Bayesian Compressive Sensing of Multishell HARDI for CSA-ODF Reconstruction

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Introduction: Acquisition time of diffusion MRI can still be a challenge in clinical settings. We propose here a multi-task Bayesian compressive sensing (MT-BCS) **[1]**, **[2]** approach to reduce acquisition time, by directly estimating the constant solid angle ODF (CSA-ODF) **[3]** and diffusion-weighted volumes from under-sampled multi-shell high angular resolution diffusion imaging (HARDI) data. The advantages of this method are: *(1)* It accounts for the spatial redundancy of the data via non-parametric clustering (multi-tasks); *(2)* It does not require user intervention to tune parameters, and *(3)* It provides the full posterior of the estimated ODF and diffusion-weighted volumes. Previous CS approaches to diffusion MRI provide only point estimates and usually require parameters that need to be tuned for each case. Already acquired datasets can also benefit from this approach, since the computed ODFs are shown to be more accurate than with the standard estimation methods.

Method: Three kinds of HARDI data sets were used to test the proposed MT-BCS approach, *(1)* Synthetic single and multi-shell data with non-staggered and staggered (i.e. directions across *b*-value are "complementary" to improve angular coverage) gradient tables, *(2)* A phantom multi-shell non-staggered HARDI dataset, and *(3)* In-vivo staggered and non-staggered multi-shell HARDI datasets. The synthetic HARDI datasets were generated using the Camino diffusion MRI toolkit that employs realistic diffusion models **[4]**. Rician noise was added in Camino to produce signal-to-noise ratios (SNRs) of 35, 25, 15, and 5. The diffusion phantom HARDI is the fiber-cup dataset containing fiber crossing, kissing, as well as fiber bundles of different orientations **[5]**. Three multi-shell HARDI datasets were obtained on a Siemens 3T Skyra system with various spatial and angular resolutions. The first dataset, with spatial resolution 1.5x1.5x1.5 mm^3, has three shells with 128 gradient directions at *b*=1000, 2000, and 3000 s/mm^2 and 10 *b*0s per shell. The second dataset, with spatial resolution 1.25x1.25x1.25 mm^3, has three shells with 256 gradient directions at *b*=1500, 2500, and 3500 s/mm^2 and 28 *b*0s per shell. The third dataset, with spatial resolution 1.25x1.25x1.25 mm^3, has six shells with 256 gradient directions at *b*=1500, 2500, 3500, 5000, 7000, and 10,000 s/mm^2 and 28 *b*0s per shell. Each dataset was corrected for eddy current, geometric distortions and head motion **[6]**. The gradient table for the synthetic and in-vivo images follow the protocol proposed in **[7]**. The proposed MT-BCS approach was compared with *qboot* (FSL library **[8]**) and a novel biexponential model **[9]**, using mean square error (MSE) for the reconstructed volumes, fiber orientation error (FOE), Kullback-Leibler (KL) divergence, and Euclidean distance between spherical harmonics (SHs) coefficients, for the estimated ODFs.

Results: The results obtained indicate that the proposed MT-BCS approach performs better than *qboot* and the biexponential model on multi-shell data, especially when staggered schemes are used, the SNR is equal or higher than 15, and the number of volumes per shell is at least 30. **Figure 1** compares the FOE for the synthetic multi-shell staggered HARDI data. **Figure 2** allows visual comparison of the orientation error at acceleration two for a multi-shell non-staggered in-vivo data set. **Figure 3** compares the KL divergence among the methods considered.

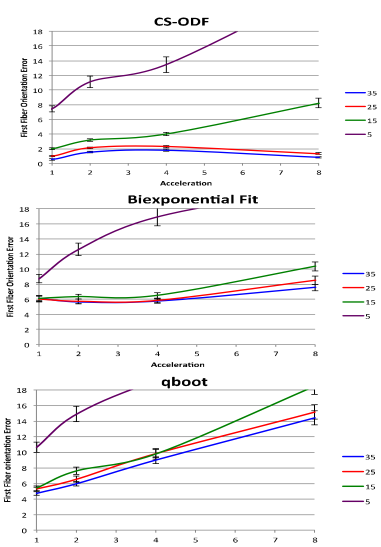

***Figure 1**- Fiber orientation error for DP-MT-CS (top), biexponential model (middle), and qboot (bottom).*

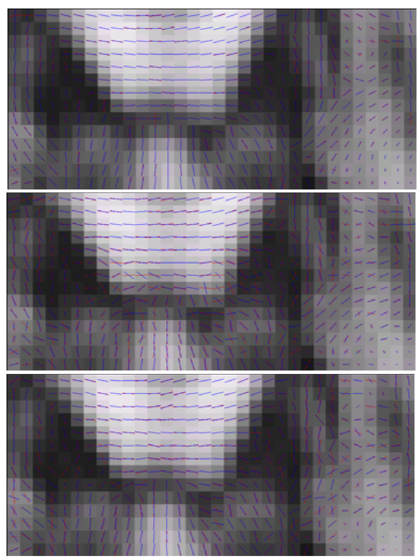

***Figure 2**- Fiber orientation at acceleration one (red) vs. acceleration two (blue) for the DP-MT-CS (top), biexponential model (middle), and qboot (bottom).*

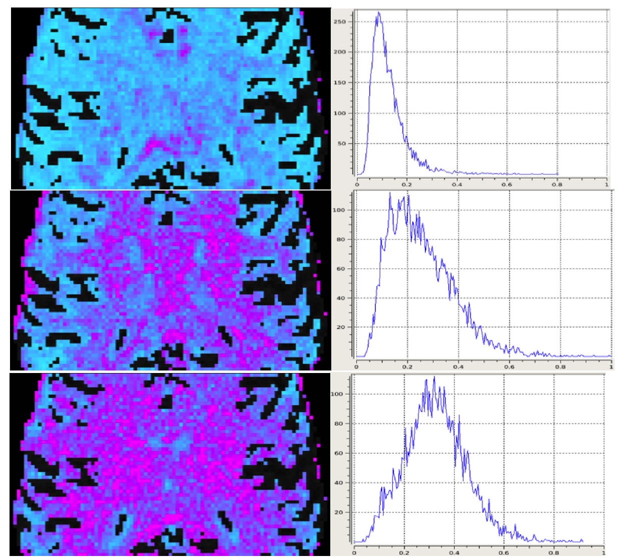

***Figure 3**- Kullback-Leibler divergence at acceleration four using CS-ODF (top), biexponential fit (middle), and qboot (bottom). Left images show a color code map of the KL divergence, while right images show the histogram.*

Conclusion: This work presents, for the first time, a multi-task Bayesian compressive sensing approach to simultaneously estimate the full posterior of the CSA-ODF and diffusion volumes in multi-shell HARDI. It improves the quality of currently acquired datasets via CS de-noising and accurate estimation of the ODF, as well as enables a reduction in the acquisition time of future acquisitions, by a factor of two to four.

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References: **[1]** Qi *et al*. *IEEE ICML*, 2008 **[2]** Duarte-Carvajalino *et al*. *MICCAI-CDMRI*, 2012 **[3]** Aganj *et al*. Magn Reson Med, 2010; 64(2):554–66 **[4]** Panagiotaki *et al*. *NeuroImage*, 2012; 59(3):2241–54 **[5]** Fillard *et al*. *NeuroImage*, 2011; 56(1):220–34 **[6]** Andersson *et al.* ISMRM 2012 **[7]** Caruyer *et al*. *MICCAI-CDMRI*, 2011 **[8]** Behrens et al. Magn Reson Med, 2003 50(5):1077-1088 **[9]** Kamath *et al*. *MICCAI-CDMRI* 2012.