Reconstruction of magnetic resonance inverse imaging using the minimum L-1 norm constraint

F-H. Lin[1,2], T. Witzel[1], J. Polimeni[1], and J. W. Belliveau[1]

[1]A. A. Martinos Center, Massachusetts General Hospital, Charlestown, MA, United States, [2]Institute of Biomedical Engineering, National Taiwan University, Taipei, Taiwan

INTRODUCTION

Magnetic resonance Inverse Imaging (InI) [1], similar to MR-encephalography [2], uses a highly parallel radio-frequency coil array to obtain spatial information by solving an inverse problem in image reconstruction in order to reduce the reliance on spatial encoding using gradient switching. Previously we used the minimum L-2 norm constraint to calculate volumetric InI reconstructions with spatially diffused source estimates. More spatially focal estimates can be obtained by a minimum L-1 norm constraint. This approach has been implemented in the minimum-current estimate (MCE) reconstruction [3] in magnetoencephalography (MEG) and electroencephalography (EEG) data. This minimum L-1 norm reconstruction was also proposed in the compressed sensing MRI [4]. Compared to the minimum L-2 norm reconstruction, our results show that InI with the minimum L-1 norm constraint can improve the spatial resolution while keeping the temporal resolution as fast as 100 ms per volume.

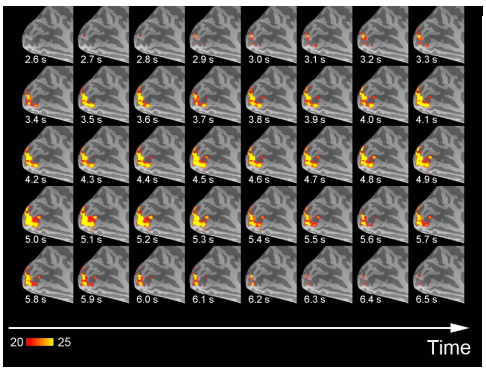
METHODS

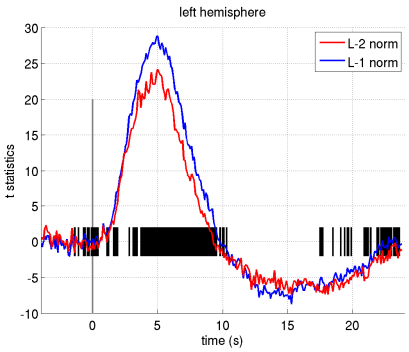
A *n*-channel InI signal **y** from the unknown image **x** in the presence of noise **e** can be formulated as $\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{e}$, where **y** and **e** are vectors of *n* data values and **x** is vector of *m* pixels. The forward matrix **A** is of size *n*-by-*m* and consists of the coil sensitivity profiles and the projection operation since only the central k-space line was acquired. The cost function to solve for x with minimum L-1 norm constraint is $\|\mathbf{y}-\mathbf{A}\mathbf{x}\|^2+\lambda|\mathbf{x}|$, where λ is the regularization parameter. To solve for **x**, we used the linear programming simplex method [4] to minimize the sum of absolute values of elements of **x**. This requires first to estimate the phase for each element of the **x**, which were estimated from the minimum L-2 norm solution: $\mathbf{x}_{l2}=\mathbf{A}^H(\mathbf{A}\mathbf{A}^H+\lambda\mathbf{C})^{-1}\mathbf{y}$, where **C** is the noise covariance matrix of the **y**. The measurement error $\|\mathbf{y}-\mathbf{A}\mathbf{x}\|^2$ was controlled to keep 95% of the total variance of **A** by singular value decomposition.

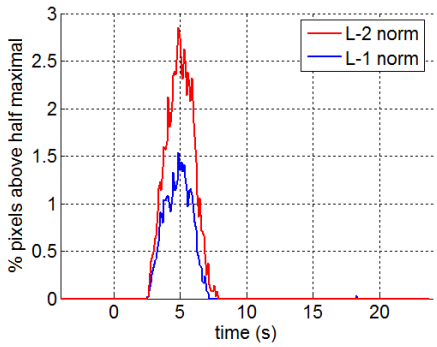
We demonstrated InI using an event-related visual fMRI experiment with an 8-Hz checkerboard stimulus. The paradigm consisted of 6 s pre-stimulus baseline, followed by 0.5 s checkerboard flashing, and then 23.5 s visual fixation. Total 32 repetitions per run and 4 runs were measured on a 3T scanner (Tim Trio, SIEMENS Medical Solutions, Erlangen, Germany) using a 32-channel head RF coil array. Data were acquired using single slice EPI read-out. The spatial resolution in the left-right direction was calculated from InI reconstruction. Parameters for the reference images were TR=100 ms, TE =30 ms, 4mm thickness, 64 slices. Accelerated InI acquisitions used the same imaging parameters with a single slab sagittal slice (256 mm thickness). The InI time series in projection images were first deconvoluted using the General Linear Model with Finite Impulse Response basis functions to estimate the hemodynamic response function (HRF) of 30 seconds duration, including a 6 seconds baseline. Subsequently, the minimum L-1 norm reconstruction was done on each time point of the HRF in the projection image to obtain volumetric reconstructions. We estimated the baseline variance, which was used to normalize HRF estimates to yield dynamic *t* statistics.

RESULTS

The figure at left shows successive frames of visual activation from a group average data (*n*=6). Snapshots were the medial aspect views of dynamic statistical parametric mapping (dSPM) of *t* statistics overlaid on the left cerebral hemisphere using an inflated brain surface model. The time courses (middle) show the minimum L-2 norm estimate reconstruction (red trace) and the minimum L-1 norm estimate reconstruction (blue trace) of the InI dSPM *t*-values within the primary visual cortex (V1) ROI. In average, the minimum L-1 norm reconstruction has a higher *t*-statistic than the minimum L-2 norm reconstruction (20% improvement). We also performed a time-point by time-point *t* test within the V1 ROI to compare the reconstructions. Statistically significant time points (*p*-value <1%) were shown with a black tick in the time series. In general, the minimum L-1 norm reconstruction provided a higher detection sensitivity compare to the minimum L-2 norm reconstruction around the peak time of the HRF. The right figure shows the time courses of the percentage pixels above the half maximum. The minimum L-1 norm reconstructions show more focal activation (less activated areas).







DISCUSSION

We demonstrate the feasibility of reconstructing InI data using the minimum L-1 norm reconstruction to obtain a higher sensitivity using a visual fMRI data across 6 subjects. Compared to the minimum L-2 norm reconsruciton, L-1 norm reconstruction is more computational intensive since no time-invariant inverse operator can be constructed. However, the deconvolution by GLM reduced the number of time point to be reconstructed dramatically. From the theory of Bayesian estimation, the L-1 norm can provide a more spatially focal estimate since the sources follow a bi-exponential distribution, whose probability density is more concentrated around zero compared to the Gaussian distribution in the minimum L-2 norm reconstruction. The choice between the minimum L-1 or L-2 norm constraint thus depends on the trade-off between the computational efficiency and detection sensitivity.

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