Patch-based reconstruction of complex MR data using dictionary learning

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Background

Sparse models have been proposed as a powerful solution to decrease acquisition times of magnetic resonance (MR) scans [1-4], which are traditionally burdened with challenging sampling rates. Their potential has already been successfully tested in dynamic MR, but the exploration of sparsity models has been limited mainly to fixed-basis transforms. In [3], dictionary learning (DL) is proposed for an adaptive patch-based reconstruction of cardiac cine using spatiotemporal patches. However, only the reconstruction of data back transformed from magnitude images was addressed, neglecting the complex nature of MR signals and making the solution impractical. We extend results in [3] for the reconstruction of complex sequences, and show that it outperforms a fixed-basis sparsity transform method. Reconstruction of complex MR data using dictionaries for static images has been reported in [4], but the methodology is not discussed.

Methods

A joint dictionary can be built by concatenating real and imaginary planes of patches, as proposed in [5] for vector valued data, obtaining satisfactory results. However, image phase often has arbitrary spatially varying contributions, so correlations between real and imaginary components may be weak. We therefore propose a simpler technique in which a dictionary is trained on magnitude example patches for independent reconstruction of real and imaginary parts.

Assuming $\hat{\mathbf{x}}_u = \mathbf{F}_u \mathbf{x}_d + \mathbf{n} \in \mathbb{C}^m$ to be the undersampled k-space acquisition, with $\mathbf{F}_u$ an undersampled Fourier transform and $\mathbf{n}$ white Gaussian noise, we seek for the sequence $\mathbf{x} \in \mathbb{C}^P$, $P \ll m$, that (1) has real and imaginary parts sparsely represented by a patch-based dictionary learned on magnitude training patches using K-SVD [6], (2) $\mathbf{F}_u\mathbf{x}$ is close to the acquisitions $\hat{\mathbf{x}}_u$ in the least square sense. Sparsifying temporal gradients was introduced in [3] to exploit the high temporal redundancy in cardiac cine and increase rate of convergence of the algorithm. A dictionary learning with temporal gradient constraint (DLTG) was developed that iteratively finds solutions of the three subproblems for complex data. We benchmarked performance of this algorithm by comparing it to k-t FOCUSS [7], which enforces sparsity in the x-f domain, and which was ideally but unrealistically optimised. Both were initialised by zero-filling $\hat{\mathbf{x}}_u$.

Fully sampled single scans of dimensions 256×256 with 30 time frames were obtained using a cardiac coil on a 1.5T Philips Achieva system on 6 subjects. The data was artificially undersampled and reconstructed. Different 2D cartesian undersampling masks were applied to every temporal frame and all DLTG reconstructions used 104 training patches to train dictionaries of 600 atoms of size $4 \times 4 \times 4$.

Results

Figure 1 shows the peak signal-to-noise ratio of complex reconstructions at various sampling ratios taking the fully sampled scan as the ground truth. DLTG achieves an improvement of $\sim$ 2.5dBs over k-t FOCUSS. Figure 2 shows a fully sampled magnitude frame from one sequence and reconstructions using both methods at an acceleration rate of 10.24. Both 2D spatial comparisons and the temporal profile examined confirm that the learned basis sparsity model produces lower error, particularly at locations of high motion.

Conclusion

The choice of sparsity model has a considerable impact on reconstruction performance for dynamic MRI. While optimal sparsity transforms are still an open question, we have shown that an adaptive patch-based model can outperform previous methods, and that the reconstruction of complex data can be easily achieved using magnitude data as training examples for independent reconstruction of real and imaginary planes.

References

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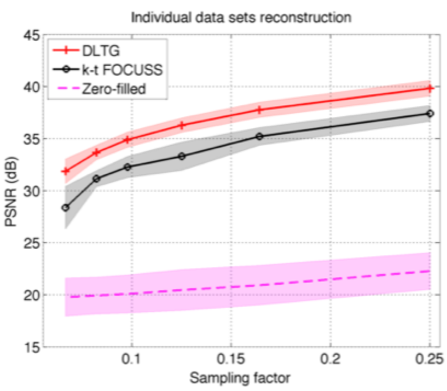

Figure 1: PSNR against sampling ratio. Plotted are mean results (bold curves) and 1 s.d. away from them (transparent bands).

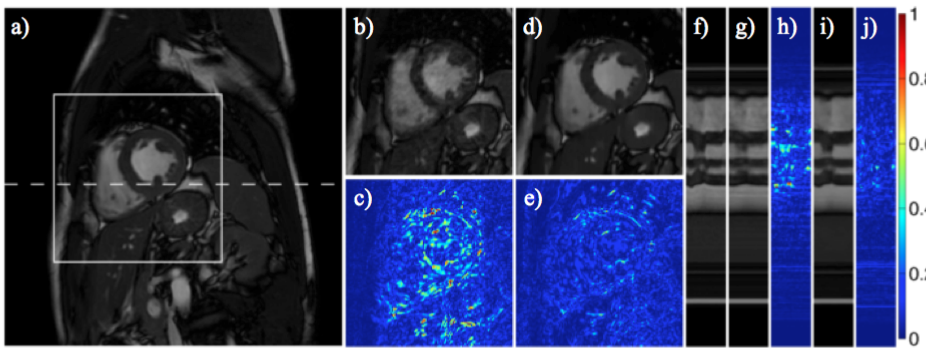

Figure 2: Visual appearance of magnitude frames at a 10.24 fold acceleration. Figures show (a) the original frame, (b) the k-t FOCUSS reconstruction (PSNR = 33.7dB), (d) the DLTG reconstruction (PSNR = 35.9dB), and (c,d) their respective errors. The temporal profile along the dashed line is shown in f. Compared are (g) the k-t FOCUSS and (i) the DLTG reconstructions, with (h,j) their errors. All error plots are amplified by 5.