Fast and Simple Patch-Based Sparse Reconstruction Exploiting Local Image Correlations

Alicia W Yang[1,2], Li Feng[1,2], Daniel K Sodickson[1], and Ricardo Otazo[1]

[1]*Bernard and Irene Schwartz Center for Biomedical Imaging, Department of Radiology, New York University School of Medicine, New York, NY, United States,* [2]*Sackler Institute for Biomedical Sciences, New York University, New York, NY, United States*

INTRODUCTION Compressed sensing (CS) MRI exploits correlations or redundancies among image components to reconstruct undersampled k-space data without aliasing artifacts [1]. Standard CS techniques use analytical transforms such as wavelets, finite differences and many others to obtain sparse representations. The sparsifying transform can also be learned from the image itself using dictionary learning techniques [2]. These transforms exploit global correlations in the image. An alternative approach is to exploit local correlations by directly enforcing sparsity on a set of similar small image patches, as described recently in the Low-dimensional-Structure Self-Learning and Thresholding (LOST) technique [3]. LOST clusters together similar patches, where similarity is defined based on Euclidean distance of pixel intensities between patches. However, LOST requires a fully-sampled reference image (i.e. low-resolution reference) to find similar patches and the search procedure is computationally intensive. In this work, we propose a reference-less and computationally efficient version of LOST by clustering together patches according to location, based on the hypothesis that most image correlations are local. The method is tested for reconstruction of accelerated high-resolution 2D and 3D MSK imaging.

METHODS Image clustering (Figure 1): Instead of searching for similar patches, our method assumes patches to be located in a small region of the image (e.g. 8x8 block). Non-overlapping patches (e.g. 2x2) within the block are clustered together to form the series p_k (e.g. 2x2x16 for the example in Figure 1). Image reconstruction: Undersampled k-space data are reconstructed by solving the following optimization problem: $\min_m \|E_u m - y\| + \lambda \sum_{k=1}^{n_b} \|PCA(p_k)\|_1$, where E_u is the undersampled encoding operator (including Fourier transform and multiplication by coil sensitivities), m is the image to be reconstructed, y is the undersampled k-space data, PCA is the Principal Component Analysis operator, p_k is the series of patches for the block k, and λ is a regularization parameter that controls the tradeoff between data consistency and sparsity. The same λ was used for each block since the sparsity level was similar. The PCA transform is used because each series of patches has a low-rank representation (Figure 2), and the optimization function was implemented using iterative soft-thresholding. Data acquisition: The proposed method was tested on 2D-FSE data acquired in the knee with retrospective 3 and 4-fold undersampling and 3D-FSE (SPACE) data acquired in the knee with prospective 6-fold acceleration. Our proposed patch-based reconstruction was compared to Curvelets [4] and LOST for the 2D data set and to wavelets for the 3D data set.

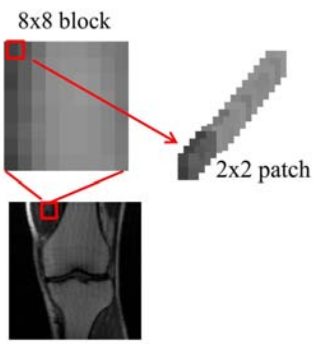

Figure 1. Image clustering into 8x8 blocks and then each block into 2x2 patches.

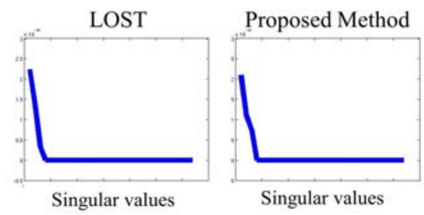

Figure 2. Singular values of one block cluster in LOST and the proposed method are comparably sparse.

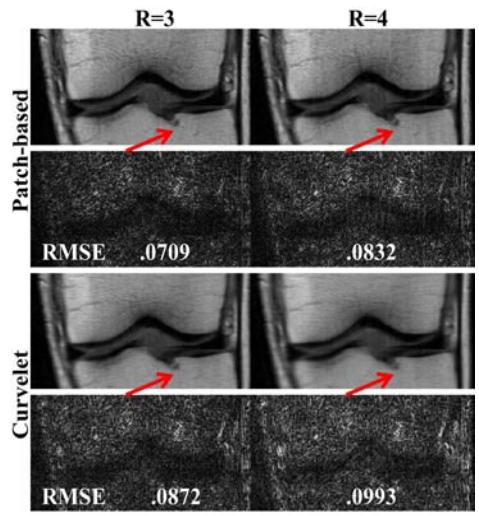

Figure 3. Reconstructed images and error for the 2D knee data set with retrospective undersampling for patch-based and Curvelet methods. Red arrows indicate more blurring in the Curvelet reconstruction.

RESULTS Patch-based reconstruction outperforms Curvelet-based reconstruction for the 2D knee example with retrospective undersampling, as indicated by the lower RMSE and reduced blurring (Figure 3). When compared with our implementation of LOST, image quality is equivalent, but reconstruction time is drastically reduced, from **4 hr 30 min** to **4 min 53s**. In prospectively undersampled 3D SPACE images, the patch-based method slightly improved image-quality compared to wavelet-based reconstruction, but was substantially faster (Figure 4).

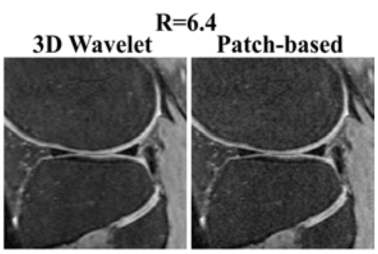

Figure 4. Reconstructed images for the 3D knee data set with prospective 6.4-fold acceleration for patch-based and wavelet reconstruction. The patch-based approach shows fewer blurring artifacts and it is substantially faster.

DISCUSSION Our patch-based sparse reconstruction outperforms standard CS approaches using analytical transforms and produces similar image quality to the previously proposed LOST technique without the need of a reference and with significant increases in computation speed. Stacking together small non-overlapping image patches that are close to each other results in similar sparsity compared with explicitly searching for overlapping correlated blocks (e.g. based on Euclidean distance), which supports our hypothesis that most of the image correlations are local. Elimination of the search process and use of non-overlapping blocks can significantly speed up reconstruction without affecting image quality. Furthermore, our patch-based method is parallelizable, which can enable real-time reconstruction.

REFERENCES [1] Lustig M et al. MRM 2007; 58:1182-95. [2] Aharon M et al. IEEE Trans Sign Proc 2005; 54:4311-4322 [3] Akcakaya et al. MRM 2011; 66:756-767 [4] Candes EJ et al. Curvelet.org