Feasibility study of fast diffusion tensor imaging based on distributed compressed sensing

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Introduction Diffusion tensor imaging (DTI) has been widely used as a powerful tool to nondestructively characterize microstructure of biological tissues, such as neuro, body and muscles [1-4]. However, most of the previous DTI studies usually suffered from lengthy data acquisition, which greatly restricted the practical application of DTI. With the emergence of compressed sensing (CS), fast data acquisition and signal recovery is realized with measuring sparse and compressible signals at a significantly smaller rate than traditionally thought necessary [5]. Recently, distributed CS (DCS) [6] was proposed to improve reconstruction performance with utilizing joint sparsity property of inter-signal correlations among multiple coils/sensors, which has been successfully used in studies of MRA and cardiac perfusion [7-8]. In the current study, theory of DCS was applied in simulated and experimental DTI data for the first time to test its possibility and feasibility of accelerating diffusion tensor data sampling.

Theory The sampling DWIs can be formulated as $y_l = F_l^u x_l + e_l$, l = 1, 2, …, L (1), where L is the diffusion direction numbers, F_l^u the under-sampled Fourier matrix of l-th direction, y_l the k-space data of the l-th direction, and e_l the additive noise. x_l can be reconstructed separately by solving the following optimization problem based on CS theory: min $\|\Psi x_l\|_1$ s.t. $\|y_l - F_l^u x_l\|_2 \le \varepsilon$ (2), where Ψ denotes the sparsifying transform. As the diffusion direction only modulates the magnitude of signal intensity, DWIs should match the joint sparse model, namely, x_l shares the same sparse support in the sparsifying transform domain with different nonzero coefficients, which is appropriate to be dealt with using DCS model. Then, Eq. (1) can be rewritten as $y = F^u X$, where $X = [x_1, x_2, \ldots, x_L]$, and x_l all could be simultaneously reconstructed from min(# of nonzero rows in X) s.t. $y = F^u X$, which could be solved with convex relaxation by minimizing a mixed l_2-l_1 norm: min $\sum_{i=1}^{n} \|B_i\|_2$ s.t. $y = F^u X$, where B_i is the i-th row of sparse coefficients matrix $B = \Psi X$.

Method Simulated DTI data was created with diffusion gradient directions applied in 6 directions of [0 ±0.618 -1], [0.618 ±1 0], and [-1 0 ±0.618] and diffusion sensitivity b = 0 and 1000 s/mm^2. Simulated noisy data with SNR of 40, 30 and 20 on averaged DWIs were obtained by adding respective Gaussian-white noise to the simulated DTI data. Imaging experiment was conducted on a 7T Bruker PharmaScan. SE-DTI was performed on a rat heart sample along left ventricular (LV) short-axis orientation. Imaging parameters were: TR/TE=1500/29ms, b-value=1000s/mm^2, 6 diffusion gradient directions, image resolution of 0.1×0.1×1.5 mm^3, and NEX=10. The scan time was ~7 hrs per sample. Polynomial variable density sampling with 20% of the k-space center fully sampled was performed on both simulate and experimental DTI datasets to achieve accelerating factors of 2, 3 and 4. Note that the sampling masks were different for DWIs among different diffusion directions to further ensure incoherence of the under-sampled data. Root mean square errors (RMSE) of fractional anisotropy (FA), mean diffusivity (MD) and fiber orientation (α) over entire LV myocardium at different reduction factors (R) was used to evaluate the reconstruction accuracy.

Table 1 RMSE of FA, MD and α of simulated data at different reduction factors.

RMSE	FA			MD (×10^{-5} mm^2/s)			α (°)		
	R = 2	R = 3	R = 4	R = 2	R = 3	R = 4	R = 2	R = 3	R = 4
Pure signal	0.023	0.032	0.033	1.77	2.57	2.40	2.78	4.32	4.56
SNR = 40	0.025	0.036	0.037	1.78	2.62	2.64	3.33	5.16	5.34
SNR = 30	0.057	0.065	0.068	3.75	4.16	4.13	8.50	9.61	9.98
SNR = 20	0.151	0.179	0.190	9.95	11.44	11.87	27.19	30.60	31.92

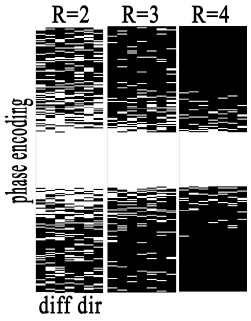

Fig. 1 Sampling masks.

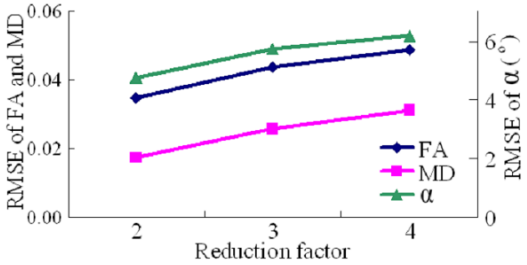

Fig. 2 RMSE of FA, MD and α. The unit of MD is ×10^{-3} mm^2/s.

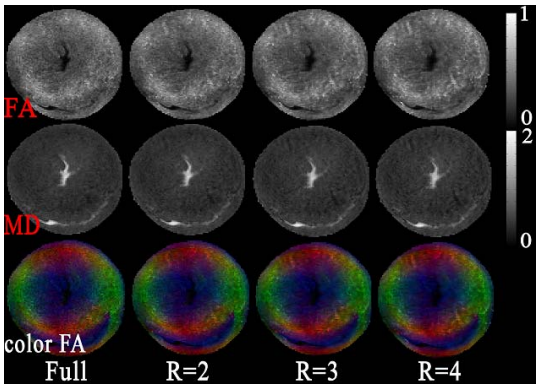

Fig. 3 FA, MD and color FA measured from full- and under- sampled data. The unit of MD is ×10^{-3} mm^2/s. Red: left-right; green-up and down; blue: in and out.

Results Fig. 1 displays the sampling masks at reduction factors of 2, 3, and 4. RMSE of FA, MD and α calculated from simulated DTI data was found to increase with reduction factors and noise contamination (Table 1). Specifically, reconstruction performance at SNR of 40 was similar with that of pure DTI data. The RMSE almost doubled at SNR of 30 compared to those with SNR higher than 40. The reconstruction accuracy became even worse when SNR was lower than 20. Reconstruction performance of DTI indices of the experimental DTI data was quantitatively analyzed in Fig. 2, from which good reconstruction performance exhibited at all accelerating rates. Respective maps of FA, MD, and color FA were illustrated in Fig. 3, and the reconstruction quality of the maps computed from down-sampled DTI data was visually comparable to those obtained from full sampled data.

Discussion In this study, DCS was applied to accelerate DTI acquisition with utilizing joint sparsity characteristics of diffusion tensor data. Reconstruction performance was evaluated in both simulated and experimental data. RMSE of FA, MD and α was found to increase with down-sampling rate and noise contamination. Based on both visual and quantitative evaluation, good reconstruction accuracy was achieved even at high accelerating rate of 4 for the experimental data, of which the SNR of averaged DWIs was ~40. In summary, both simulation and experimental results indicate the feasibility of the proposed method to speed diffusion tensor imaging, which would greatly help to broaden its potential practical applications in the future.

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Acknowledgments NSFC 30900387, GIRTF-LCHT, NSFGD 9478922035-X003050, BRPSZ JC200903170437A and JC201005270311A.