Dictionary based reconstruction of dynamic complex MRI data

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Background:

The use of sparse models for the reconstruction of undersampled data has been proposed as a very powerful solution for shortening acquisition times of magnetic resonance (MR) scans [1-4]. Their benefits are of particular interest in dynamic imaging such as cardiac cine, where the traditional Nyquist criterion imposes challenging spatiotemporal sampling rates. Sparse recovery methods have already been developed for this imaging modality but the vast majority only consider fixed-basis transforms to provide a sparsity domain for MR sequences, which are suboptimal. In [5], this problem is overcome with the use of dictionary learning (DL) techniques that adapt the transform basis to the data. This advantage was confirmed in [6] on cardiac cine data but only the reconstruction of data back transformed from magnitude images was addressed. This neglects the full complex nature of MR signals and can make the proposed solutions impractical. We propose an algorithm related to that in [5], but able to reconstruct magnitude and phase sequences, and show that its performance surpasses that of a widely cited fixed-basis sparsity transform method.

Methods:

Sparsity models for cardiac data have mainly been limited to the x-f support [2,3], wavelets [3] and total variation (TV) [4]. While these fixed-basis domains can supply sparse representations for many examples, they do not achieve the sparsest representation possible for any given example. DL techniques can adapt a basis set to a particular training dataset such that it can be represented more sparsely than the aforementioned transforms. Furthermore, enforcing TV sparsity in sequences disregards the differences in sparsity levels across space and time, even though it can be easily checked empirically that temporal gradients (TGs) are very often sparser than spatial gradients.

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 propose a reconstruction that seeks a sequence $\mathbf{x} \in \mathbb{C}^P$, $P \gg m$, that (1) has real and imaginary parts that can be sparsely represented by a patch-based learned dictionary, (2) has a magnitude part with sparse temporal gradients, and (3) $\mathbf{F}_u\mathbf{x}$ is close to the acquisitions $\hat{\mathbf{x}}_u$ in the least square sense. We refer to the algorithm supplying this reconstruction as the dictionary learning temporal gradient (DLTG) algorithm. The optimisation task is broken down into three subproblems that iteratively find solutions to constraints 1, 2 and 3, and is initialised with a zero-filled version of $\hat{\mathbf{x}}_u$. The single dictionary used to code real and imaginary parts of $\mathbf{x}$ is trained with 3D spatiotemporal patches extracted from the magnitude sequence using the K-SVD algorithm [7]. We benchmarked performance of this algorithm by comparing it to k-t FOCUSS [2], which enforces sparsity in the x-f domain. Performance of k-t FOCUSS was optimised using the ground truth result to compare to the best reconstructions possible, even though this cannot be done in practice.

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 5 subjects. The data was artificially undersampled and reconstructed. Different 2D cartesian undersampling masks were applied to every temporal frame using the method in [2]. All experiments used 10000 training patches to train dictionaries of 600 atoms of size 4×4×4.

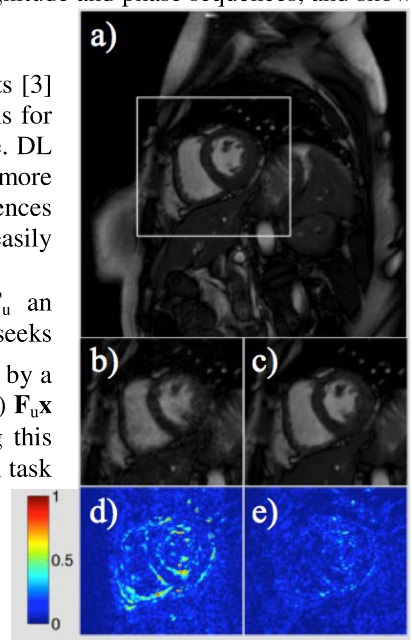

Fig. 1. (a-c) Temporal frame from one example sequence and its reconstructions provided by k-t FOCUSS (PSNR = 32.84 dB) and DLTG (PSNR = 35.18 dB) at a 10.23-fold acceleration. (d,e) Error maps for k-t FOCUSS and DLTG amplified by 4.

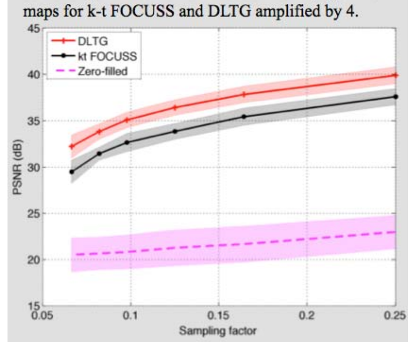

Fig. 2. PSNR against sampling ratio. Bold curves represent mean results and transparent bands are one ± standard deviation away.

Results:

Figure 1 shows a fully sampled magnitude image during systole from one subject and reconstructions using both methods at an acceleration rate of 10.23. Difference images (c,d) confirm the learned basis sparsity model produces lower error, with the high dynamism around the heart during systole better captured. Figure 2 shows the peak signal-to-noise ratio performance of the complex reconstructions at various undersampling ratios taking the fully sampled scan as the ground truth (mean values +/- 1 SD for the 5 subjects). DLTG achieves an improvement of about 2.5 dBs over k-t FOCUSS across all accelerations tested. Further experiments revealed that the enforcement of TG sparsity only improves reconstruction quality considerably at very low sampling factors, but accelerates convergence speed greatly in all cases considered.

Conclusion:

Sparse representations can accelerate dynamic MR acquisition, but choice of sparsity model has a considerable impact on performance. While optimal sparsity transforms are still an open question, we have shown that a patch-based approach to adapt a model can outperform previous methods. Furthermore, employing global auxiliary sparsity constraints that are suitable like TG sparsity can improve reconstruction quality as well as accelerate the convergence of the patch-based reconstruction. Most importantly, the algorithm presented allows the reconstruction of complex data, which is an essential feature for any MR reconstruction.

References:

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