Compressed Sensing based Diffusion Spectrum Imaging (CS-DSI) tractography

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Introduction: The theory of Compressed Sensing (CS) [1,2,3] shows great promise toward accelerating Diffusion Spectrum Imaging (DSI) by reducing number of diffusion measurements [4,5]. For successful recovery of an unknown signal via CS, undersampling patterns that generate incoherent noise-like artifacts are selected [6]. However, finding an "optimal" sampling pattern that generates incoherent artifacts and possesses near "universality" to recover accurately "all" unknown ensemble average propagators (EAPs) is a challenging task for a Cartesian grid of small size such as 7x7x7 or 11x11x11 [5]. An inappropriately selected sampling pattern complicates accurately recovering fiber orientations in all voxels of interest, causing erroneous tractography. In this study, we present a novel L_1-based total variation CS approach in conjunction with a sampling scheme that overcomes the difficulty of finding a universal sampling pattern, leading to CS-DSI tractography of quality comparable to a fully-sampled reference and significantly better than partial Fourier (pF) filling.

Theory: As most energy is concentrated near the origin of q-space and SNR decreases away from the origin for most EAPs, the inner samples of q-space within a sphere of radius r grid units should be a good candidate for a "universal" sampling pattern. The severe ringing artifacts caused by missing high frequency components are removed by CS reconstruction minimizing the L_1 norm of spatial finite-differences (i.e., discrete gradient in all 3 dimensions), where CS approach minimizing the total variation constraint of the EAP is shown to be effective [5]. Imposing an additional constraint of "real" on the EAP allows CS reconstruction using samples only in a hemispherical region of a Cartesian grid of q-space.

Method: Simulations of synthetic diffusion data and all reconstructions were performed in MATLAB. Rician distributed noisy synthetic diffusion data (3D 7x7x7 grid, 90° and 70° crossing angles, b0-SNR=30, fiber mixing fractions (f_1:f_2) of 0.2:0.8 to 0.5:0.5, FA=0.80 for each fiber) were generated using a Gaussian mixture model with slow exchange. A radius of sphere limiting measurements in a 3D grid was gradually decreased from 3.61 (102 samples in hemisphere), 3.4 (86), to 3.2 (74) to reduce the number of samples. The EAP was CS reconstructed from undersampled data using Nesterov's algorithm (NESTA) [7]. A human brain dataset [8] was obtained using a 3T MR scanner with a maximum gradient strength of 40 mT/m equipped with an 8 channel head array coil using a twice-refocused single-shot EPI sequence, of size 64×64×40, FOV = 185×185 mm, pixel spacing = 2.89x2.89 mm, slice thickness = 2.9 mm, TR/TE=6200/118 ms, diffusion time (Δ) and diffusion pulse duration (τ) Δ/τ=80/35 ms, and maximum b-value = 4000 s/mm^2. Fiber orientations of up to 3 per voxel were estimated from local maxima of the Orientation Distribution Function (ODF) and imported to DSI Studio [8] for whole-brain multi-fiber streamline tractography. Commonly used tractography parameters such as Euler's method with angle threshold >45° and the step size of half voxel (=1.44mm) were employed. Tracks were displayed and filtered in TrackVis [9].

Results and Discussion: Figure 1 compares ODFs reconstructed by CS to those reconstructed by 3D IDFT of zero-filled undersampled data after synthesizing missing q-space by conjugate synthesis (partial-Fourier). As radius decreases, i.e., fewer samples are acquired, the ODF reconstructed by CS contains gradually more erroneous estimated fiber orientations (false positive) (compare ODFs in blue circles) and missing some fiber orientations when fibers were mixed unequally (compare ODFs in orange circles). In all undersampled cases, our proposed CS-DSI method outperforms the pF method (compare ODFs in purple circles with identical number of samples) in terms of accuracy of fiber orientations and matching the number of underlying crossing fibers. Considering the differences in estimated fiber orientations between DSI203 and pF102, the pF method exploiting real, positive, and symmetric properties of the diffusion process may not be sufficient to estimate accurately fiber orientations from noisy diffusion data. In contrast, CS-DSI using the same 102 samples significantly reduces false positives for both 90 and 70 degree crossings, suggesting possible improvements in DSI-based streamline tractography.

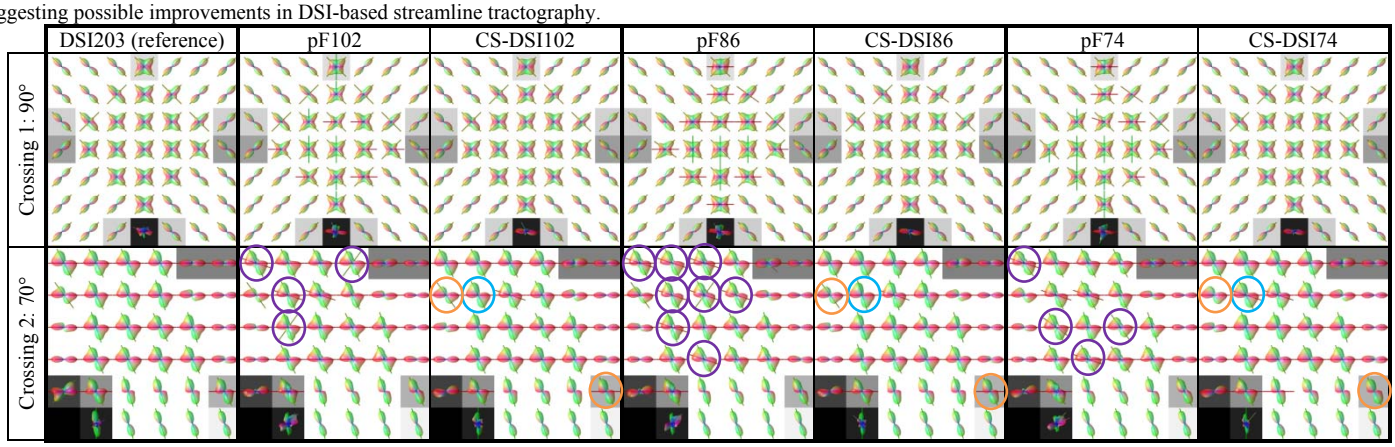
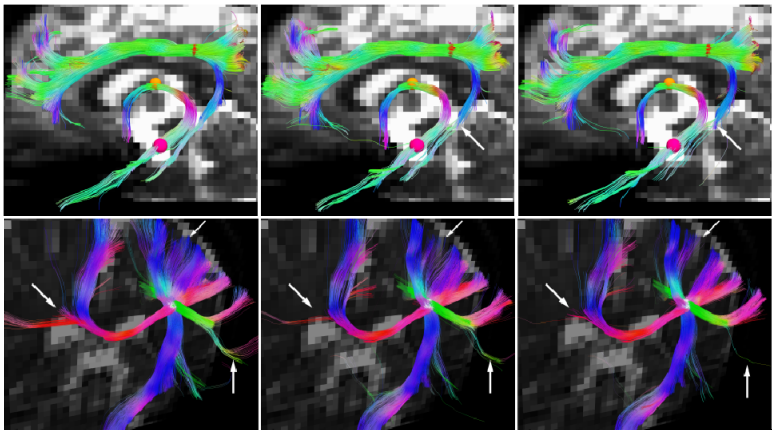


Fig. 1: Simulated crossing: ODF maps of two crossing regions with vectors representing estimated orientations of up to 3 fibers per voxel. DSI203 is a fully-sampled reference. pF102, 86, and 74 are the partial-Fourier (pF) results (with number of samples as indicated) and CS-DSI is compressed sensing DSI approach with samples as indicated. The circled regions in purple highlight significant difference between pF and CS-DSI.



Results of human brain tractography are shown in Figure 2 for the fully-sampled reference (DSI203,7x7x7 grid), CS-DSI74, and pF74. The CS-DSI based tractography results using 74 samples possess comparable quality to the fully sampled reference with some thinning of tracks indicated by arrows. As shown in the simulation study, since more spurious fiber orientations appear with an acceleration factor of R=2.74 (203/74) compared to the fully-sampled reference, the quality of tractography on CS-DSI estimated fiber orientations decreases, indicated by missing or broken tracts. However, it is clear that our CS-DSI method produces tracts that are more similar to the fully-sampled reference than partial-Fourier. As most DSI based brain connectivity studies adopt hemispheric sampling, our CS-DSI method could be used to reprocess existing datasets for more accurate connectivity measures.

Fig. 2: Comparison of tractography results: (left) DSI203, (middle) CS-DSI74, (right) pF74. (top row) cingulum and fornix tracts, (bottom row) 3 fiber crossing region where the callosal fibers, corticospinal tract and superior longitudinal fasciculus intersect.

References: [1] Candes E et al., *IEEE TIT* 2006;52:489-509. [2] Candes E et al., *IEEE TIT* 2006;52:5406-425. [3] Donoho D, *IEEE TIT* 2006;52:1289-1306. [4] Lee N et al., *Proc ISMRM* 2010 p1697. [5] Menzel MI et al., *MRM* 2011:66:1226-1233. [6] Lustig et al., *MRM* 2007;58:1182-1195. [7] Becker S et al., *SIAM J.Imag. Anal.* 2011;4:1-39. [8] DSI Studio: http://dsi-studio.labsolver.org/. [9] TrackVis: http://trackvis.org/