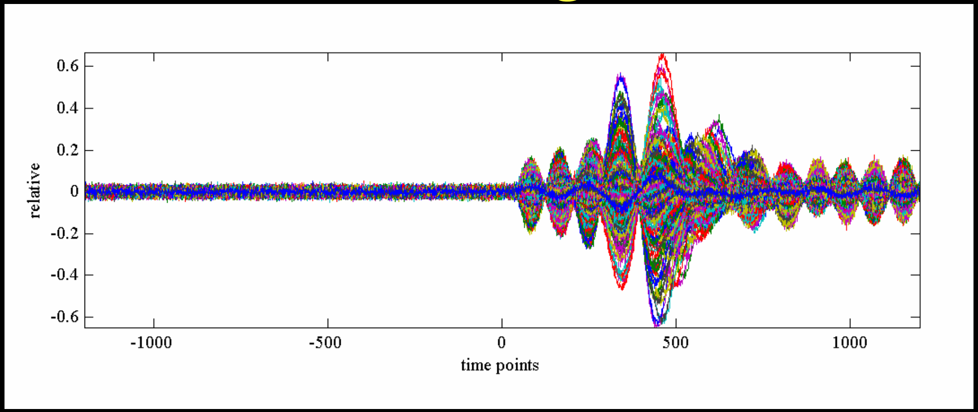


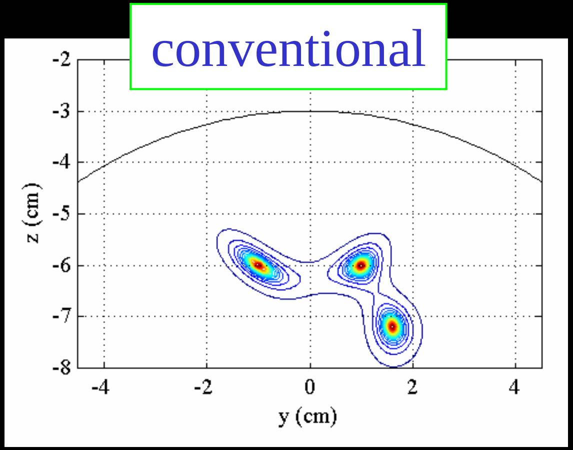




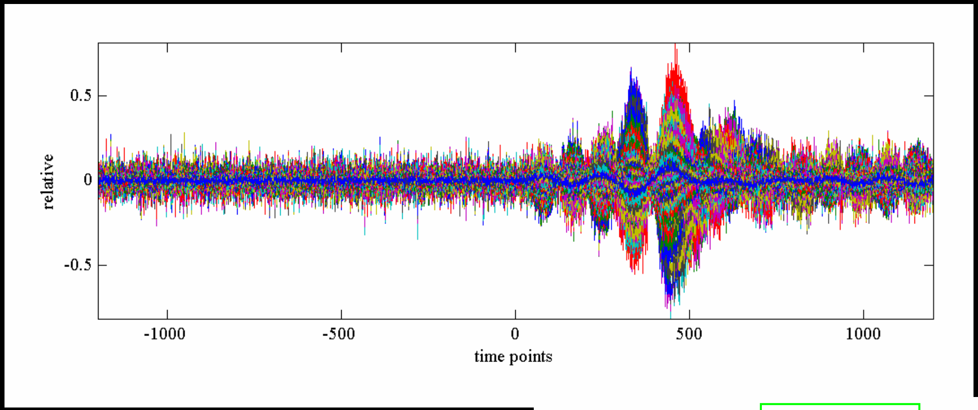
Generate 100 background sources with random time courses

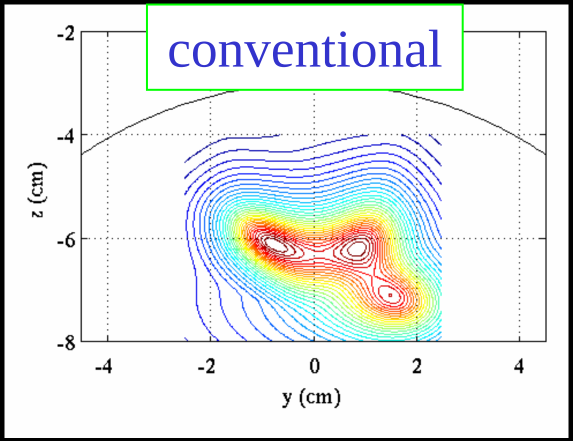
Data without background sources

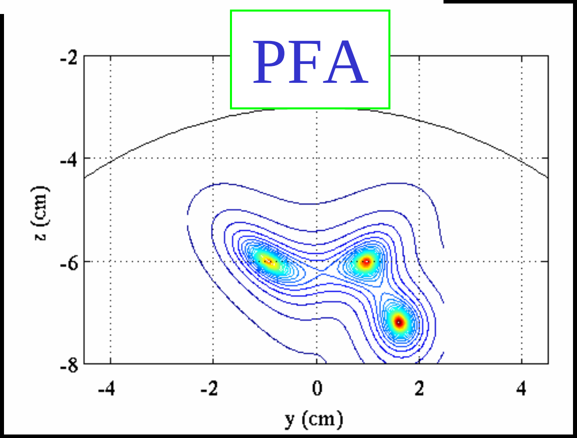


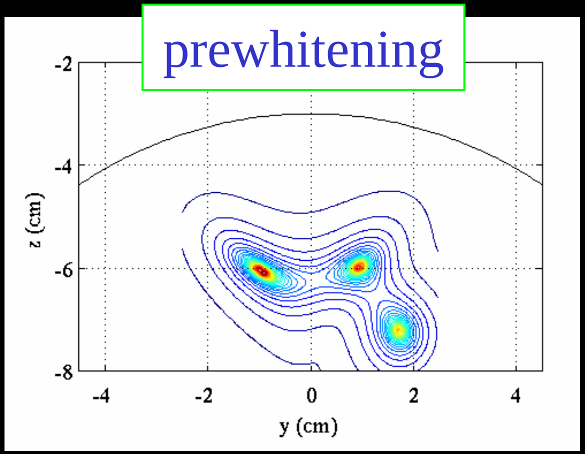


Data with background sources

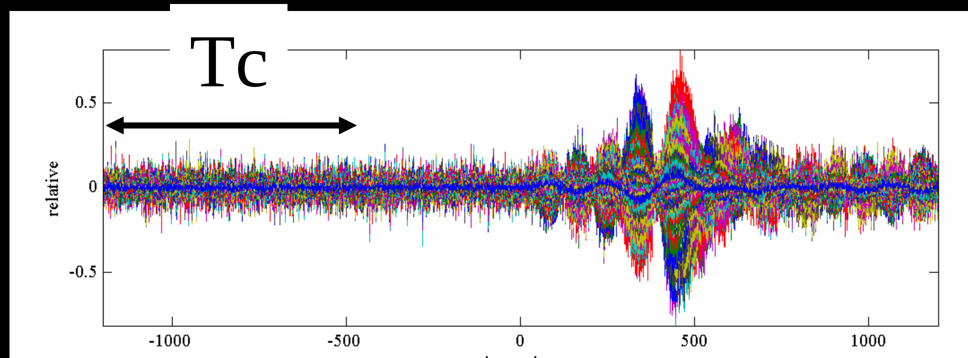








Computer Simulation: Robustness to insufficient control data



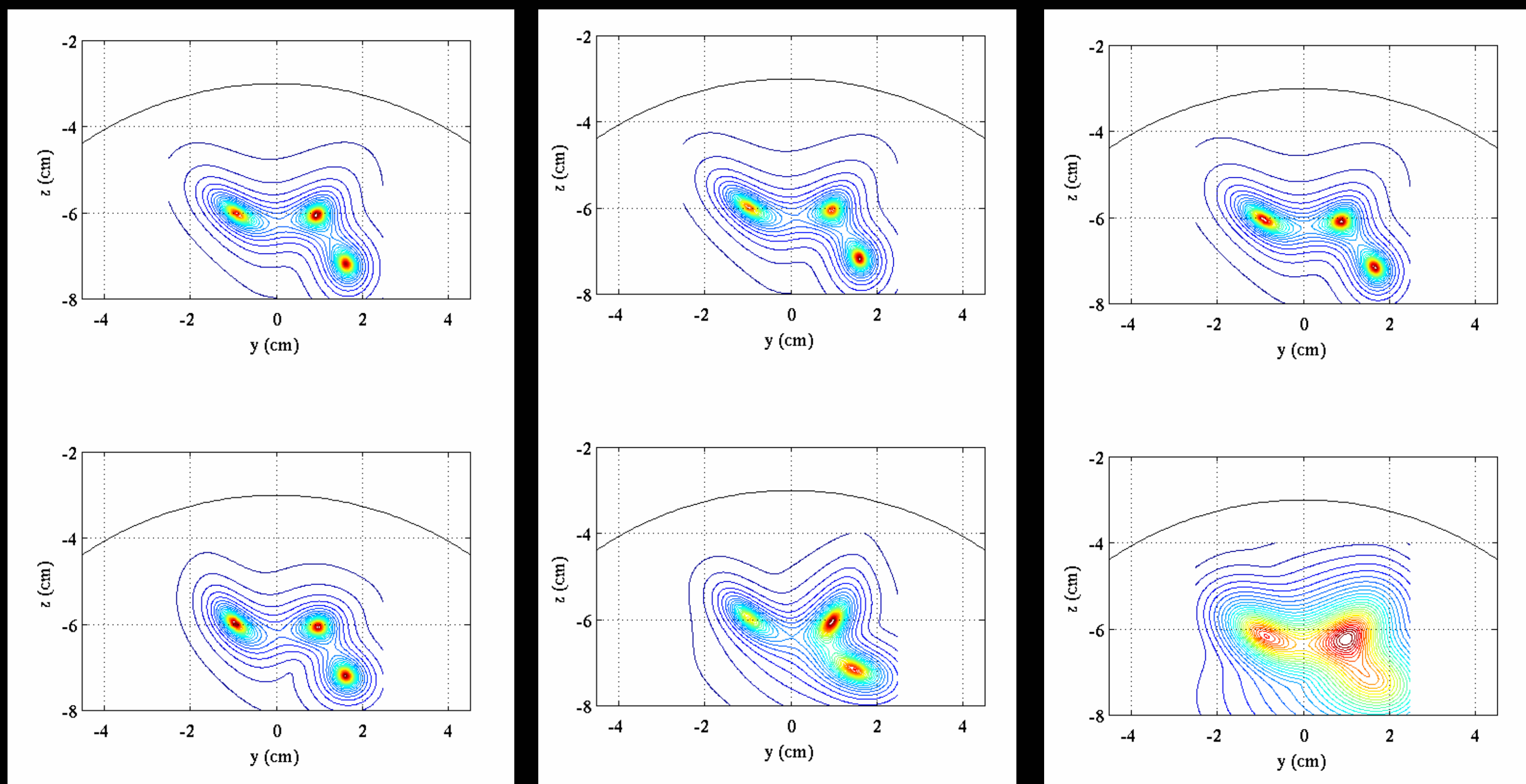
Tc:400 time points

Tc:200

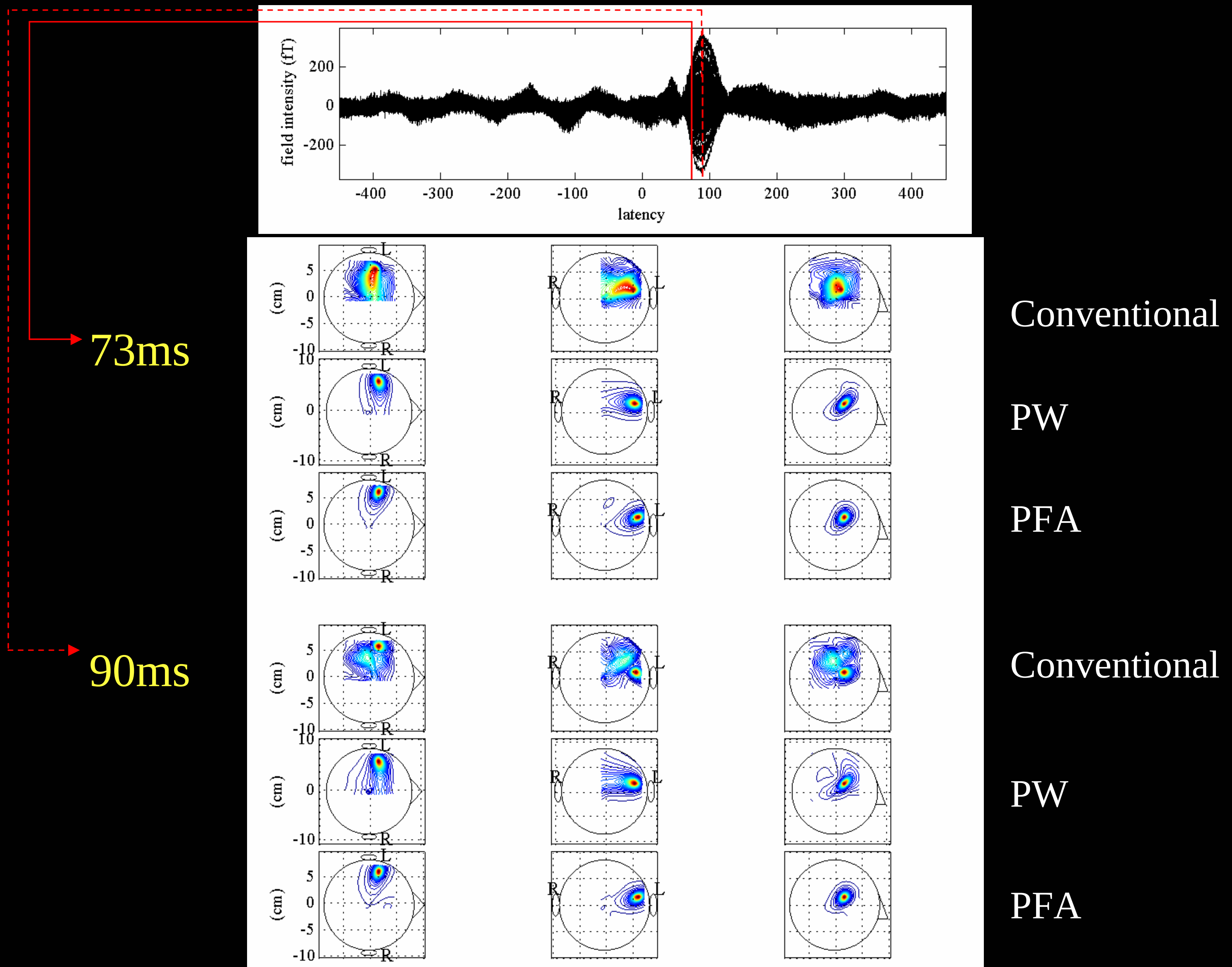
Tc:100

PFA

PW



Auditory evoked field



Non-ideal scenarios for two-condition measurements

Some target sources are also active in the control condition

Task: $$\boldsymbol{b}(t) = \boldsymbol{b}_S(t) + \boldsymbol{b}_I(t) + \boldsymbol{n}(t)$$

Control: $$\boldsymbol{b}_C(t) = \boldsymbol{b}_S(t)' + \boldsymbol{b}_I(t) + \boldsymbol{n}(t)$$

Some sources are active only in the control condition

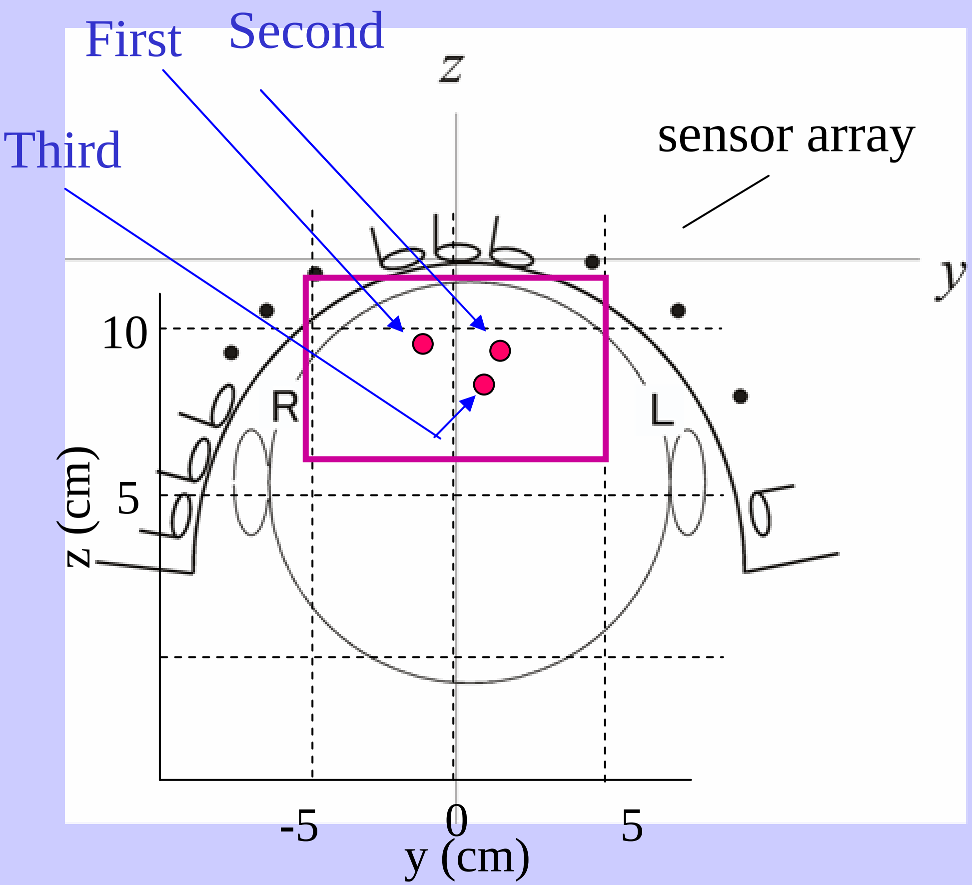
Task: $$\boldsymbol{b}(t) = \boldsymbol{b}_S(t) + \boldsymbol{b}_I(t) + \boldsymbol{n}(t)$$

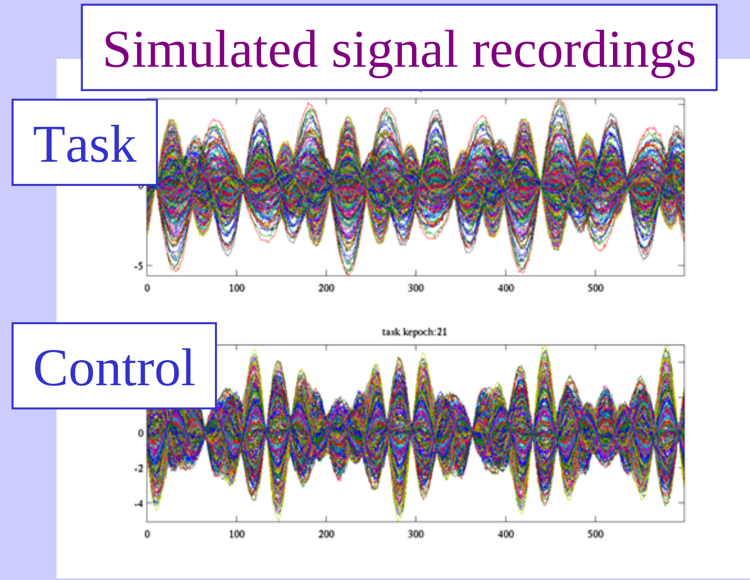
Control: $$\boldsymbol{b}_C(t) = \boldsymbol{b}_I(t) + \boldsymbol{n}(t) + \boldsymbol{b}_\Delta(t)$$

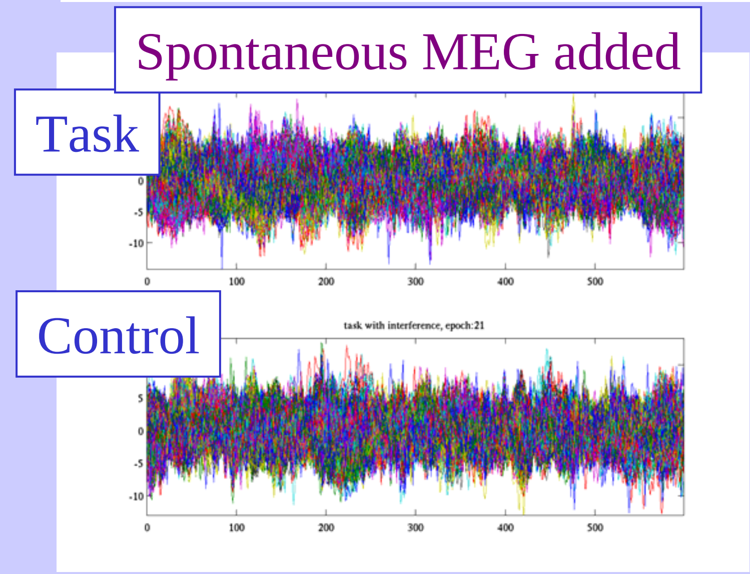
These additional terms may affect the performance of PFA

Prewhitening technique is robust in these scenarios, as discussed at
poster P-163, (session P4-1) 8/22 3:00—5:00PM

Computer simulation for non-ideal scenarios





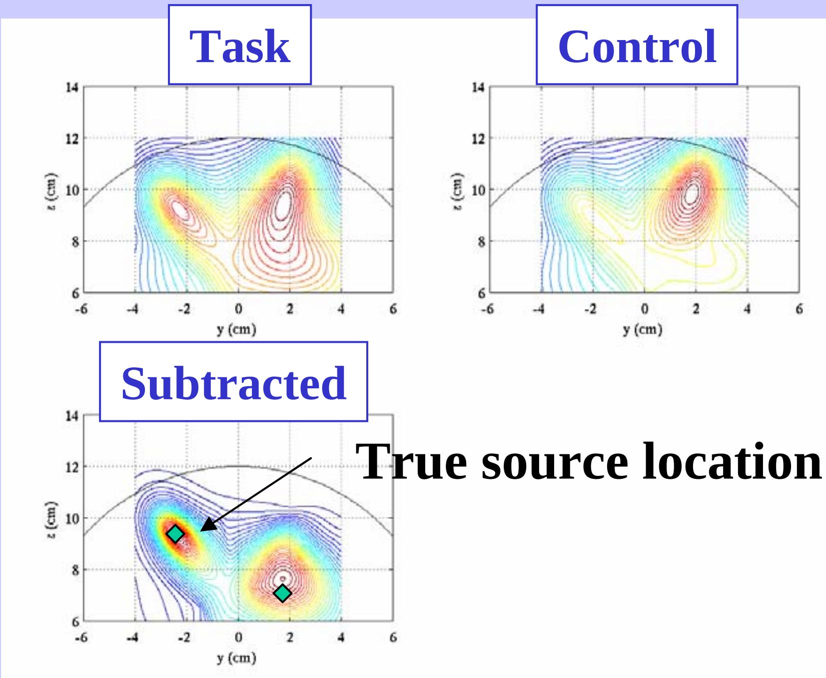


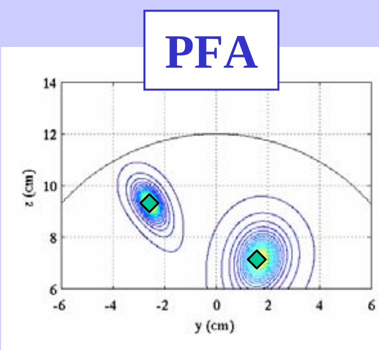
Relative source intensity

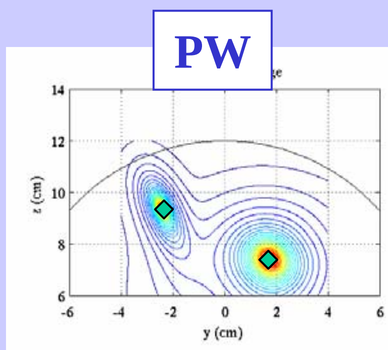
	control	task
First source	1	1.5
Second source	1.5	1.5
Third source	1	1.5

96 paired data sets generated

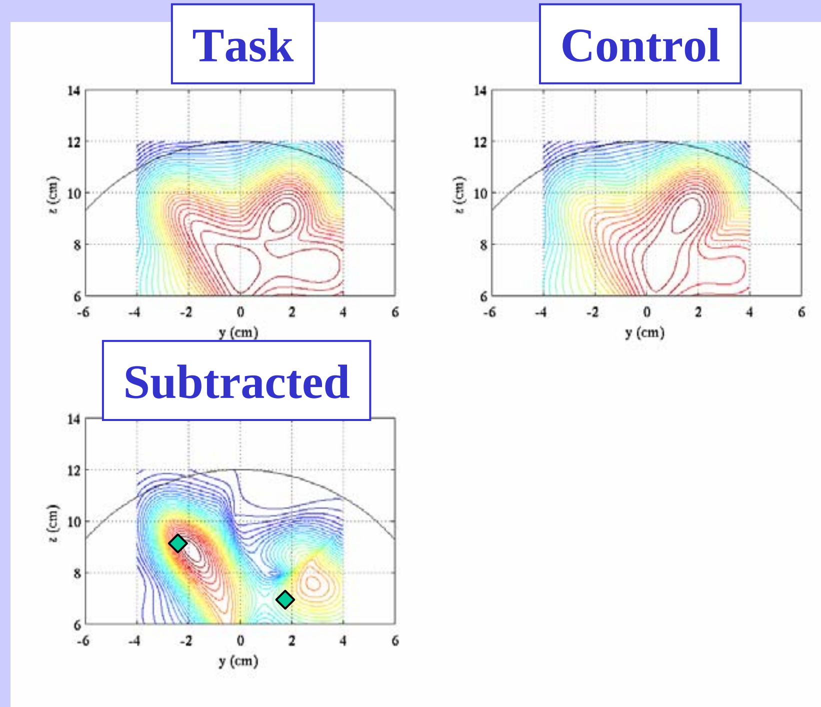
Signal-to-Interference Ratio:0.5

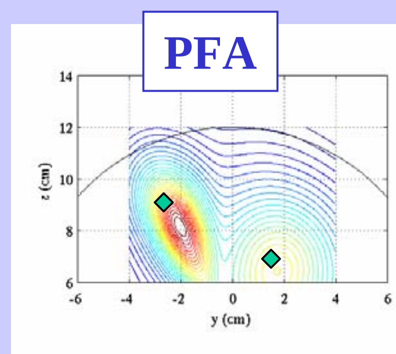


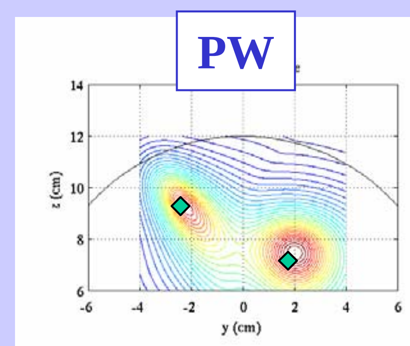




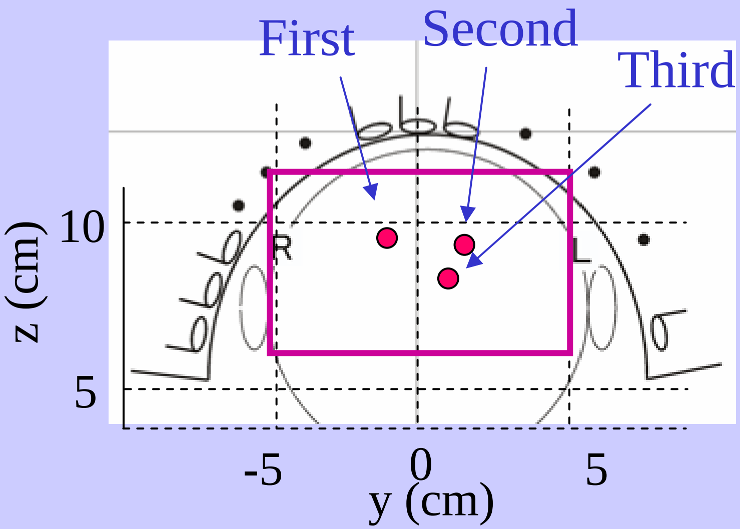
Signal-to-Interference Ratio:0.25







Signal-to-Interference Ratio:0.33

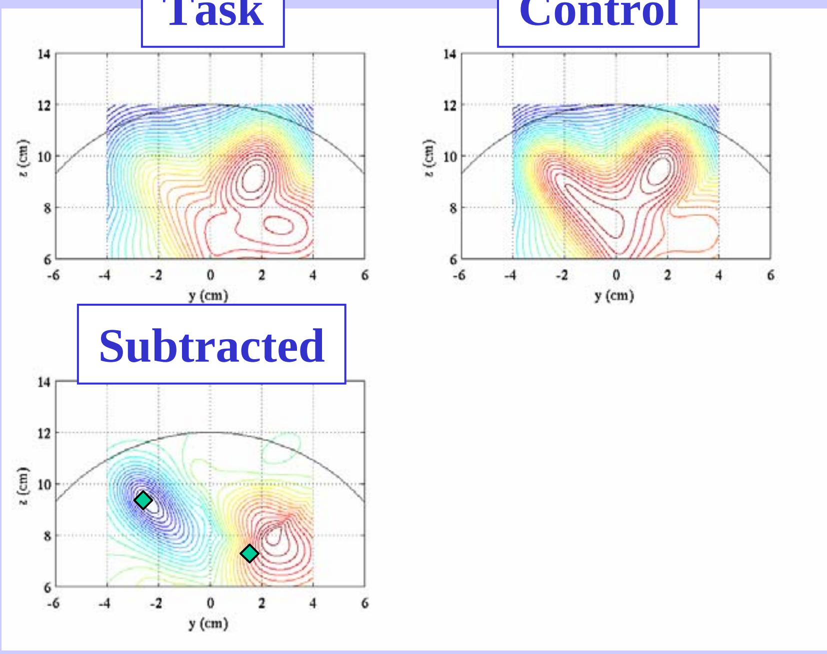


Relative source intensity

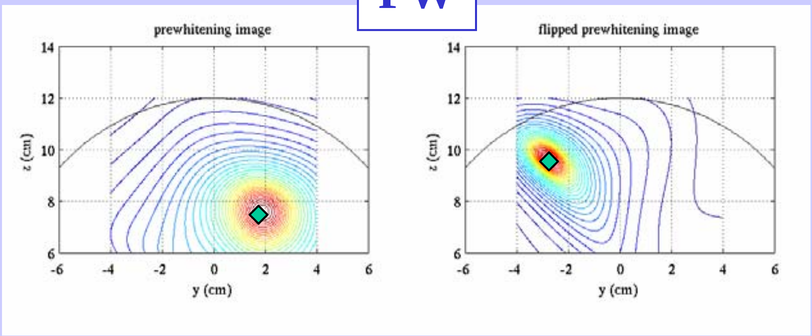
	control	task
First source	1.5	1
Second source	1.5	1.5
Third source	1	1.5

Task **Control**

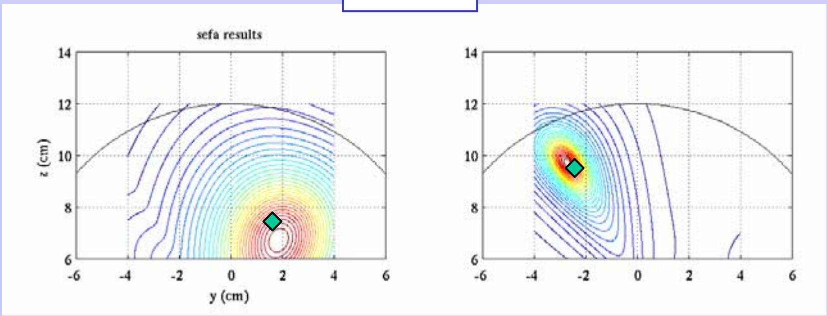
Subtracted



PW



PFA



Summary

•We propose two methods to obtain source reconstruction robust to the existence of large background brain activity.

1) Prewhitening beamforming

2) Partitioned factor analysis + adaptive beamforming

•Both methods are effective in ideal two-condition measurements.

•Partitioned factor analysis is very robust to a case where the number of time samples is small.

•Both methods are significantly robust to non-ideal scenarios of two-condition experiments. However, prewhitening method gives smaller source estimation bias than the PFA method.


Thank you for your attention