Compressed sensing reconstruction of prospectively under-sampled cardiac diffusion tensor MRI

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TARGET AUDIENCE: Scientists interested in accelerated diffusion MRI

PURPOSE: Diffusion tensor imaging (DTI) is used to study cardiac tissue architecture, but is limited by long scan times. Compressed sensing (CS) offers a means to reduce scan times by acquiring only a subset of k-space. Existing methods use sparse models that make assumptions about the underlying mechanics of diffusion (for example, the sum-of-tensors model[1]), or that the diffusion-weighted images are sparse in the wavelet domain[2]. In contrast, data-driven transforms have been shown to dramatically improve signal reconstruction compared to off-the-shelf transforms[3]. Herein, we present a learnt sparse model for CS reconstruction of under-sampled k-space in DTI. We use this model to perform reconstruction of prospectively under-sampled cardiac DTI.

METHODS: One ex-vivo rat heart (female, SD) was excised, fixed in 3.5% formalin doped with gadolinium, and embedded in agarose gel. MRI was performed using a 9.4T preclinical scanner (Agilent Technologies, Santa Clara, CA). Fully sampled 3D fast spin echo DTI were acquired, with TR / TE1 = 200 / 10.3 ms, echo train length = 8, resolution = 100 µm isotropic, δ = 2 ms, Δ = 6 ms, b_{max} = 1000 s/mm^2, #B_0 images = 4, #DW directions = 30, acquisition time = 6h. Prospectively under-sampled data were subsequently acquired with acceleration factors ranging from 2 to 5.
The under-sampled data were acquired by sampling more sparsely towards the periphery of k-space, with the successive echoes in the echo train grouped in bands to mitigate discontinuities in T2-weighting (see Figure 1). Each under-sampled volume had a different randomised sampling scheme (with the same T2 weighting) to increase incoherence.
Reconstruction was performed by solving $\mathbf{V}^* = \mathrm{argmin}_{\mathbf{V}\geq\mathbf{0}} \|\mathcal{F}(\mathbf{X}) - \mathbf{Y}\|_2^2 + \beta_1\|\psi^{-1}(\mathbf{V})\|_{\mathrm{TV}} + \beta_2\|\mathbf{V}\|_1$, where $\mathbf{X} = \psi^{-1}(\mathbf{V})e^{j\boldsymbol{\phi}}$ is the reconstructed diffusion-weighted data, $\mathcal{F}$ is the Fourier transform, $\mathbf{Y}$ is the acquired data in k-space, ψ is a sparsifying transform, $\boldsymbol{\phi}$ is the phase of the diffusion-weighted data, and $\beta_{1,2}$ are tuning coefficients. The sparsifying transform ψ is the sparse linear model defined by a dictionary **D**, such that **X**=**D*****V**. The dictionary was trained using the online learning algorithm of Mairal et al.[3], and solving the optimisation problem on the fully-sampled images $\mathbf{X}_{\mathrm{full}}$ as follows: $\mathbf{D}^*, \mathbf{V}^* = \mathrm{argmin}_{\mathbf{D}\geq\mathbf{0},\mathbf{V}\geq\mathbf{0}}\|\mathbf{X}_{\mathrm{full}} - \mathbf{D} * \mathbf{V}\|_2^2 + \beta_3\|\mathbf{V}\|_1$. The trained dictionary contained 258 elements, and β_3 was set to 0.1.
The reconstructed data were fit to a tensor, and the signal intensity (SI) in b=0 images, mean apparent diffusion coefficient (ADC), and fractional anisotropy (FA) for the variably sampled data, were compared.

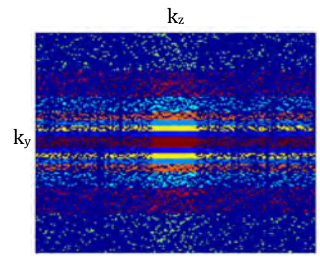

Figure 1: Successive echoes are colour coded in k-space that is 5x under-sampled.

RESULTS & DISCUSSION: Figure 2 displays SI, ADC, and FA difference maps of prospectively under-sampled data. In general, spatial resolution decreases with increasing under-sampling. Edge artefacts increase with higher acceleration. Figure 3 displays the histograms of SI, mean ADC, and FA in the myocardium. While mean ADC is robust to high accelerations, SI and FA decrease with higher acceleration factors. The FA RMSE was 0.034 and the ADC RMSE was $0.054 \times 10^{-3} mm^2/s$ at 5x under-sampling, comparing favourably against the results of a recent retrospective wavelet-based approach[2].

CONCLUSION: Compressed sensing using dictionaries offers a method for accelerating DTI with minimal compromise to image quality. To the authors' knowledge, this is the first study using CS to reconstruct prospectively under-sampled cardiac DTI.

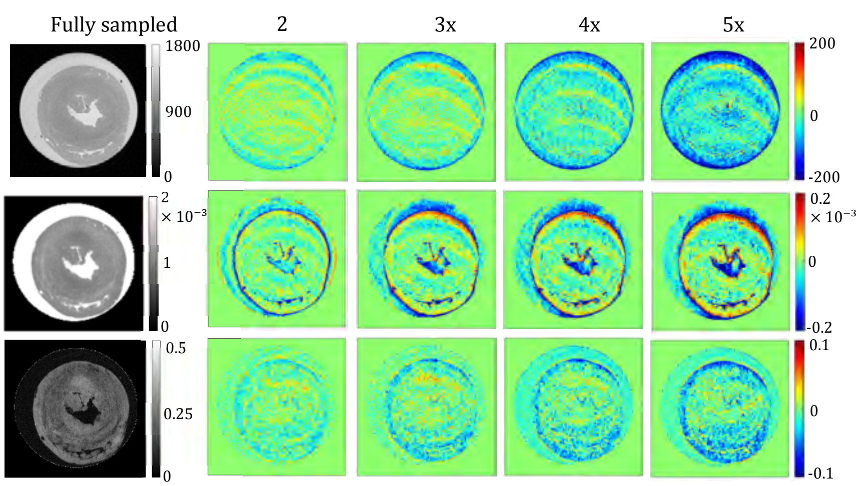

Figure 2: Signal intensity (b=0), top, mean ADC, middle, and FA, bottom, values for the fully sampled image (left), and difference values (right) for reconstructed images with under-sampling of 2-5x. Note the smaller dynamic range used to amplify the difference images.

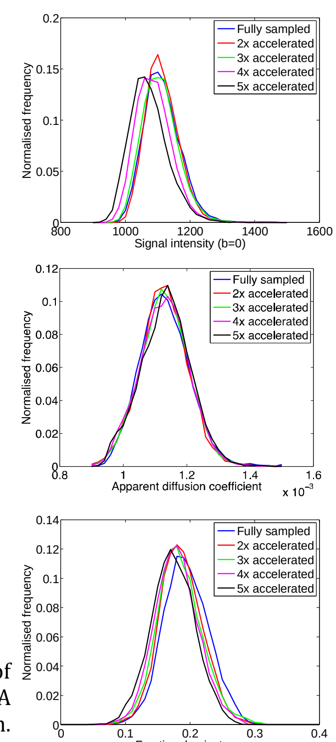

Figure 3: Histograms of the SI, mean ADC, and FA in the myocardium.

REFERENCES:
[1] Mani et al. *MRM* (2014)
[2] Wu et al. *MRM* (2014)
[3] Mairal et al. *Proc. ICML*. (2009)

ACKNOWLEDGEMENTS
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