SNR-dependent Quality Assessment of Compressed-sensing-accelerated Diffusion Spectrum Imaging Using a Fiber Crossing Phantom

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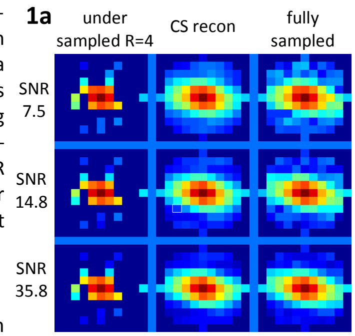
Introduction: The study of diffusion properties by MRI methods has gained significant importance for understanding the central nervous system [1]. Nyquist sampling of q-space [2] in diffusion spectrum imaging (DSI) [3] requires sampling the diffusion propagator on a Cartesian grid. To first approximation, the signal in q-space can be regarded as Gaussian, which admits a sparse representation in an appropriate (i.e. wavelet or total variation) domain. Based on that assumption a novel method has been proposed to accelerate DSI by randomly undersampling q-space [4] and by reconstructing missing data points using compressed sensing (CS). The simulation results and the vivo experiments of that work indicated that full q-space can be reconstructed up to an acceleration factor of 4. However, for a more realistic evaluation, experimental MR data at different SNR levels as well as a reliable ground truth are needed. In this work, multiple repetitions of a DSI acquisition of a crossed fiber diffusion phantom [5] were acquired to generate data in a wide range of noise levels. Based on this data the SNR-dependent performance of CS-DSI can be analyzed.

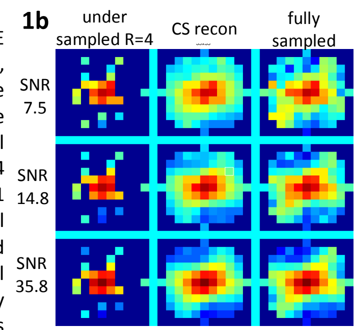
Theory: In an undersampled DSI experiment the CS approach [4] computes the data *x* in the reciprocal *r-space* by solving

$$\min_x \|Ax - y\|_2 + \lambda \|\Psi x\|_1 \qquad (1)$$

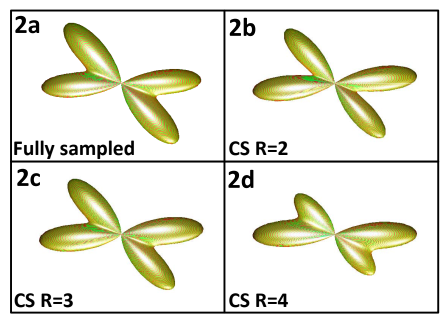
With *y* the undersampled q-space data, *A=MF* (undersampling operator and Fourier transform) and Ψ a sparsifying transform (wavelet or total variation). Eq. 1 can be solved using standard iterative shrinkage/thresholding algorithms (ISTA) [6].

Methods: Echo-planar DSI experiments of a crossed fiber phantom [5] were performed using a 3T GE MR750 MR scanner (GE Healthcare, Waukesha, WI, USA), equipped with an 32 channel head coil (TE =96.2ms, TR=3.8s, 64x64, FOV=16 cm, slice=2mm, ASSET factor 2, bmax=6.000 s/mm²) using an 11x11x11 q-space cube where 515 points were sampled within a sphere. The experiment was repeated 22 times to provide a range of SNR levels by complex averaging, which in comparison to magnitude averaging, reduces the magnitude bias due to Rician noise distribution. The highest SNR level corresponds to the average of all 22 acquisitions and was used as the ground truth for the experiment. 105 voxels with one directional fiber (Fig. 1a) and 24 voxels with crossed fibers (Fig. 1b) were analyzed. Different randomly chosen Gaussian undersampling patterns with 257, 171 and 128 (R=2,3,4) sampling points were applied to the data. Afterwards the full q-space was reconstructed by ISTA using total variation (TV) as transform Ψ. Subsequently the Root Mean Square Error (RMSE) of the reconstructed and of the fully sampled q-space for each SNR level with respect to the ground truth as well as principal invariants (diffusion eigenvalues and fractional anisotropy (FA)) were computed for the undersampled, the CS-reconstructed and the fully sampled case. The angular accuracy was examined by calculating the orientation error of the main eigenvector for the single fiber data and the orientation errors of the maxima of the orientation distribution functions (ODFs, e.g. Fig. 2a-d) for the crossed fiber data.





Results: Figures 3a,b show the RMSE for the CS reconstructed q-space (R=2,3,4) as well as for the fully sampled data for a single fiber voxel (Fig. 1a) and a crossed fiber voxel (Fig. 1b), respectively. For low SNR data, the RMSE is even smaller for the CS reconstructed than for the fully sampled q-space of the same SNR level. With increasing SNR however, the RMSE of the fully sampled q-space decreases quickly while the RMSE of the CS reconstructed q-space reaches a minimum and does not benefit much from the better SNR. In Fig. 4a the FA of a single voxel is plotted for the fully sampled, undersampled and CS reconstructed q-space. While FA is underestimated for low SNR levels, CS reconstruction reduces the underestimation and performs better than the undersampled data. The RMSE of FA over all pixels (Fig. 4b) confirms that observation. Angular accuracy of the principal eigenvector of the diffusion tensor can also be improved by CS recon (Fig. 5a). The ODFs of the crossed fiber voxels lose sharpness with increasing undersampling factor (Fig. 2a-d). However the maxima are still clearly distinguishable (Fig. 5b).



Discussion: The SNR-dependent analysis of fiber crossing phantom showed that in an low SNR regime the CS reconstructed data might be superior not only to the undersampled but even to the fully sampled data. The remaining error for high SNR levels might be due to the error introduced by the TV-model. While the results for R=2 and 3 are fairly close, the quality of the CS reconstruction starts deteriorating more rapidly for R=4. Also the derived metrics show a clear benefit of the CS reconstruction if compared to the undersampled case.

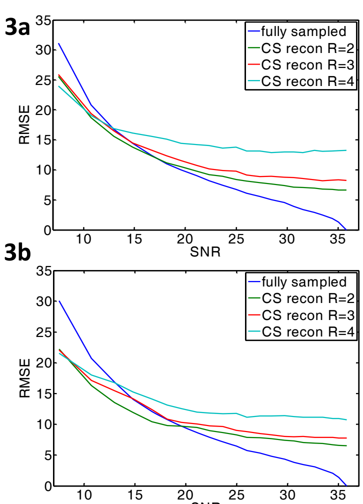


Fig. 3a,b: RMSE of q-space for a single (a) and a crossed (b) fiber voxel

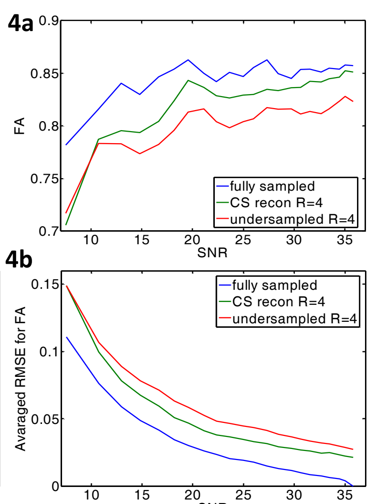


Fig. 4a: FA for a single fiber voxel,
Fig. 4b: RMSE for FA of all single fiber voxels

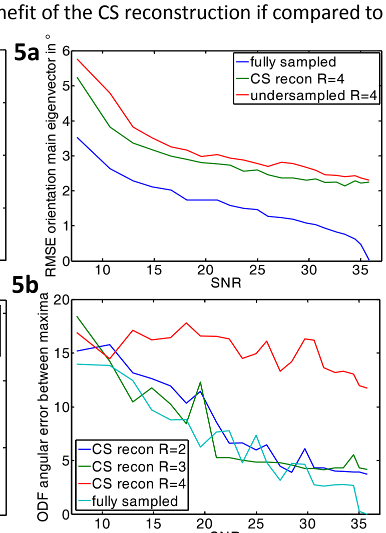


Fig. 5a: RMSE orientation of pricipal eigenvector
Fig. 5b: RMSE angle between the crossed fibers

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