Evaluation of Diffusion Spectrum Imaging Reconstruction with Trained Dictionaries use of 3T MR

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Introduction: Diffusion spectrum imaging (DSI) yields a description of the complex intravoxel distributions of fiber orientations via the diffusion Ensemble Average Propagator (EAP) [1]. However, substantially long scan time (> 1 hour) has greatly limited its clinical application. Recently several methods using compressed sensing (**CS**) reconstruction [2,3] have been developed to accelerate DSI [3,4,5]. Given the undersampled *q-space* signal, the CS-DSI reconstructions use iterative shrinkage algorithms [5] to recover the EAP by imposing sparsifying transforms. Although the recent advancement of CS techniques shows promising results at the intravoxel level, the quality of tractography from CS-DSI acquired by clinical scanners has not yet investigated. In this study, we evaluate the performance of a dictionary learning framework to obtain the EAP from *in vivo* undersampled DSI data [6], with an aim to reduce acquisition time to a clinical time frame (< 20 minutes) without jeopardizing critical image information.

Methods: Three sets of half-hemispheric DSI data, including DSI257, DSI101 and DSI61 directions with maximal b values of 4000 s/mm^2.(2.0x2.0 mm, 128x128, TR=9000~10000 msec, minimal TE) were acquired on two healthy volunteers, one male and one female, using a 3T GE MR750 clinical MR scanner equipped with 32 coils. *CS Reconstruction:* The q-space signal of half-hemispheric DSI data were first projected to the other half hemisphere of q-space by assuming antipodal symmetry followed by CS schemes, using the K-SVD adaptive dictionaries algorithm [7] for sparse representation of the training data coupled with the Focal Underdetermined System Solver (FOCUSS) algorithm [8] (**Dictionary-FOCUSS**) and L2 regularization of the spatial EAP [6]. We used a set of DSI515 data from the Human Connectome Project (**HCP**) or his/her own DSI257 for dictionary training to reconstruct DSI101 (acceleration R~2.5) and DSI61 (R~4). Error metrics (the root mean square error (RMSE) between no acceleration and with acceleration) of EAP were estimated by artificially subsampling of HCP DSI515 and DSI257. We qualitatively evaluated generalized fractional anisotropy (GFA) and tractograms, including the cingulum bundles and optic pathways for comparisons.

Results and Discussion: The RMSE of EAP by downsampling HCP DSI515 up to R=9 is around 10 %, compared to 20% using our DSI257, indicating that use of HCP DSI515 for training would yield better result of CS-DSI. **Fig. 1** shows the RGB maps of GFA of DSI257 (**A**) and CS-DSI101(**B**, both data were preprocessed for motion and distortion correction), and-CS DSI61 reconstructed using HCP DSI515 (**C**) or DSI257 (**D**) of his / her own brain for dictionary learning, respectively. Among them, the GFA of CS-DSI61 using DSI257 for dictionary training has the lowest SNR

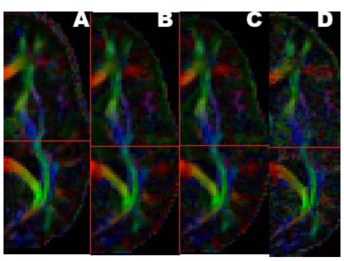
Fig. 1. 

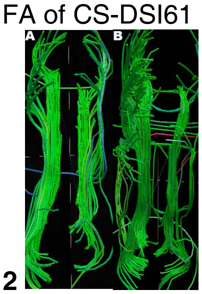
Fig. 2 

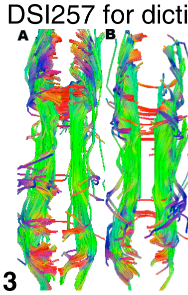
Fig. 3 

Fig.2 and **Fig. 3** are the examples of the reconstructed cingulum bundles at cingulate gyri in a male volunteer (**Fig. 2**) of DSI257, **Fig. 2A**) and CS-DSI101 using HCP DSI515 (**Fig. 2B**), where the number of streamline from CS-DSI tractography are comparable to that of DSI, but CS-DSI tends to create more spurious streamlines; and a female volunteer (**Fig. 3**) with CS-DSI61 using HCP DSI515 (**Fig. 3A**) and DSI 257 (**Fig. 3B**) for dictionary training, where using HCP DSI515 for training reconstructs more streamlines of the cingulum bundle than using DSI257 for training. **Fig. 4**,shows the optic pathways, including optic tracts, optic chiasma (**Fig. 5**) and posterior optic radiations interconnecting the primary visual cortex, of DSI257 (**Fig. 4A**) and CS-DSI101 (**Fig. 4B**). CS-DSI101 reconstructs more streamlines than DSI257 at the optic chiasma. The results of CS-DSI based tractography possess comparable quality to the half-fully sampled reference. In addition, the results suggest that using better quality of a training data set, even acquired from different brains or scanners, would improve the accuracy of CS-DSI based tractography.

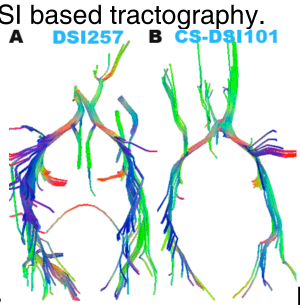


Fig. 4

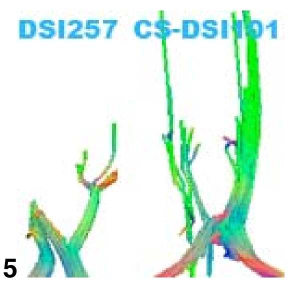


Fig. 5

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] Bilgic B et al. *JMRI*. [7] Ahaton et al. *IEEE TSP* 2006*JMRI*. [8]