

UNDERSAMPLED MRI RECONSTRUCTION WITH TRAINED DIRECTIONS FROM A GUIDE IMAGE



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I. Introduction

Undersampling the k-space data can speed up magnetic resonance imaging (MRI) at the cost of introducing the aliasing artifacts. These artifacts can be obviously reduced by enforcing the sparse representation of the magnetic resonance (MR) image with respect to a pre-constructed basis or dictionary [1]. Insufficient sparse representation for images usually results in artifacts in the reconstruction. In this work, sparsifying transform is trained from a guide image to reduce the reconstruction error.

A parameter of patch-based directional wavelets (PBDW), indicating the geometric direction of each patch [2], is trained from the reconstructed image using conventional compressed sensing MRI methods, and incorporated into the sparsifying transform to provide the sparse representation for the image to be reconstructed [3]. Simulation results on phantom and in vivo data indicate that the proposed method outperforms conventional compressed sensing MRI methods on preserving the edges and suppressing the noise. Besides, the proposed method is not sensitive to the initial image when training directions. The journal paper was published in [3].



II. Training the geometric directions in PBDW

A geometric direction w_j in an image patch $\mathbf{b}_j = \mathbf{R}_j \mathbf{x} \in \mathbb{C}^N$ is trained according to

$$w_j = \arg \min_{\theta_{j,d} \in \Theta} \|\tilde{\mathbf{c}}_{j,d}(\theta_{j,d}, \mathcal{S}) - \Psi^T \mathbf{P}(\theta_{j,d}) \mathbf{b}_j\|_2^2$$

among the candidate directions $\Theta = \{\theta_1, \theta_2, \dots, \theta_d, \dots, \theta_D\}$.

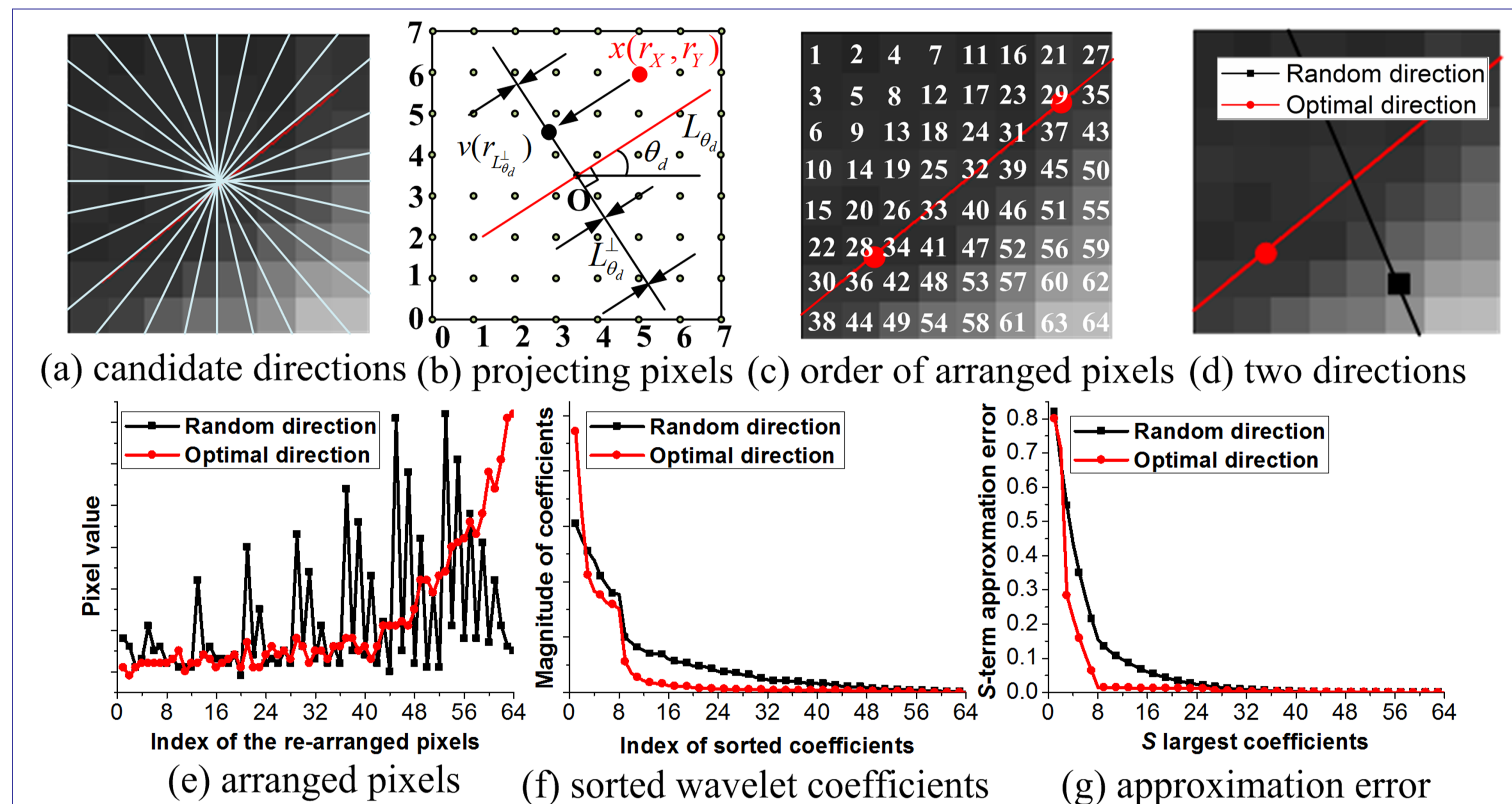


Fig.1 Train the geometric direction



III. PBDW-based MRI reconstruction with a guide image

For undersampled MRI, an initial guide image is reconstructed by enforcing the sparsity of image in shift-invariant discrete wavelet (SIDWT) domain [3] which can mitigate blocky artifacts in reconstruction. With the geometric directions \mathbf{W} for J patches, the reconstruction formulation is as follows:

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{A}_w \mathbf{x}\|_1 + \frac{\lambda}{2} \|\mathbf{y} - \mathbf{F}_U \mathbf{x}\|_2^2, \mathbf{W} = \{w_1, \dots, w_j, \dots, w_J\}$$

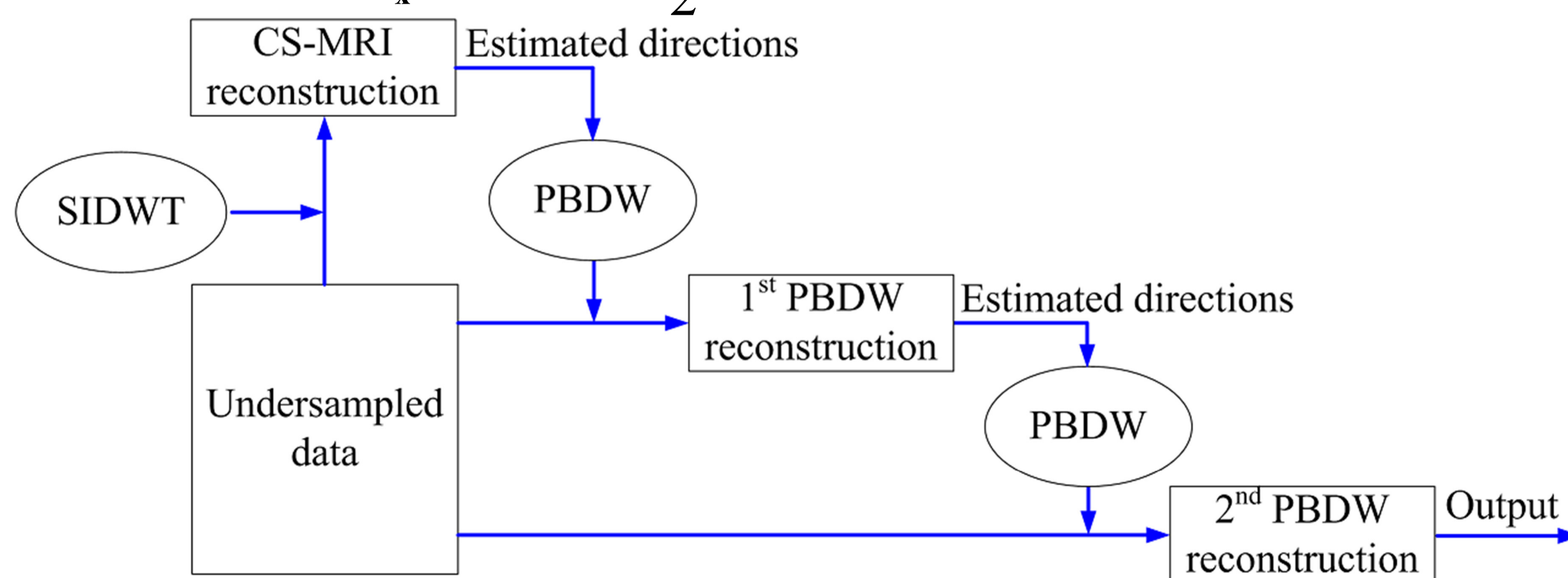


Fig.2 Flowchart of the proposed method



IV. Results and conclusions

Brain image in Fig. 4(b) is acquired from a healthy volunteer at a 3T Siemens Trio Tim MRI scanner with the T2-weighted turbo spin echo sequence (TR/TE = 6100/99 ms, FOV=220 × 220 mm², slice thickness=3 mm). We specify the regularization parameter $\lambda=10^6$ for total variation (TV), SIDWT and the proposed method. The relative l_2 norm error (RLNE) defined as $e(\hat{\mathbf{x}}) = \|\hat{\mathbf{x}} - \tilde{\mathbf{x}}\|_2 / \|\tilde{\mathbf{x}}\|_2$ is adopted to measure the error between the reconstructed image $\hat{\mathbf{x}}$ and the fully sampled image $\tilde{\mathbf{x}}$.

Conclusions: Training the geometric directions from incomplete k-space data can better preserve the edges than conventional sparse reconstruction methods did.

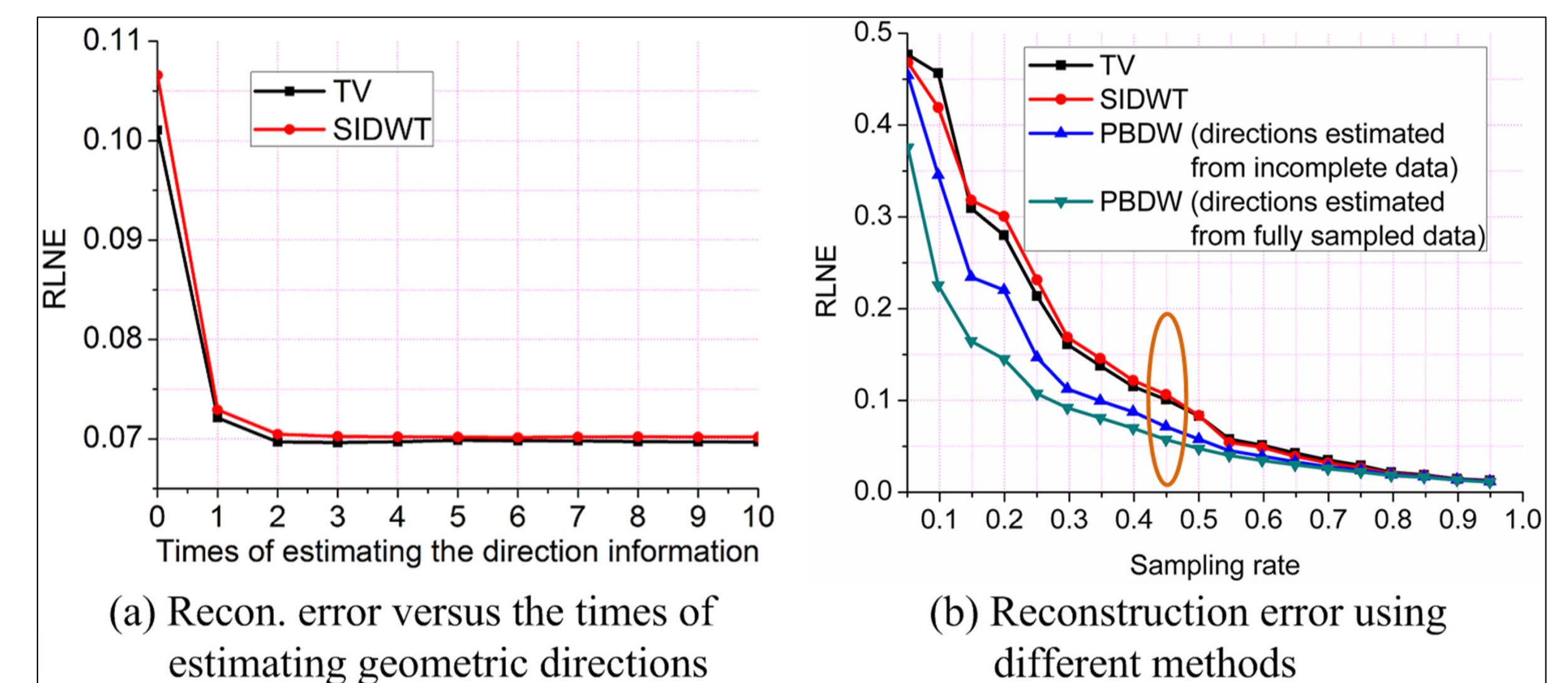


Fig.3 Reconstruction error

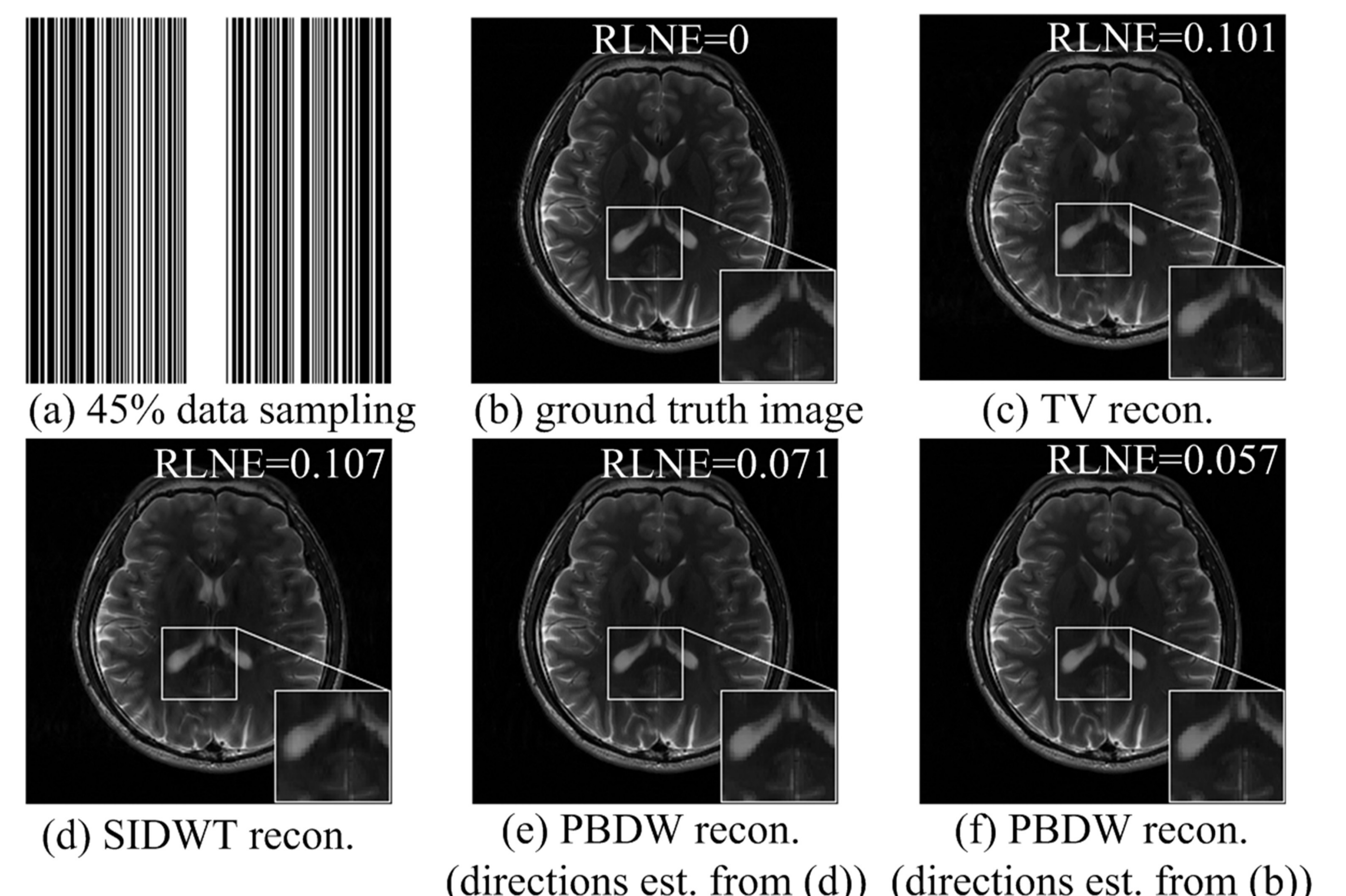


Fig.4 Reconstructed images



V. References

- [1] Lustig M., et al.. *Magnetic Resonance in Medicine* 58 (2007) 1182-1195. [2] Peyre G. and Mallat S.. *ACM Transactions on Graphics* 24 (2005) 601-608. [3] Qu X.B. et al.. *Magnetic Resonance Imaging*, doi:10.1016/j.mri.2012.02.019, 2012.