Fast dictionary learning-based compresssed sensing MRI with patch clustering

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Introduction: Compressed sensing (CS) can speed up magnetic resonance (MR) imaging by reconstructing images from few k-space data. However, the sparse approximation in CS plays a fundamental role in reconstructing a faithful image. Previous CS-MRI methods used pre-defined sparse transforms [1,2], which work well for only a certain type of images. Recently explored adaptive transforms [3-7] can provide a better sparse approximation to the target images. But these training processes are based on all the patches and usually time-consuming. In this work, we proposed a Fast Dictionaries Learning from the Classified Patches (FDLCP) to reconstruct MR images. This approach takes use of the geometric directions in classified similar patches followed by fast dictionary learning process.

Method: The FDLCP reconstruction method can be simplified into four processes and the flowchart is shown in Figure 1. First, a reference image is produced by using the classic shift-invariant discrete wavelet transform (SIDWT)[3]. Second, patches are classified into several classes based on their geometric directions (Figure 2(b)) [3]. Third, an orthogonal dictionary is trained for patches in the same class via a fast learning method [8]. Finally, the MR image is reconstructed from the undersampled k-space data using the trained dictionary. Repeating the training and reconstruction processes in FDL can obtain a higher quality of reconstruction.

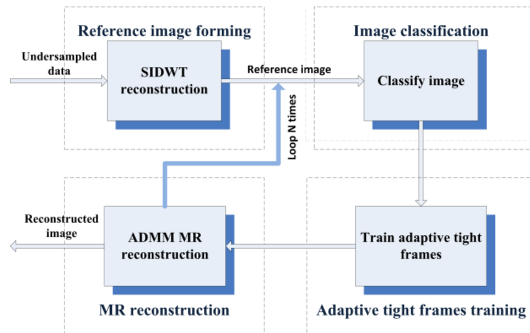

Fig. 1. The flowchart of FDLCP reconstruction method

The MR image is reconstructed by solving the following minimization problem:

$$\min_{\mathbf{x}} \frac{\lambda}{2}\|\mathbf{y}-\mathbf{F}_{\mathrm{U}}\mathbf{x}\|_2^2 + \sum_{k=1}^{K}\sum_{q=1}^{Q}\left\|\boldsymbol{\Psi}_k \mathbf{C}_{k,q}\mathbf{R}_q\mathbf{x}\right\|_1 \quad \text{s.t.}\quad \boldsymbol{\Psi}_k^{\mathrm{T}}\boldsymbol{\Psi}_k = \mathbf{I}(k=1,2,\ldots K) \qquad (1)$$

where $\mathbf{R}_q$ is an operator denoting extracting patches, $\mathbf{C}_{k,q}$ is an indicator function implying that whether the q^{th} patch belongs to k^{th} class or not, and $\boldsymbol{\Psi}_k$ is a trained dictionary for k^{th} class patches. The l_2 norm term enforces data consistency, the l_1 norm term promotes sparsity, and the parameter λ is the tradeoff between the sparsity and the data consistency.

Results: The T2-weighted brain MR imaging data (size 256 x 256) is acquired from a healthy volunteer by a 3-T Siemens Trio Tim MRI scanner using the T_2-weighted turbo spin echo sequence(TR/TE=6100/99ms, 220 x 220mm^2 field of view, 3 mm slice thickness) [3]. The proposed FDLCP method is compared with another adaptive reconstruction method called PBDW [3]. Figure 2 (c-d) shows the proposed method suppressed the artifacts better than PBDW. The reconstruction error, the relative l_2 norm error (RLNE)[3] of FDLCP is 0.0887, which is lower than that 0.0923 using PBDW.

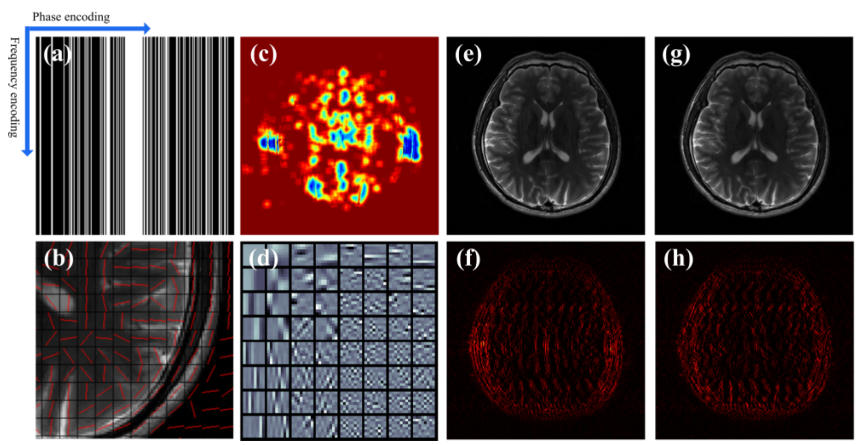

Fig. 2. A comparison of FDLCP method versus PBDW method. (a) Cartesian sampling pattern with 35% data sampled; (b) a region of classified reference image in which the red lines indicate the geometric direction of patches; (c) one of the classified patches that has the vertical geometric direction; (d) the corresponding adaptive dictionary to the classified patch in (c), each small block stands for an atom base; (e-f) reconstructed image using CATF and its reconstructed error; (g-h) reconstructed image using PBDW and its reconstructed errors.

Conclusions: We proposed a dictionaries learning method in compressed sensing MRI, which fast learns adaptive dictionaries from the classified patches with the same geometric structures. The trained dictionaries take advantage of the patches structure information and providing better sparse representations. The proposed method shows its advantage over the recently proposed patch-based dictionary learning method, PBDW, both in reducing artifacts and minimizing reconstruction error.

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References

1. Lustig, M., *et al.*, Sparse MRI: The application of compressed sensing for rapid MR imaging. ***Magnetic Resonance in Medicine***, 2007. 58(6): 1182-1195.

2. Qu, X., *et al.*, Iterative thresholding compressed sensing MRI based on contourlet transform. ***Inverse Problems in Science and Engineering***, 2010. 18(6): 737-758.

3. Qu, X., et al., Undersampled MRI reconstruction with patch-based directional wavelets. ***Magnetic Resonance Imaging***, 2012. 30(7): 964-977.

4. Qu, X., *et al*., Magnetic resonance image reconstruction from undersampled measurements using a patch-based nonlocal operator. ***Medical Image Analysis***, 2014. 18(6): 843-856.

5. Aharon, M., *et al.* , K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation. ***IEEE Transactions on Signal Processing***, 2006. 54(11): 4311-4322.

6. Ravishankar, S. *et al.*, MR image reconstruction from highly undersampled k-space data by dictionary learning. ***IEEE Transactions on Medical Imaging***, 2011. 30(5): 1028-1041.

7. Liu, Q., *et al.*, Adaptive dictionary learning in sparse gradient domain for image recovery. ***IEEE Transactions on Image Processing***, 2013. 22(12): 4652-4663.

8. Cai, J.-F., *et al.*, Data-driven tight frame construction and image denoising. ***Applied and Computational Harmonic Analysis***, 2014. 37(1): 89-105.