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Patch-based dictionaries for parallel MRI reconstruction

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Background:

Parallel Magnetic Resonance Imaging (MRI) [1] and Compressed Sensing (CS) [2] are two dominant techniques for the acceleration of MRI acquisition. CS theory can be used in conjunction with a parallel MRI reconstruction to control noise amplification provided a sparse model appropriate for the object being imaged is used. Highly sparse representations such as overcomplete patch-based and adaptive dictionaries, have shown greater potential than complete and non-adaptive transforms [3-5], but have not yet been tested for parallel MRI. Here we propose an iterative reconstruction for parallel MRI using dictionaries.

Methods:

Assuming $m \in \mathbb{C}^P$ to be the magnetisation image of interest, its acquisition can be accelerated by a factor $R = P/Q$ acquiring parallel k-space samples $y = MFS_Em \in \mathbb{C}^{QC}$, where S_E is a sensitivity encoding operator, F is a 2D Fourier transform, M is an undersampling mask operator selecting only Q samples per coil, and C is the number of coils. The SPIRiT method [1] poses the reconstruction as the solution to $\min_x \|Mx - y\|_2^2 + \lambda_1^2 \|(G-I)x\|_2^2 + \lambda_2^2\, T(x)$, with G a calibration matrix that is computed from the fully sampled centre of k-space and T(x) a penalty term that can be sparsity promoting. The use of wavelets has been proposed as a L1 sparsity penalty to control noise amplification, but at high acceleration factors it becomes insufficient and can introduce unnatural looking artifacts.

We propose the use of an overcomplete patch-based dictionary $D \in \mathbb{C}^{n\times N}$, $N>P\gg n$, to impose highly sparse representations of $\sqrt{n}\times\sqrt{n}$ overlapping patches from image m. The reconstruction is defined as the result of $\min_{x,\Gamma} \|Mx - y\|_2^2 + \lambda_1^2 \|(G-I)x\|_2^2 + \lambda_2^2\|\gamma_i\|_0$ s.t. $\Sigma_i\|R_iS_DF^Hx - D\gamma_i\|_2^2 < \varepsilon$, where S_D is a sensitivity decoding operator such that $S_DS_E = I \in \mathbb{R}^P$, R_i extracts patch i from an image, and γ_i is the sparse coding of patch $R_iS_DF^Hx$ in dictionary D, and populates column i of Γ. This optimisation problem can be solved by alternating the minimisation with respect to x and Γ with the initialisation $\Gamma = 0$ and $x = M^Ty$. The dictionary can either be fixed-basis such as a Discrete Cosine Transform (DCT) dictionary, or can be trained using Dictionary Learning (DL).

The method is evaluated against wavelet regularised SPIRiT on a simulated phantom and on raw Cartesian k-space data from 5 subjects using a SSFP cardiac cine sequence obtained using 32-coils on a 1.5T Philips Achieva system. The data was acquired fully sampled with no SENSE acceleration and retrospectively undersampled by randomly selecting Phase encode lines using a Poisson distribution. A fully sampled central k-space region of 17 lines was preserved for coil calibration purposes. Dictionaries with N = 196 atoms of size n = 8×8 were trained offline on the fully sampled image for the phantom and on a different patient scan for the MR images.

Results:

Figure 1 shows reconstructions of a simulated 8-coil acquisition of a phantom with k-space SNR of 30dB accelerated by 7. Without regularisation, noise amplification is evident (b, c). This can be reduced with L1 wavelet regularisation, but natural features of the image are lost (d, e). The dictionary regularisation proposed is able to control noise amplification and keep image features (f-i), especially with prior training (h, i). Figure 2 shows the PSNR and MSSIM at different acceleration rates of the phantom, and figure 3 shows results on raw MRI data. The dictionary-based method produced the lowest error for the 5 MRI reconstructions tested.

Conclusion:

CS can be used to counteract the inherent noise amplification of parallel MRI reconstructions. Adaptive overcomplete dictionaries are able to provide sparser representations than complete frames, and so can provide reconstructions with improved performance.

References:

[1] Lustig et al., MRM 2010;64(2):457-71. [2] Candes et al., IEEE IT 2006;52(2):489-509. [3] Aharon et al., IEEE TIP;15(12):3736-45. [4] Ravishankar et al., IEEE TMI 2011;30(5):1028-41. [5] Caballero et al., MICCAI 2012;1:256-63.

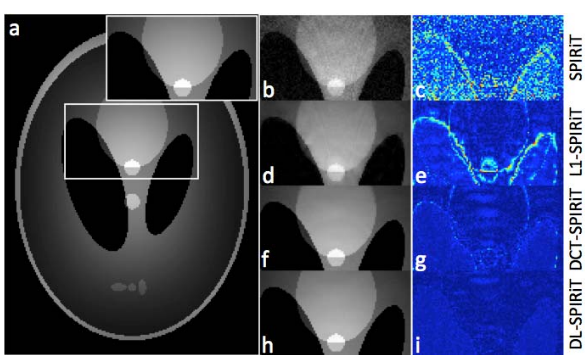

Figure 1 – Phantom reconstruction at R=7: Original (a), SPIRiT (b,c), L1-SPIRiT (d,e), DCT-SPIRiT (f,g), DL-SPIRiT (h,i).

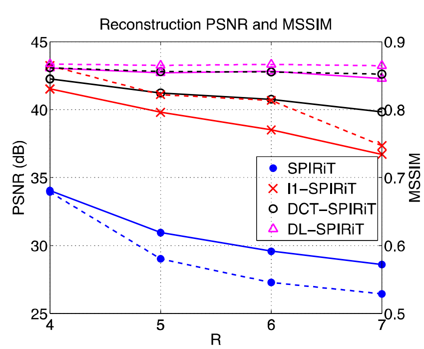

Figure 2 – PSNR (solid) and MSSIM (dashed) performance against acceleration rate in phantom simulation.

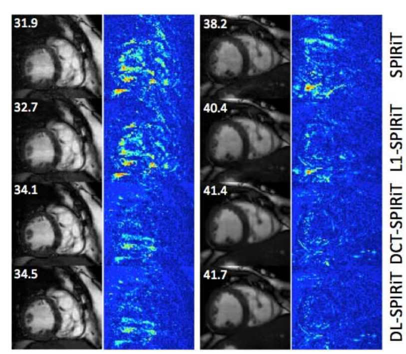

Figure 3 – MRI reconstructions at R=10. Reconstruction figures show PSNR levels in dBs.