Eigenspace Minimum L1-Norm Beamformer Reconstruction of Functional Magnetic Resonance Inverse Imaging of Visuomotor Processing

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INTRODUCTION

Dynamic magnetic resonance (MR) inverse imaging (InI) can improve the temporal resolution of blood oxygen level dependent (BOLD) contrasts fMRI to the order of milliseconds [1]. In InI, the spatial resolution and the source localization accuracy both critically rely on the signal-to-noise ratio (SNR) of the measurements [1]. The localization of the functional activity in ill-posed InI measurements with improved SNR can be done by employing beamformers. Many beamformers are mainly derived from minimizing the output variance of spatial filters quantified by the L2 norm. And the results are usually spatially blurred. Previously, source localizations based on the L1 norm minimization has been proposed to give spatially focal estimates of neuronal currents measured by the magnetocephalography (MEG) [2][3]. Mathematically, the minimization of the L1 norm has always been applied to the current distribution itself. To our knowledge, there has no studies incorporating the minimization of the L1 norm in the design of spatial filter for functional brain imaging analysis yet. Here we propose a beamformer approach combining the eigenspace of the measured data and the L1 norm minimization of the spatial filters' output noise amplitudes. The method was found capable of reconstructing hemodynamic signals in both spatial and temporal fashion and providing less blurry functional images than LCMV beamformer in our visuomotor experiments.

METHODS

The noise-whitened InI measurement for one pixel in the accelerated projection image within the FOV is denoted as $\mathbf{Y}_w$, which can be expressed as $\mathbf{Y}_w = \mathbf{A}_w \cdot \mathbf{X} + \mathbf{n}_w$, where $\mathbf{A}_w$ is the noise-whitened reference (fully gradient encoded data in 3D) providing the sensitivity over the magnetization to be reconstructed in each channel of a coil array, $\mathbf{X}$ is the image to be reconstructed and $\mathbf{n}_w$ is the whitened noise. The time-course correlation matrix $\mathbf{D} = \mathbf{E}[\mathbf{Y}_w \cdot \mathbf{Y}_w^T]$ can then be calculated. Assuming $\mathbf{D}$ has a rank $\mathbf{Z}$, the eigenvalue decomposition on $\mathbf{D}$ can generate two signal $\mathbf{D_S}$ and noise $\mathbf{D_N}$ correlation matrices, that is, $\mathbf{D}=\mathbf{D_S}+\mathbf{D_N}$, where $\mathbf{D}_S = \mathbf{U}_S \cdot \Sigma_S \cdot \mathbf{V}_S^T = [\mathbf{U}_1, \cdots, \mathbf{U}_p] \cdot \mathbf{diag}\ (\lambda_1, \cdots, \lambda_p) \cdot [\mathbf{V}_1, \cdots, \mathbf{V}_p]^T$, $\mathbf{D}_N = \mathbf{U}_N \cdot \Sigma_N \cdot \mathbf{V}_N^T = [\mathbf{U}_{p+1}, \cdots, \mathbf{U}_Z] \cdot \mathbf{diag}\ (\lambda_{p+1}, \cdots, \lambda_Z) \cdot [\mathbf{V}_{p+1}, \cdots, \mathbf{V}_Z]^T$, and $\boldsymbol{\lambda}_i$ ($\mathbf{i}$=1..$\boldsymbol{Z}$) are the descending-sorted eigenvalues, i.e. $\boldsymbol{\lambda}_1 > \ldots > \boldsymbol{\lambda}_p > \ldots > \boldsymbol{\lambda}_Z$, and $\mathbf{U}_i$, $\mathbf{V}_i$, are associated eigenvectors. $\mathbf{D_S}$ is derived from $\mathbf{D}$'s first $\mathbf{p}$ largest eigenvalues and their associated eigenvectors, while $\mathbf{D_N}$ is obtained from the rest eigenvalues, $\boldsymbol{\lambda}_{p+1}, \boldsymbol{\lambda}_{p+2}, .., \boldsymbol{\lambda}_Z$ and their associated eigenvectors. Since the measurement data had been whitened prior to the eigenvalue decomposition, the noise power now is normalized to unity. The threshold selected for the first $\mathbf{p}$ largest eigenvalues and its associated eigenvectors can then be done by selecting eigenvalues larger than 1 [4]. We propose the eigenspace minimum L1 norm beamformer $\mathbf{W}_{L1}$ as a minimization problem with the objective function: $\mathbf{min}_{W_{L1}} \left\| \mathbf{W}_{L1}^T \cdot \mathbf{D}_N^{1/2} \right\|_1$, subject to the linear constraint: $\mathbf{W}_{L1}^T \cdot \mathbf{A}_w = \mathbf{I}$, where $\left\| \bullet \right\|_1$ is the notation for L1 norm minimization and $\mathbf{D}_N^{1/2} = \mathbf{U}_N \cdot \Sigma_N^{1/2}$. The reconstructed source will be $\mathbf{X} = \mathbf{W}_{L1}^T \cdot \mathbf{Y}_w$.

The fMRI experiment used a voluntary visuomotor task: the subjects were asked to respond with the button pressing using their right hand after perceiving the visual checkboard stimulus (500 ms duration, 100% contrast) at the right visual hemifield. Ten healthy subjects were recruited in this study with informed consent. The InI was measured with TR=100 ms and TE=30 ms using a flip angle of 30 from a 3T scanner (Tim Trio, Siemens Medical Solutions, Erlangen, Germany) with a 32-channel head coil array. Each run of the experiment last for 4 minutes and 32 trials of the stimulus were randomly presented. Each subject was measured for four runs. The analysis of the fMRI InI data followed our previously published method [1] using the General Linear Model with the finite impulse response (FIR) basis function. The minimum L1 norm beamformer reconstructions were calculated using the CVX program [5].

RESULTS

Areas at the contralateral visual and motor cortices were found active in the reconstructed images. These two ROIs were respectively selected for further analysis of the time courses. The group averaged time courses of t-values at these two ROIs were linearly scaled between [0 1]. We chose the threshold of 0.4 and 0.2 for motor and visual ROIs, respectively. The spatial reconstruction clearly shows that eigenspace L1 norm beamformer offers much better spatial resolution than LCMV beamformer. The figure below right shows linearly scaled time courses. We found that the visual ROI has the onset time at 2.1s, the peak time at 3.7s, and the full-width-half-maximum (FWHM) of the time course 5.4s, while M1 area has the onset time at 2.8s, the peak time at 4.4s, and the FWHM 4.7s.

DISCUSSION

The eigenspace L1 norm beamformer $\mathbf{W}_{L1}$ was found to provide sparse reconstructions. The localization results matched our previous beamformer analysis [1]. The normalized time courses show motor cortex response lags averagely behind visual cortex response by 700ms. Such latency is consistent with the causal sequence in our visuomotor experimental design. In the future, we will systematically compare reconstruction mechanisms using different minimum L1 and the L2 norm constraints to achieve the optimal strategy for data analysis in fMRI InI measurements.

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