Sparse source cluster reconstruction by compressed magnetic resonance inverse imaging

Wei-Tang Chang[1,2], Jyrki Ahveninen[1], and Fa-Hsuan Lin[1,2]

[1]*Martinos center for biomedical imaging, Massachusetts general hospital, Charlestown, Massachusetts, United States,* [2]*Biomedical engineering, National Taiwan University, Taipei, Taiwan*

INTRODUCTION

Functional MRI (fMRI) with blood-oxygen level dependency (BOLD) contrast [1, 2] measures the hemodynamic response secondary to neural activity. Using the magnetic resonance inverse image (InI) technique, the scan time per brain volume can be reduced from 2 s [3] to 100 ms [4]. Mathematically, InI reconstruction generalizes the parallel MRI (pMRI) reconstruction from an over-determined linear system to an under-determined linear system in order to reduce the time in k-space transverse and therefore achieve a high temporal resolution. Considering that the spatial distribution of BOLD activation along the projection direction could be diffuse or focal, using minimum-norm estimation (MNE) which favors diffuse solutions [4] or minimum-current estimation (MCE) which favors focal solutions [5] does not adequately reflect the underlying source distribution. In this study, we aim to develop an alternative InI reconstruction method to **accommodate both focal and diffuse source distribution** based on the hypothesis that the spatial distribution of BOLD activation is compressible. The sparsity of the estimates in the transformed domain can be achieved by minimizing the ℓ^1-norm of the basic coefficients of the representation. We incorporate the constraint of minimizing the ℓ^1-norm of estimated activation source with the ℓ^1-norm of wavelet-transformed activation source. Such integration is to promote spatial sparsity to generate separable activity and to reduce the bias toward diffuse inverse estimates when using the wavelet transformation sparsity alone. In addition, the discrepancy between the modeled and observed data is adaptively controlled to reduce the noise sensitivity of the solution.

METHODS

The time-series images $\mathbf{y}(t)$ on an n_c-channel RF coil array can be formulated as $\mathbf{y}(t)=\mathbf{A}\mathbf{s}(t)+\mathbf{n}(t)$, where t indicates time, and $\mathbf{y}(t)$ is an n_c-by-1 vector. n_c denotes the number of array channels. $\mathbf{s}(t)$ is the to-be-reconstructed image vector with matrix size of n_s-by-1, where n_s is the number of image voxels. $\mathbf{A}$ is the 'forward operator' with matrix size of n_c-by-n_s and $\mathbf{n}(t)$ is a n_c-by-1 vector denoting the contaminating noise. Here $\mathbf{y}(t)$ is the estimated hemodynamic response function (HRF), consisting of 6 s pre-stimulus period and 24 s post-stimulus period. We presume that the efficiency of the source compression can be reasonably quantified by the ℓ^1-norm of the sources in the standard domain and wavelet-transformed domain [6]. The cInI can be mathematically described as constrained minimization of a cost function

$\min_{\mathbf{s}(t)} \|\mathbf{M}\mathbf{s}(t)\|_1+\lambda\|\mathbf{s}(t)\|_1$, s.t. $\|\mathbf{y}(t)-\mathbf{A}\mathbf{s}(t)\|_2^2<\varepsilon$, where $\mathbf{M}$ denotes the biorthogonal wavelet transformation matrix. A suitable ε can be chosen by requiring that probability of $\|\mathbf{y}(t)-\mathbf{A}\mathbf{s}(t)\|_2^2 \geqq \varepsilon$ is reasonably small. In addition, the regularization factor λ in eq.(2) is set as 3. Both the values of ε and λ are selected according to the simulations (not shown here).

MRI data was collected with a 3T MRI scanner with 32-channel coil array (Tim Trio, Siemens Medical Solutions, Erlangen, Germany). The InI functional scan was collected using a single-slice echo planar imaging (EPI) readout, exciting one thick coronal slab covering the whole brain (FOV 256 X 256 X 256 mm; 64 X 64 X 1 image matrix). Partition phase encoding along the anterior-posterior axis was removed to accelerate the acquisition. We used TR=100 ms, TE=30 ms and bandwidth=2056 Hz. Besides, to validate localization EPI data were also collected using the following parameters: TR = 2s, TE = 30 ms, flip angle = 90° slice thickness = 3.75 mm. We demonstrated cInI using an event-related fMRI experiment with an 8-Hz checkerboard visual stimulus shown on the participants' left or right visual field. The paradigm consisted of 0.5 s checkerboard flashing with a 2 s of minimum inter-stimulus interval. Total 60 trials per run (30 trials for left/right visual stimuli) and 3 runs (3 minutes per run) were measured. EPI data included 60 stimuli per run and 3 runs (3 minutes per run) in total.

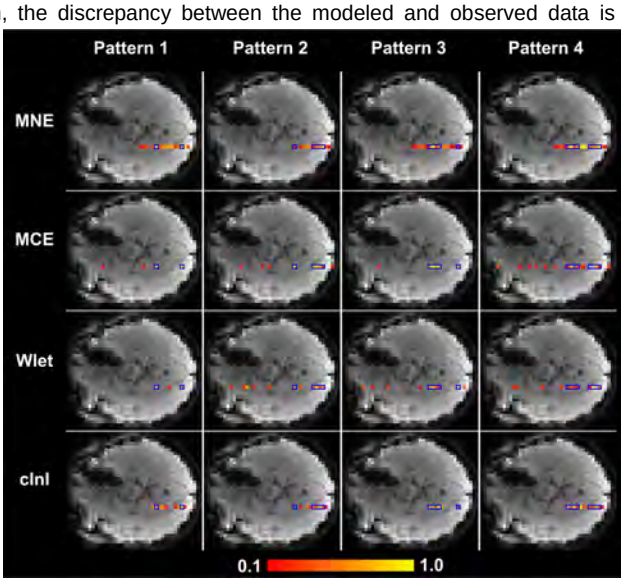

Figure 1

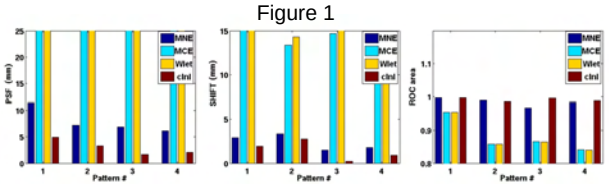

Figure 2

RESULTS

Figure 1 shows the brain maps of simulation results in visual cortex. The blue blocks highlight the simulated activation sources which were selected from the visual cortex. Four different spatial patterns (focal-focal, focal-diffuse, diffuse-focal, diffuse-diffuse) of activation sources are tested. In this study we compare cInI with three other different reconstruction methods: minimum norm estimates (MNE) which minimizes the ℓ^2-norm of source estimates, minimum current estimates (MCE) which minimizes the ℓ^1-norm of source estimates, and wavelet estimates (Wlet) which minimizes the ℓ^1-norm of wavelet transformed source estimates. In Figure 1, MNE solutions are spatially diffuse while MCE and Wlet are spatially disperse. On the contrary, cInI provides more reliable estimates toward focal, diffuse and hybrid patterns. As for the quantitative results in figure 2, cInI generally outperforms the other methods in terms of point spread function (PSF), shift and areas under ROC curves. Figure 3 shows the empirical results of cInI reconstruction. The cInI localized the BOLD activations at visual cortex, which were consistent with those measured by EPI.

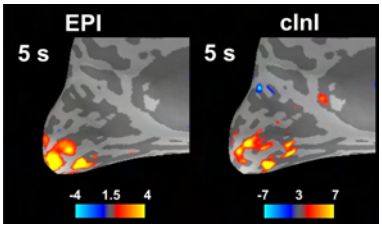

Figure 3

DISCUSSION

To better estimate the focal and diffuse source distribution along the projection direction, we propose the reconstruction method of cInI which minimizing the ℓ^1-norm of both the source estimates and the wavelet transformed source estimates. The quantitative results showed that cInI has higher spatial resolution than MNE and MCE, which favor either focal or diffuse solutions. Validated by the EPI results, cInI demonstrates the feasibility on empirical data. With such improved spatial resolution, cInI can be applied to dynamic MRI acquisition to achieve better spatiotemporal resolution.

REFERENCES

1. Kwong, K.K., et al., Proc Natl Acad Sci U S A, 1992. 89(12): p. 5675-9.
2. Ogawa, S., et al., Proc Natl Acad Sci U S A, 1990. 87(24): p. 9868-72.
3. Mansfield, P., et al., Journal of Physics C: Solid State Physics, 1977. 10(3): p. 55-L58.
4. Lin, F.H., et al., Magn Reson Med, 2006. 56(4): p. 787-802.
5. Lin, F.H., et al., Proc. Intl. Soc. Mag. Reson. Med. (2009); 4594
6. Chang, W.T., et al., Neuroimage, 2010. 53: p146-160