Parallel magnetic resonance imaging via dictionary learning

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INTRODUCTION
The combination of compressed sensing and parallel imaging (CS-PI) has shown great potential in accelerating MR imaging. However, most existing CS-PI techniques focus on exploiting analytic transform which prefers fixed structure information and only pursues limited sparsity, with very little attention to adaptive sparse representation [1]. Motivated by the fact that dictionary learning (DL) is a powerful tool in simultaneous image detail preservation and noise suppression while promoting the image sparsity [2-4], this paper proposes a DL based sensitivity encoding (SENSE) approach to accurately reconstruct MR images from undersampled multi-channel k-space data. Specifically, the proposed approach regularizes the targeted image with sparse representation over a learned dictionary and formulates the reconstruction as an L2-DL minimization problem, where the L2 term enforces the data fidelity and DL captures the structure information while suppressing the artifacts and noise. The proposed method has been evaluated on an in vivo brain dataset and shown encouraging performances.

THEORY AND METHOD SparseSENSE [5-7] is a straightforward way to combine CS and PI and can be formulated as $\|\mathbf{Ex}-\mathbf{y}\|_2^2+\|\mathrm{T}(\mathbf{x})\|_1$ where $\mathbf{E}$ is the sensitivity encoding matrix comprising Fourier encoding and sensitivity weighting. $\mathbf{x}$ is the image to be reconstructed in vectorized form and T is the sparsifying transform such as finite-difference and wavelet. In our work, we employ the dictionary learning technology to adaptively represent the desired image in the SparseSENSE model. The proposed approach formulates the reconstruction problem as follows:

$$\arg\min_{\mathbf{x}}\left\{\frac{\mu}{2}\|\mathbf{Ex}-\mathbf{y}\|_2^2+\min_{\mathbf{D},\Gamma}\sum_{l=1}^{L}\left[\frac{\lambda}{2}\|\mathbf{R}_l\mathbf{x}-\mathbf{D}\boldsymbol{\alpha}_l\|_2^2+\|\boldsymbol{\alpha}_l\|_1\right]\right\}$$

where $\mathbf{R}_l\in\mathbb{R}^{M\times N}$ is the extraction matrix to get the samples from the image $\mathbf{x}$, $\mathbf{D}\in\mathbb{C}^{M\times N}$ is the adaptive sparse representation base known as the dictionary, and $\boldsymbol{\alpha}_l\in\mathbb{R}^N$ is the corresponding sparse coeffcient for the lth sample $\mathbf{R}_l\mathbf{x}\in\mathbb{C}^M$ and $\Gamma=[\boldsymbol{\alpha}_1,\ldots,\boldsymbol{\alpha}_L]\in\mathbb{R}^{N\times L}$. As we can see, the first term in the cost function enforces data fidelity in k-space and the second term captures the structure information while promoting the sparsity. We have employed the "divide and conquer" strategy and separated the reconstruction problem into two subproblems: the dictionary learning problem and the image update problem. During the process, the k-space data has been updated as well to add more fine details back.

EXPERIMENT We evaluated the proposed approach on a fully sampled transversal brain dataset which was acquired on a 3T scanner (SIEMENS MAGNETOM TrioTim syngo MR B17) with a 12-channel head coil and T2-weighted turbo spin-echo (TSE) sequence (TE=91.0ms, TR=5000ms, FOV=20×20 cm, matrix=256×270, slice thickness=3mm). Informed consent was obtained from the imaging subject in compliance with the Institutional Review Board policy. Undersampled measurements were retrospectively obtained using the 1D variable density random sampling mask. The sensitivity map was estimated from the pre-scan. The total variation (TV) based SENSE was evaluated on the dataset as well. For fair comparisons, the same stop criterion on the relative change of $\mathbf{x}$ was used and the sum-of-square reconstruction from full data is used as the reference.

RESULTS AND DISCUSSION The reconstruction results of the proposed approach and TVSENSE with acceleration factors of 3 and 5 are presented in Fig. 1. It can be observed that TVSENSE starts to exhibit smoothing while the reconstruction of DLSENSE is quite similar to the reference when the acceleration factor is low. With the rise of the acceleration rate, more obvious blur could be observed in the TVSENSE reconstruction. Furthermore, as dictionary learning is a strong tool to adaptively capture the structure information, quite a few details lost by TVSENSE are preserved by using the proposed approach. For a close-up look, the zoom-in results have also been presented. It can be clearly seen that DLSENSE possess more fine details.

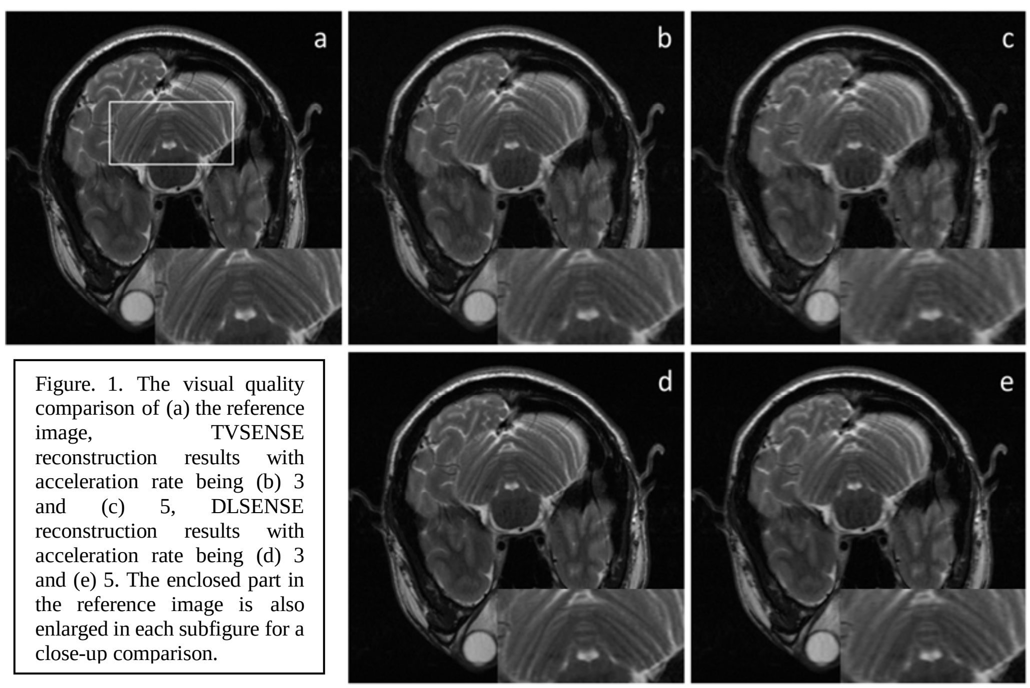

Figure. 1. The visual quality comparison of (a) the reference image, TVSENSE reconstruction results with acceleration rate being (b) 3 and (c) 5, DLSENSE reconstruction results with acceleration rate being (d) 3 and (e) 5. The enclosed part in the reference image is also enlarged in each subfigure for a close-up comparison.

CONCLUSION We propose to integrate dictionary learning with sensitivity encoding for accelerating parallel MR imaging. Experimental results demonstrate that dictionary learning could effectively suppress the noise and artifacts and preserve more details compared to conventional SparseSENSE model with fixed sparsifying transform.

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