

ITERATIVE SELF-CONSISTENT MAGNETIC RESONANCE INVERSE IMAGING

T-M. Huang¹, T. Witzel², W-J. Kuo³, and F-H. Lin^{1,2}

¹Institute of Biomedical Engineering, National Taiwan University, Taipei, Taiwan, ²Martinos Center, Massachusetts General Hospital, Charlestown, MA,

United States, ³Institute of Neuroscience, National Yang-Ming University, Taipei, Taiwan

INTRODUCTION

Dynamic magnetic resonance inverse imaging [1] offers an unpredicted temporal resolution for BOLD fMRI. All InI reconstructions trade off the spatial resolution for a high temporal resolution. The localization accuracy of InI depends on the signal-to-noise ratio (SNR) of the measurements. Previously, we found that k-space InI (K-InI) reconstruction [2] provides a higher spatial resolution compared with the image domain method [3] based on the GRAPPA formulation [4]. In parallel MRI, self-consistency has been reported as an important property to make accurate reconstructed images using arbitrary k-space sampling patterns [5]. Here we hypothesize that the SPIRiT (iterative self-consistent parallel imaging reconstruction) reconstruction can further improve K-InI reconstruction. Preliminary results suggest that this iterative reconstruction in k-space with a consistency constraint provides a higher spatial resolution.

METHODS

The SPIRiT reconstruction first assumes that there is a calibration region to generate a GRAPPA operator \mathbf{G} . Let \mathbf{x} denote the whole k-space to be reconstructed, after applying \mathbf{G} operator, the reconstructed image \mathbf{Gx} should be consistent with \mathbf{x} , $\mathbf{Gx} = \mathbf{x}$. Let \mathbf{y} be the vector of measured data from all coils, and \mathbf{D} denotes the sampling operator matched to the accelerated acquisition, the consistency in data acquisition is ensured by $\mathbf{y} = \mathbf{Dx}$. Taking both constraints together, the desired k-space reconstruction can be formulated as an optimization problem: $\min \{ \|\mathbf{Gx}-\mathbf{x}\|^2 \}$ subject to $\|\mathbf{Dx}-\mathbf{y}\|^2 \leq \epsilon$, where ϵ controls the consistency. Different from SPIRiT, InI uses a highly sub-sampled \mathbf{D} operator. Specifically, InI acquires only 1 projection image to achieve 100 ms temporal resolution. Accordingly, \mathbf{D} has 32 rows when a 32-channel RF coil array is used for parallel detection. We used iterative Conjugated Gradients (CG) method to solve \mathbf{x} by minimizing the following cost:

$|\mathbf{Dx}-\mathbf{y}|^2 - \lambda(\epsilon) \|\mathbf{Gx}-\mathbf{x}\|^2$, where λ is the regularization parameter balancing two individual costs. Practically, \mathbf{x} from the previous iteration was used to compare the output of \mathbf{Gx} in this iteration. In dynamic imaging, a fully sampled reference scan was used to derive \mathbf{G} . The estimation \mathbf{G} is similar to K-InI, except that we can choose a proper calibration area and a kernel size to ensure that the estimation is an over-determined linear system with sufficient accuracy.

We demonstrated SPIRiT 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 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 EPI readout with frequency encoding along the inferior-superior direction and phase encoding along the anterior-posterior direction. The spatial resolution in the left-right direction was calculated from SPIRiT reconstruction. Specifically, we collected reference images (TR=100 ms, TE =30 ms, flip angle = 30°, 4mm thickness, 64 partitions) for the estimation of SPIRiT reconstruction coefficients. Accelerated acquisitions were collected from the same sequence but the partition encoding steps were left out. SPIRiT reconstructions were calculated for each channel and each time point separately.

RESULTS

To evaluate the reconstruction, we used the reference scan to simulate InI acquisition and calculate the normalized root mean square error (nRMSE) with the reference scan. The SPIRiT reconstruction used the initial guess \mathbf{x}_0 from the reference scan can generate reconstruction with much more spatial features than K-InI (top panel). The middle panel shows successive SPIRiT frames of visual activation from a single subject. Snapshots were the medial aspect views of dynamic t statistics maps overlaid on the left cerebral hemisphere using an inflated brain surface model. The critical threshold was $t = 7.0$ (uncorrected p -value $<10^{-4}$). The time course shows the average of minim-norm estimate InI (black), K-InI (blue), SPIRiT (red) t statistics within the visual cortex ROI. Both K-InI and SPIRiT InI reconstructions had higher peak t statistics than MNE InI.

DISCUSSION

Comparing to K-InI, SPIRiT InI reconstruction with a proper initial guess \mathbf{x}_0 can improve image quality and speed up CG convergence significantly. In InI and K-InI, reconstruction is basically an ill-posed inverse problem. In SPIRiT InI, however, the image reconstruction can become an over-determined linear system because of additional constraints on k-space data consistency. Since SPIRiT InI is only marginally well conditioned, it is possible to further stabilize the reconstruction by adding regularization and using prior information.

REFERENCES

- [1] Lin, F. H., T. Witzel, et al., Magn Recon Med, 2006, 56: 787-802.
- [2] Lin, F. H., T. Witzel, et al., NeuroImage, 2010, 49, 3086-98
- [3] Lin, F. H., T. Witzel, et al., Neuroimage, 2008, 42, 230-47.
- [4] Griswold et al., Magn Recon Med, 2002, 47: 1202-10
- [5] Lustig. PhD Thesis, Stanford

