Evaluation of Compressed Sensing based Diffusion Spectrum Imaging use of 3T MR

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Introduction: Diffusion spectrum imaging (DSI), sampling in diffusion encoding space (*q-space*) and yielding a description of the diffusion Ensemble Average Propagator (EAP), is capable of resolving complex distributions of intravoxel fiber orientations [1]. However, substantially long scan time (~ 1 hour) has greatly limited its clinical application. Recently several methods using compressed sensing (CS) [2,3] have been developed to accelerate DSI [3,4,5]. Given the undersampled *q-space* signal, the CS reconstruction uses an iterative shrinkage algorithm [5] to recover the reciprocal diffusion displacement space (*r-space*) data by imposing sparsifying transform. In this study, we evaluate the performance of CS algorithms [3,4,7] on both simulated and *in vivo* DSI data, with an aim to reduce acquisition time to a clinical time frame (~ 20-25 minutes) without jeopardizing critical image information. Methods: Simulation Study: Two sets of fiber simulations were performed using Gaussian Mixture Model (crossing angles= 50° , 60° , 70° , FA=0.5, 0.6, 0.7, mean diffusivity=0.77 [8,9]) added with Rician noise (signal-to-noise (SNR) = 35) at maximal b values (bmax) 4000 s/mm² (7³ cube, 3.61 radius in grid unit) and 6000 s/mm² (11³ cube, 5.0 radius in grid unit). In vivo Study: Two sets of DSI data (1.8x1.8 mm, 128x128) (bmax=6000 s/mm², DSI515-direction, TR/TE=5000/117 msec; bmax=4000 s/mm², DSI203-direction, TR/TE=9000/110 msec) were acquired on a healthy volunteer using a 3T GE MR750 clinical MR scanner equipped with a 32 Channel Head Coil. CS Reconstruction: The data were retrospectively undersampled using variable density schemes (acceleration factor (R) =2, 3, 4). Three CS reconstruction schemes, including the K-SVD adaptive dictionaries algorithm [10] for sparse representation of the training data coupled with the Focal Underdetermined System Solver (FOCUSS) algorithm [11] (Dictionary-FOCUSS), the simple ℓ_1 -norm penalty in the diffusion displacement space with the FOCUSS (ℓ_1 -FOCUSS), and the ℓ_1 -norm penalty with the Nesterov's algorithm (ℓ_1 -NESTA) [11], were evaluated for computation efficiency, error metrics (RMSE between reconstruction and noiseless ground truth in simulations, no acceleration and with acceleration in vivo), generalized fractional anisotropy (GFA), and tractograms. An additional DSI123-direction was also acquired for the comparison. **Results and Discussion:** The simulation results in **Fig. 1** show that Dictionary-FOCUSS performed better than ℓ_1 -FOCUSS and ℓ_1 -NESTA at both 7³ and 11³ cubes. Human brain CS DSI data also found the similar trends of RMSE in different acceleration factors (results not shown).







Fig. 2,3: GFA (Fig.2) of a human brain and tractograms (Fig. 3) of the anterior callosal fibers and the dorsal cingulum bundles of DSI515 (A), CS-DSI515, R=5 (B), DSI203, (C), CS-DSI203, R=2 (D), and DSI123 (E). The results of CS-DSI203 (R=2, Fig. 2D, 3D) based tractography possess comparable quality to the fully sampled reference of DSI203 (Fig.2C, 3C) and relatively better than DSI123. Our DSI515 data had inferior quality, likely due to low SNR (high bmax) and greater motion (long scan time). Although the results of CS-DSI, using diffusion weighted MRI acquired in about 20 minutes by a 3T clinical scanner is promising; the long post-processing time (several days) may hinder the application of CS-DSI to the clinical environment.

Reference: [1] Wedeen et al., *MRM* 2005. [2] Candès, et al., IEEE TIT 2006. [3] Lustig et al., *MRM* 2007. [4] Menzel et al., *MRM* 2011. [5] Bilgic et al., *MRM* 2012. [6] Lee et al., *Proc ISMRM* 2012. [7] Daubechies et al., *Commun Pure Appl.Math* 2004. [8] Kuo et al., *NeuroImage* 2008. [9] Yeh et al.,*IEEE TME* 2010. [10] Ahaton et al. *IEEE TSP* 2006. [11] Gorodnitsky et al.,*IEEE TSP* 1997. [12] Becker et al., SIAM J.Imag. Anal. 2011.