Dynamic Magnetic Resonance Inverse Imaging using Linear Constrained Minimum Variance Beamformer

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INTRODUCTION

Inspired by the source localization methods in electroencephalography (EEG) and magnetoencephalography (MEG) [1], magnetic resonance Inverse Imaging (InI) uses a highly parallel radio-frequency coil array to solve an inverse problem in image reconstruction [2]. Due to its intrinsic ill-posed nature, InI has a non-delta point-spread function. Previously we introduced the minimum-norm estimate (MNE) reconstruction on the InI data based on the minimal L-2 norm of the source estimates. Here we propose an alternative InI reconstruction method using a linear constrained minimum variance (LCMV) beamformer, which minimizes the point-spread function of the reconstruction kernel by suppressing signal leakage from all image voxels other than the one to be reconstructed [3]. We present the LCMV InI data reconstruction algorithm and demonstrate its performance using a visual fMRI experiment with a 32-channel head array coil at 3T. We also demonstrate the improved spatial resolution of LCMV InI reconstruction compared to MNE InI reconstruction.

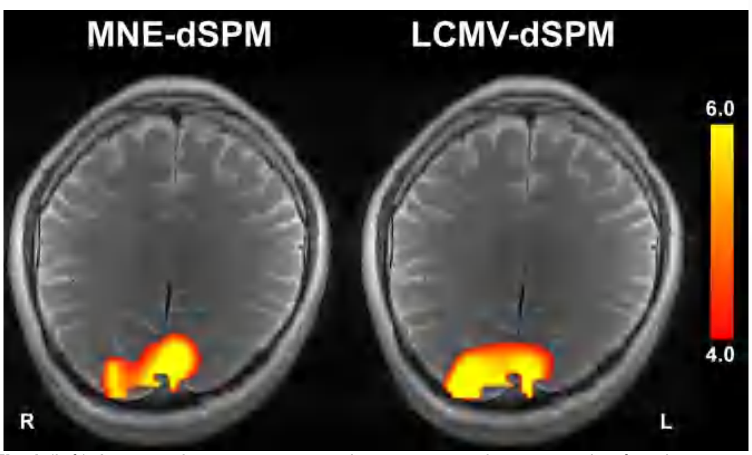
METHODS

For each image voxel to be reconstructed, the LCMV beamformer calculates a spatial filter $\mathbf{W}(\rho)$ to reconstruct the intensity of the voxel with index ρ by minimizing the cost function $\mathbf{W}(\rho)^H(\mathbf{D}+\lambda\,\mathbf{C})\,\mathbf{W}(\rho)$ with the constraint $\mathbf{W}^T(\rho)\mathbf{A}(\rho') = 1$ if $\rho = \rho'$ and 0 otherwise. Here $\mathbf{A}$ is the "forward operator" consisting of the coil sensitivity profiles of the channels in the array and the aliasing operation, $\mathbf{C}$ is the noise covariance matrix of the array, $\mathbf{D}$ is the data covariance matrix, and λ is a regularization parameter. $\mathbf{W}(\rho)$ can be analytically derived as $\mathbf{W}(\rho) = \mathbf{A}(\rho)^H\,(\mathbf{D}+\lambda\,\mathbf{C})^{-1} / \mathbf{A}(\rho)^H(\mathbf{D}+\lambda\,\mathbf{C})^{-1}\mathbf{A}(\rho)$. Similar to the dynamic statistical parametric mapping (dSPM) used in conjunction with MNE (MNE-dSPM), LCMV beamformers can also be noise-normalized (LCMV-dSPM) to otain statistical parametric maps. The modified spatial filter is then $\mathbf{W}_{\mathbf{dspm}}(\rho)= \mathbf{W}(\rho)/\mathrm{sqrt}(\mathbf{W}(\rho)^H\mathbf{C}\,\mathbf{W}(\rho))$.

We demonstrated InI in an event-related visual fMRI experiment with an 8-Hz checkerboard stimulus. The experimental paradigm consisted of 6 seconds pre-stimulus baseline, followed by 2 seconds of a flashing checkerboard, and then 20 seconds fixation. A total of 40 repetitions were measured. We used a PRESTO sequence [4] to collect ultra-fast MR InI acquisitions with TE=30 ms, TR=20ms, Flip angle=20 degrees on a 3T scanner (Tim Trio, SIEMENS Medical Solutions, Erlangen, Germany) using a 32-channel head RF coil array [5]. After InI reconstruction, fMRI time courses from all channels were first detrended and subsequently averaged across repetitions to improve the SNR. The reconstructed data were also spatially smoothed by 6-mm Gaussian kernel. Using the 6 second pre-stimulus interval as the baseline and to estimate the noise covariance, we calculated the dynamic *t*-statistics maps in 20-ms temporal resolution.

RESULTS

Figure 1 shows the InI *t*-statistics maps of dSPM reconstructions using MNE and LCMV methods. The images were overlaid on a high-resolution Turbo-Spin-Echo (TSE) image to illustrate anatomical features. The time-series activation maps were averaged between 6 and 10 seconds after the onset of the stimulus to capture strong functional activation. Strong occipital lobe activations were observed in both reconstructions, while LCMV provided larger activation area (1335 mm^2) than MNE (1134 mm^2). The time courses from the occipital region-of-interest defined by the intersection of both MNE-dSPM and LCMV-dSPM were shown in **Figure 2**. We observed that both MNE-dSPM and LCMV-dSPM showed similar significant activation peaks at approximately 6 seconds after the end of the checkerboard stimulus..



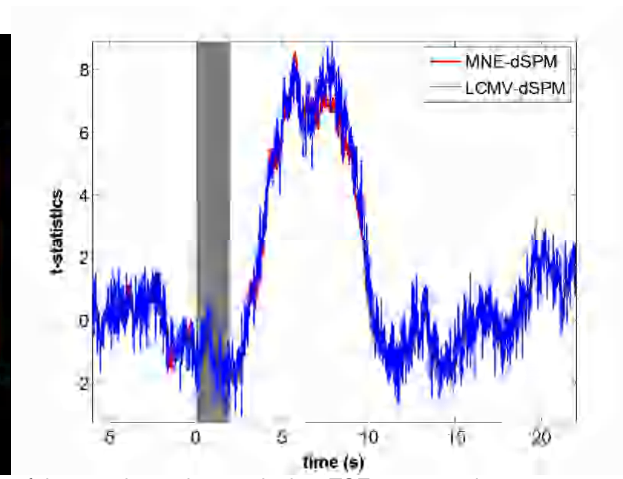


Fig.1 (left) Averaged *t*-statistics maps between 6 and 10 seconds after the onset of the visual stimulus overlaid on TSE anatomical images
Fig.2 (right) Time courses of average t-statistics in the occipital ROI from both MNE-dSPM and LCMV-dSPM

DISCUSSION

We demonstrated MR Inverse Imaging (InI) reconstructions using linear constrained minimum variance (LCMV) beamformers. Similar to previous work employing MNE reconstructions, noise-normalized LCMV dynamic statistical parametric maps can be calculated. LCMV beamformers are utilized to minimize the voxel point-spread function associated with the inverse-problem based image reconstruction. Our experimental data showed that LCMV compared to MNE provides a more robust and stronger detection of visual cortex activation evoked by the checkerboard stimulus.This is likely due to the reduced point-spread and crosstalk from neighboring voxels. Compared with MNE based InI reconstruction, LCMV provides a qualitatively similar result and should be considered as an alternative of InI reconstruction method for dynamic fMRI experiments.

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