Multi-resolution champagne beamformer

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Summary

The sparse Bayesian source imaging (Champagne) algorithm has proven to be effective for neuromagnetic imaging [1,2]. It is robust to various types of noise and interference, and it can reconstruct multiple sources, even when they are highly correlated [2]. However, one serious problem of the algorithm is that it is computationally expensive because of its iterative nature.

In this paper, we propose a novel algorithm, called multi-resolution champagne beamformer. In the proposed algorithm, the first step estimates the model data covariance by using the sparse Bayesian scheme, and the second step implements the adaptive beamformer source imaging using the data covariance estimated in the first step[3]. The key point of the algorithm is to exploit our empirical findings that the quality of the estimated data covariance does not very much depend on the voxel size in the first step, while the voxel size primarily determines the quality of the source reconstruction in the second step.

Therefore, we can significantly shorten the computational time by using a low-resolution voxel grid in the first step but still obtain the high-quality source images by using a high-resolution grid in the second step.

Computer simulation verifies the performance of the algorithm. Unlike the conventional adaptive beamformer, which uses a sample covariance matrix, the proposed champagne beamformer can be applied to a case where correlated sources exist and a case where only a short time window with a small number of time sample is available.

The algorithm may be useful in non-brain electrophysiological imaging such as cardiac imaging in which problems of correlated sources and/or a short time window are common.

References

[1] Wipf DP et al. , Neuroimage. 2010; 49(1): 641-55.

[2] Sekihara S and Nagarajan SS, Electromagnetic brain imaging: a Bayesian perspective, Springer, 2015.

[3] Wipf DP and Nagarajan SS, *Proceedings of the 24th international conference on Machine learning* (pp. 1023-1030). ACM.

Sparse Bayes source imaging (Champagne) algorithm

Data model: $$\boldsymbol{y} = \boldsymbol{F}\boldsymbol{x} + \boldsymbol{\varepsilon}$$

Probability model: $$p(\boldsymbol{y} \mid \boldsymbol{x}) = N(\boldsymbol{y} \mid \boldsymbol{F}\boldsymbol{x}, \sigma^2 \boldsymbol{I})$$

$$p(\boldsymbol{x}) = N(\boldsymbol{x} \mid 0, \boldsymbol{\Upsilon})$$

The hyper parameter $\boldsymbol{\Upsilon}$ is obtained through maximizing the marginal likelihood

$$\log p(\boldsymbol{y} \mid \boldsymbol{\Upsilon}) = -\frac{1}{2}\left[\mid \boldsymbol{\Sigma}_y \mid + \boldsymbol{y}^T \boldsymbol{\Sigma}_y^{-1} \boldsymbol{y} \right],$$

where the model data covariance is defined as

$$\boldsymbol{\Sigma}_y = \sigma^2 \boldsymbol{I} + \boldsymbol{F}\boldsymbol{\Upsilon}\boldsymbol{F}^T$$

This maximization can be implemented in several ways, and the one we have developed is described in [1,2].

Champagne beamformer

The champagne beamformer uses the model data covariance derived from the champagne algorithm[3]:

$$\boldsymbol{w}(\boldsymbol{r}) = \frac{\boldsymbol{\Sigma}_y^{-1}\boldsymbol{l}(\boldsymbol{r})}{\boldsymbol{l}^T(\boldsymbol{r})\boldsymbol{\Sigma}_y^{-1}\boldsymbol{l}(\boldsymbol{r})}$$

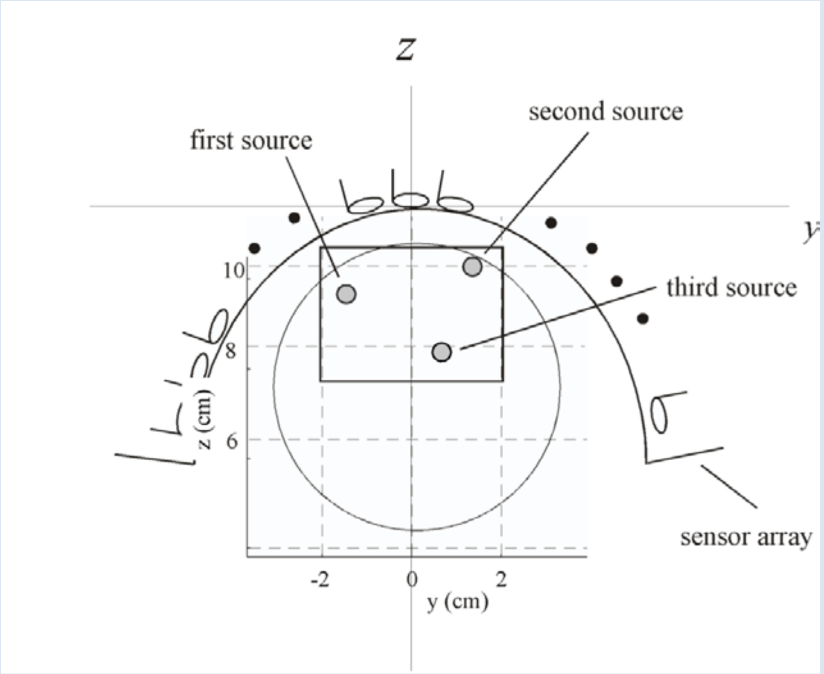
The conventional adaptive beamformer uses the sample data covariance $\boldsymbol{R}$ derived from a data time window containing many time points[4]:

$$\boldsymbol{w}(\boldsymbol{r}) = \frac{\boldsymbol{R}^{-1}\boldsymbol{l}(\boldsymbol{r})}{\boldsymbol{l}^T(\boldsymbol{r})\boldsymbol{R}^{-1}\boldsymbol{l}(\boldsymbol{r})}$$

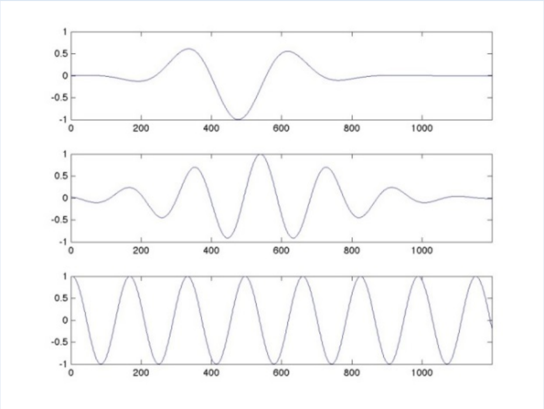
[4] Sekihara K and Nagarajan SS, *Adaptive spatial filters for electromagnetic brain imaging*. Springer, 2008.

Data generation for computer simulation

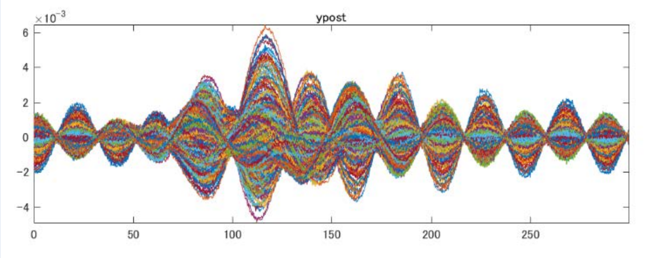
Computer simulation geometry



Time courses assigned to the three sources



Simulated sensor recordings



275 (CTF) whole head sensor array was assumed for data generation.

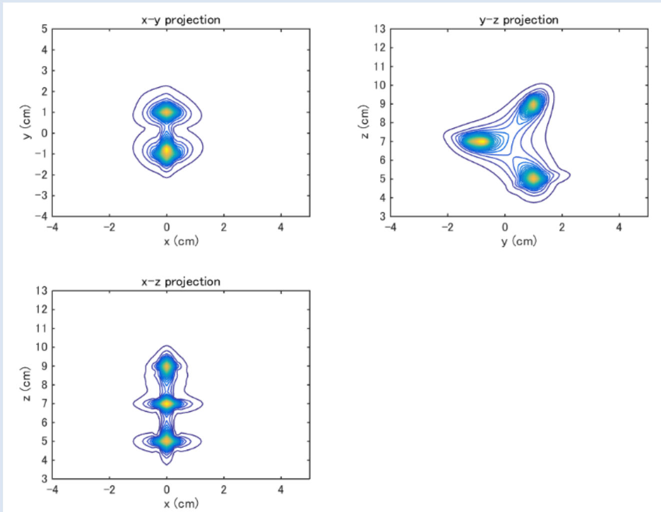
The model data covariance was estimated with voxel grid of 1.5cm.
The beamformer scan was performed with voxel grid of 0.2cm.

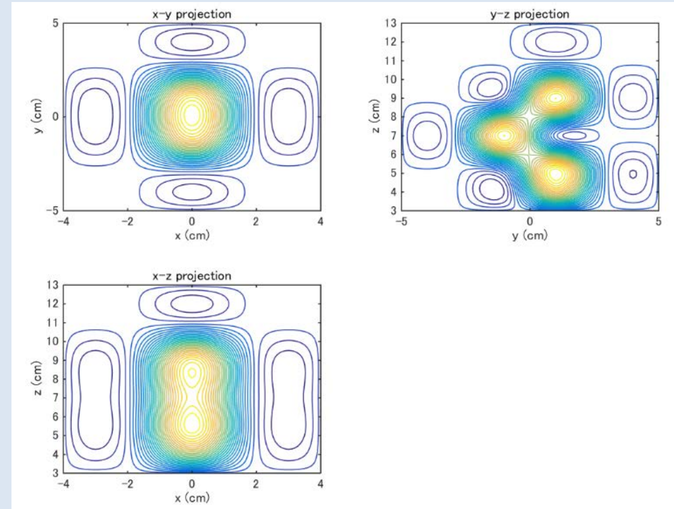
Results of Computer Simulation with no array mismatch

Champagne beamformer images with 2mm voxels

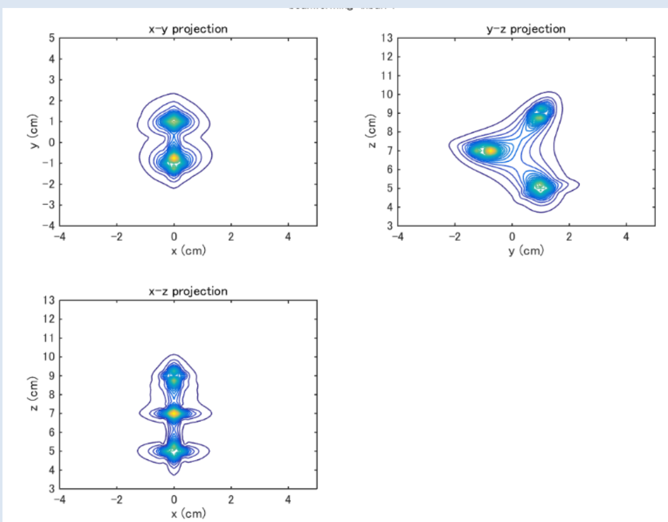
Champagne images with 1.5cm voxels

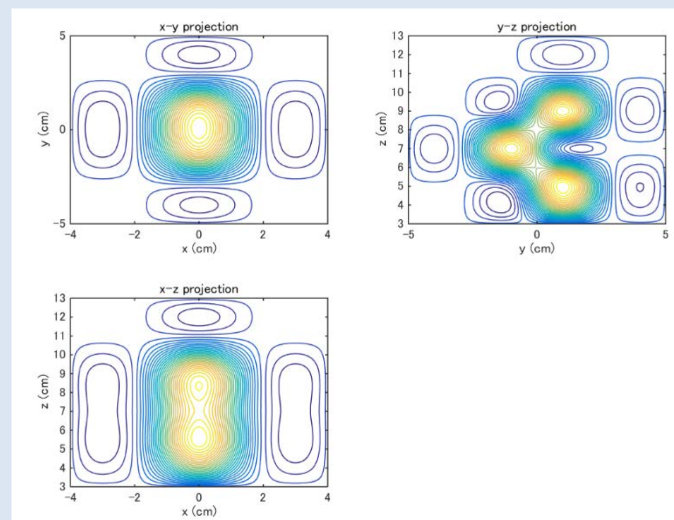
SNR:8





SNR:4





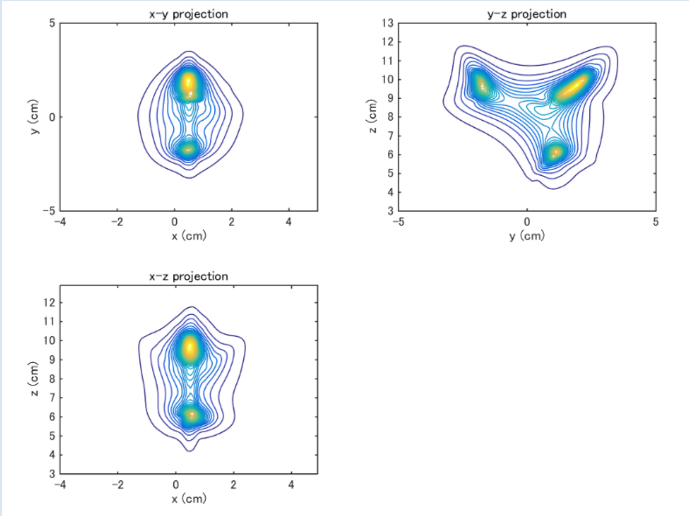
coordinate of three sources: [0 -1 7], [0. 1 9], [0. 1 5] (cm)

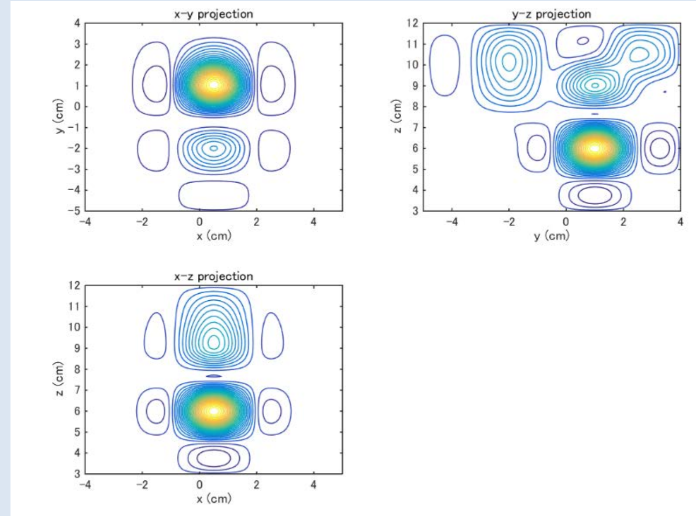
Results of Computer Simulation with array mismatch

Champagne beamformer images with 2mm voxels

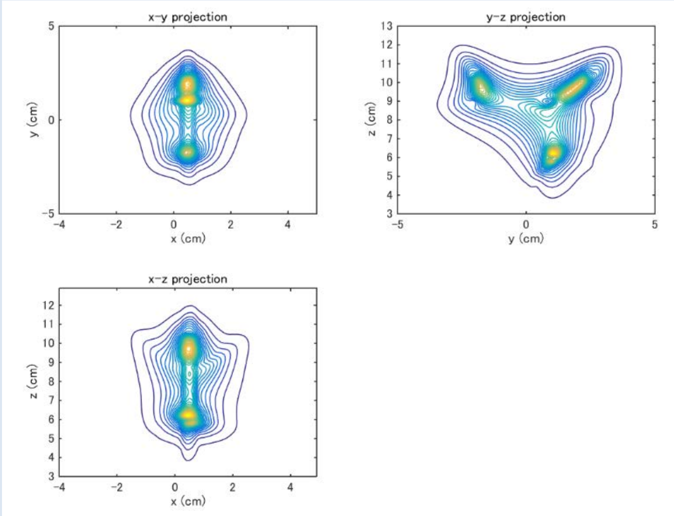
Champagne images with 1.5cm voxels

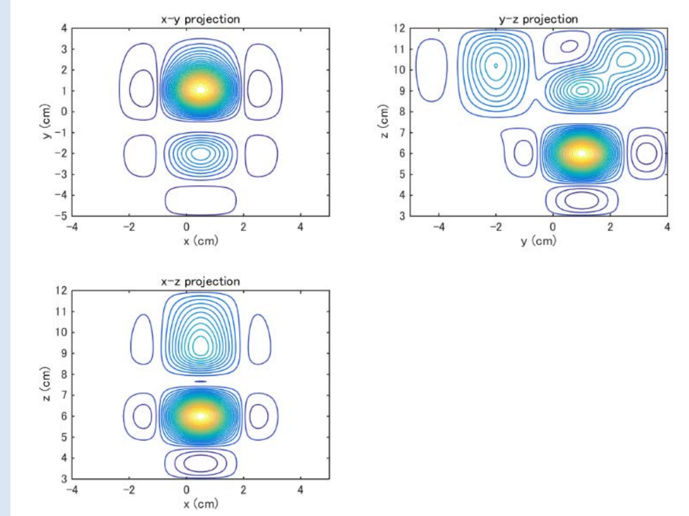
SNR:8





SNR:4



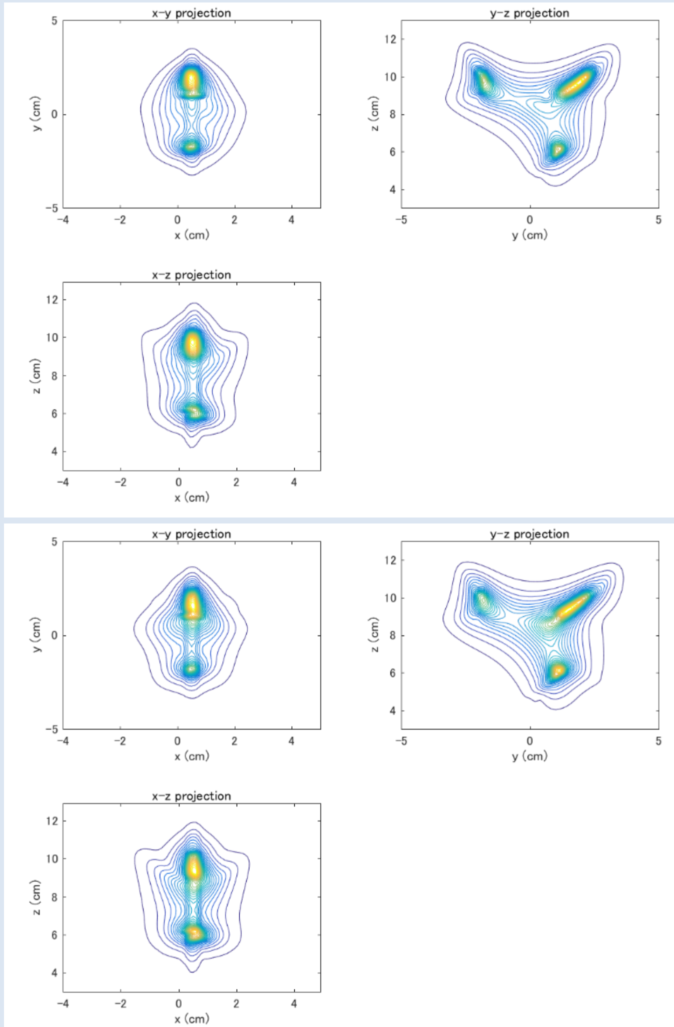


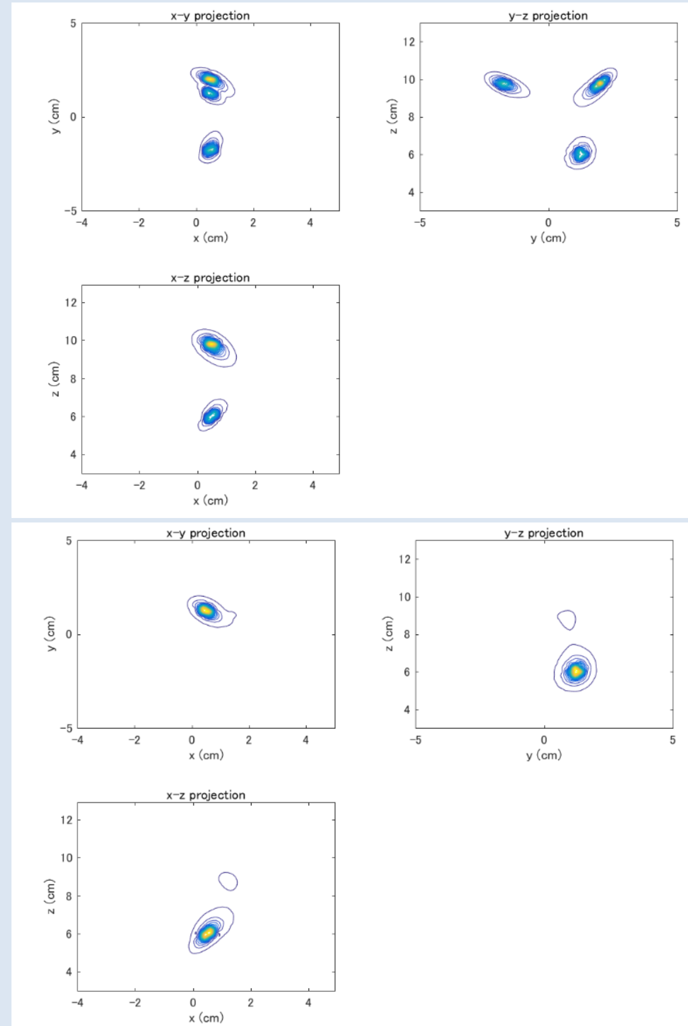
coordinate of three sources: [0.5 -1.75 9.75], [0.5 2 9.75], [0.5 1.25 6] (cm)

Reconstruction of perfectly correlated sources

Champagne beamformer images

Conventional beamformer images



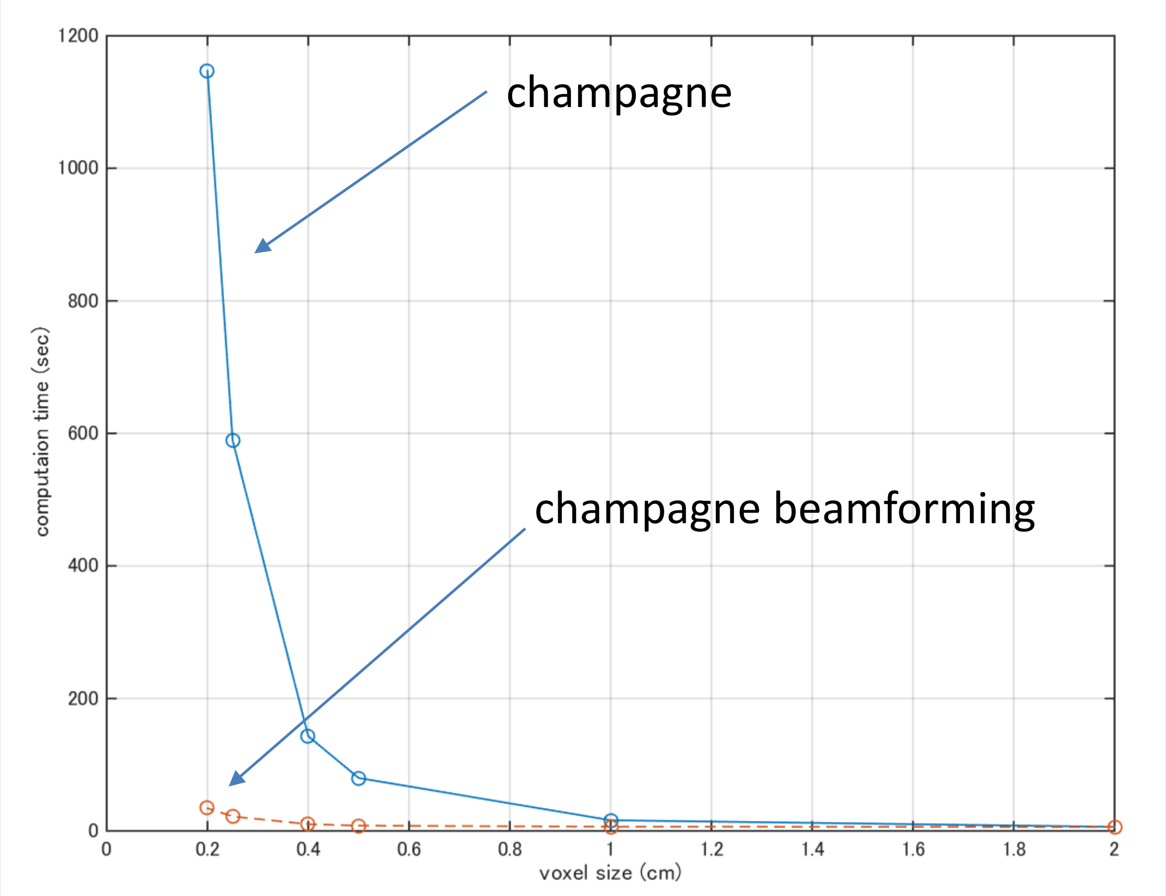


no source correlation

nearly perfect source correlation

The first and the second (the upper two) sources are nearly perfectly correlated in the bottom case.

Comparison of computational time



Condition

# of iteration: 400
# of time points: 1200
# of sensor channels: 275
reconstruction volume: 9cmX9cmX9 cm

Intel® Core i7 3.4GHz
32GB memory
64 bit windows 7
matlab 2014b