Accelerated Compressed Sensing of Diffusion-Inferred Intra-Voxel Structure through Adaptive Refinement

B. A. Landman[1,2], H. Wan[2,3], J. A. Bogovic[3], P. C. van Zijl[4,5], P-L. Bazin[6], and J. L. Prince[2,3]

[1]Electrical Engineering, Vanderbilt University, Nashville, TN, United States, [2]Biomedical Engineering, Johns Hopkins University, Baltimore, MD, United States, [3]Electrical and Computer Engineering, Johns Hopkins University, Baltimore, MD, United States, [4]F.M. Kirby Center, Kennedy Krieger Institute, Baltimore, MD, United States, [5]Biomedical Engineering, Johns Hopkins University, Nashville, TN, United States, [6]Radiology, Johns Hopkins University, Baltimore, MD, United States

Introduction: The characterization of multi-fiber structures within a voxel has potential for broad clinical applications in advanced fiber tracking methods and tissue classifications approaches. Detailed characterization of this structure with q-ball [1] or diffusion spectrum imaging [2] is severely limited by practical considerations such as long scan times, low signal-to-noise ratio (SNR), and hardware constraints. Although typically considered an image reconstruction technology, compressed sensing is a promising technique for the identification of diffusion-inferred intra-voxel structure (e.g., Crossing Fiber Angular Resolution of Intra-voxel structure, CFARI [3,4]). Notably, compressed sensing requires less data (and thus less scan time) than q-ball imaging and can utilize typical diffusion tensor imaging (DTI) acquisitions. Computational complexity is a major limitation of compressed sensing techniques as currently proposed for diffusion-inferred intra-voxel structure. "Efficient" numerical techniques are available for the nonlinear optimization problem in compressed sensing; however, these techniques are still far more involved than linear tensor estimation or the common Levenberg-Marquardt non-linear tensor fitting methods. Herein, we propose a technique for accelerated compressed sensing of diffusion-inferred intra-voxel structure utilizing adaptive refinement of a multi-resolution basis set. Adaptive CFARI yields similar accuracy to the full CFARI with a tenfold reduced complexity.

Methods and Results: Adaptive CFARI can be used with either traditional [3] or non-negative [4] CFARI. Here, we use non-negative CFARI (CFARI+). In CFARI+, each voxel is modeled as a finite mixture of discrete and independent compartments. The observed signal, S_k, along the k^{th} diffusion weighting direction (g_k) is determined by the exponential mixture model, $S_k = S_0 \sum_i^N f_i e^{-b\, g_k^T \mathrm{D}_i\, g_k} + \eta$ where S_0 is a noise-free reference signal in the absence of diffusion weighting, N is the number of possible compartments (tensors) within each voxel, f_i is the (unknown) mixture component for each compartment, b is the diffusion sensitization parameter, D_i is the tensor associated with the i^{th} compartment, and η is a noise term that follows a Rician distribution. It is assumed that the *reconstruction basis* $\{\mathrm{D}_i\}$ — i.e., the set of possible diffusion tensors that may comprise a voxel — is fixed and known (herein, fractional anisotropy=0.7, mean diffusivity=1 mm^2/s). CFARI+ mixture fractions are determined with compressed sensing criteria, $f = \mathrm{argmin}_{f:f_i\in[0,\infty)} \|S f - y\|_{L2} + \beta \|f\|_{L1}$, where β is a strictly positive *sparsity regularization parameter* and f_i are restricted to be non-negative. CFARI+ accuracy improves with larger basis sets, but so does the computational time required as shown in Figure 1. A basis set with at 253 directions can be estimated in an average time of 32 ms per voxel (approx. 6 hours per brain). All times are reported for a single core 1.6 GHz notebook.

Adaptive CFARI uses the same compressed sensing method as CFARI+ but shortens the time needed per voxel by decreasing the number of directions used in the sensing matrix. To achieve this, two passes are exploited. A first pass uses a small basis set, ζ_1 (herein, a 7$^{\text{th}}$ order tessellation of a tetrahedron, 55 directions, the minimum angle between two directions is 16°). CFARI+ with ζ_1 produces a coarse estimate of the intra-voxel structure in only 1.5 ms. Voxels with all mixture estimates below a set threshold (ε=0.1) are interpreted as isotropic and not reprocessed. A second pass of the remaining voxels is performed on a modified basis set (ζ_3) derived from ζ_1 and a larger basis set ζ_2 (consisting of a 13$^{\text{th}}$ order tessellation of a tetrahedron, 253 directions, 6.5° separation). However, not all 253 directions are used in ζ_3. For each direction in ζ_1 that produces a mixture fraction greater than ε in the first pass, all directions of ζ_2 that are within 12° of that direction are added to the directions of ζ_1 to form ζ_3 – which is determined on a per-voxel basis. On average, this adds 7 extra directions for each direction in ζ_1 with a mixture fraction that exceeds ε. If the number of directions that exceed ε is greater than a set threshold (herein, 5), then that voxel is reprocessed using the full ζ_2. Estimation time averaged 3.2 ms per voxel with a mean of 70±6 directions in the second pass.

Simulations were conducted with a crossing fiber model: Two tensors (fractional anisotropy=0.7) were randomly selected to cross between 45º and 90º for 1,000 Monte Carlo simulations. Synthetic observations with Rician noise were simulated with an SNR of between 10:1 and 40:1 (on an unweighted reference, Figure 2) for a typical DTI protocol. For an *in vivo* study, a healthy volunteer (M, 20 y/o) was scanned on a Philips 3T Achieva system with an eight channel head coil. Two traditional DTI acquisitions were acquired (each scan 4 min 4 s: 30 directions, b=700 s/mm^2, 5 averaged reference scans, SS-EPI, TR/TE=6410/69 ms). All scans achieved axial whole brain coverage (65x2.2 mm slices) with in plane resolution of 0.94^2 mm (212^2 mm FOV, 96^2 matrix, SNR 15-20:1). Consistency of analysis with each CFARI approach was assessed (Figure 3). Note that the length of vectors is normalized within plots, but not across plots. The median angular difference between the adaptive and 253 direction CFARI was 8.5º, while it was 32º between CFARI with 55 and 253 directions. All analyses were performed with open source tools developed as part of the Java Image Science Toolkit (JIST, http://www.nitrc.org/projects/jist/ [5]).

Discussion: The computational complexity of CFARI is approximately proportional to the square of the size of the reconstruction set (Figure 1). Since both passes of Adaptive CFARI use a small subset of the total possible directions, the algorithm is significantly faster without having to sacrifice accuracy. The adaptive resolution compressed sensing approach is shown to be highly effective in accelerating reconstruction of intra-voxel structure and enabling more practical application of CFARI in time-sensitive settings, routine data analysis, or in large studies. The successful results suggest that adaptive refinement of the basis set may be appropriate in other compressed sensing settings where coarse to fine approximation is possible.

References: [1] D. S. Tuch, "Q-ball imaging," MRM, 52(6), 1358-72 (2004). [2] V. J. Wedeen, et al. ISMRM (2000). [3] B. A. Landman, et al. CDMRI Workshop at MICCAI, New York, NY (2008). [4] B. A. Landman, et al. SPIE Medical Imaging, San Diego, CA (2010). [5] B. A. Landman. DTI Workshop at ISMRM (2009).

Funding: NIH/NINDS 1R01NS056307, NIH/NCRR-P41RR15241 and NIH/NIA N01-AG-3-2124

Table 1. Simulated Estimation Error

Dataset	# Basis Directions	SNR 15:1	SNR 25:1	SNR 40:1
1x DTI	55	13.9±6.2°	11.8±5.3°	10.7±4.8°
30 Directions	253	13.2±6.3°	9.1±4.1°	6.9±2.5°
	Adaptive	11.3±5.2°	8.6±4.2°	7.3±3.6°
2x DTI	55	12.2±5.5°	10.5±4.5°	9.7±4.1°
60 Directions	253	10.6±4.8°	7.5±3.0°	6.0±1.8°
	Adaptive	10.9±5.3°	8.6±4.2°	7.5±3.6°

Error shown ± standard deviation.

Fig. 1. Estimation Time

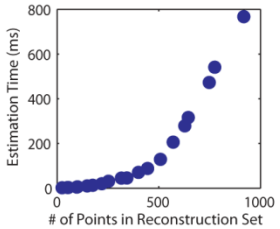


Fig. 2. Angular Error

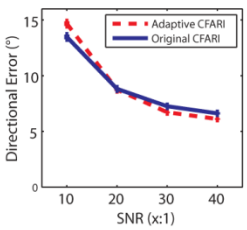
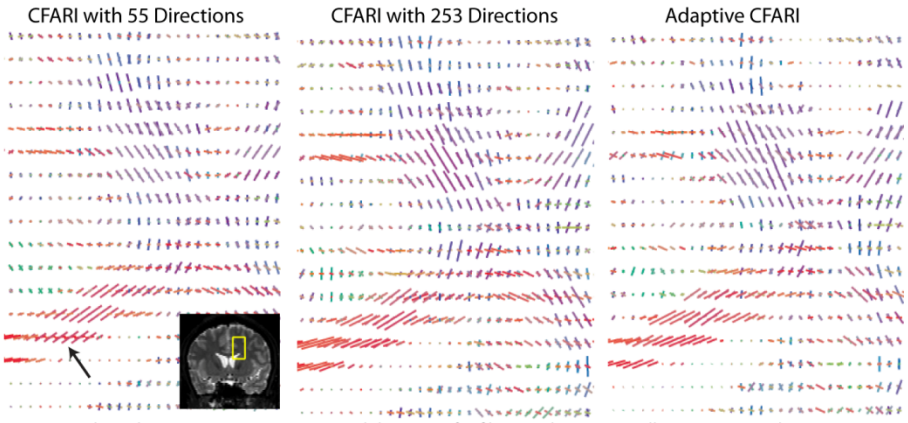


Fig. 3. Comparison of Intra-Voxel Direction Estimates with Two Repetitions of DTI Data



With 55 directions, note two estimated directions for fibers in the corpus callosum (arrow) where one dominant direction would be expected and is estimated with the other approaches.