FAST MOTION-COMPENSATED ODF RECONSTRUCTION FROM UNDER-SAMPLED MULTI-CHANNEL MULTI-SHOT NON-CARTESIAN DIFFUSION IMAGING DATA AT HIGH ANGULAR AND SPATIAL RESOLUTION

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TARGET AUDIENCE: Researchers who are interested in high spatial and resolution diffusion imaging schemes. Applications such as pre-surgical planning and the study of human brain connectivity can greatly benefit from high spatial and angular resolution diffusing imaging.

PURPOSE: Multi-channel multi-shot non-Cartesian diffusion imaging can offer better image quality than conventional Cartesian diffusion imaging for high spatial resolution applications, in terms of better SNR and lower T2* artifacts. Coupled with HARDI acquisitions, these schemes can enable the reconstruction of diffusion orientation distribution function (ODF) at high angular and spatial resolution, which in turn enables high-resolution fiber tracking. However, the main drawback of the above scheme is the sensitivity of the multi-shot imaging to motion artifacts. To compensate, the reconstruction algorithm has to account for the motion induced phase errors resulting from each shot and each coil for every diffusion direction, resulting in very long reconstruction times. For example, a 12-channel acquisition with 3 shots takes about 3 hours to perform a motion-compensated reconstruction of the diffusion ODF from a 64 direction diffusion data for a single slice. The main focus of this work is to accelerate the motion-compensated reconstruction of multi-shot multi-channel non-Cartesian imaging schemes, with focus on ODF reconstruction from high angular resolution diffusion data.

METHODS: The image reconstruction from a multi-channel non-Cartesian acquisition is typically solved using an iterative sensitivity encoded (SENSE) reconstruction scheme (1) that solves the optimization problem: $\widehat{\boldsymbol{v}} = arg\,\min_v \|\boldsymbol{E}(\boldsymbol{v}) - \boldsymbol{y}\|_2^2$. Here the encoding matrix E is the combination of the non-uniform Fourier transforms coefficients and coil sensitivity weights and y is the k-space data. For a multi-shot imaging scheme, the above approach results in motion induced artifacts since the motion-induced phase errors between shots are not included in the reconstruction. For a motion compensated recovery, the encoding matrix in the traditional SENSE reconstruction is replaced with the combination of non-uniform Fourier transforms coefficients and the composite sensitivity weights corresponding to each channel and each shot (2). This extension significantly increases the dimensionality and computational cost of the reconstruction. See fig. 1(a) for a graphical representation of forward model $\mathbf{E}(\boldsymbol{v})$. A straightforward implementation of the above scheme is prohibitively time consuming due to the large number of FFTs and griddings involved in the computation of $\mathbf{E}^{\mathbf{H}}(\mathbf{E}(\boldsymbol{v}))$ in the conjugate gradient steps of the iterative recovery scheme (fig 1(b)). An efficient implementation of $\mathbf{E}^{\mathbf{H}}(\mathbf{E}(\boldsymbol{v}))$ is proposed in the context of motion-compensated reconstruction of multi-shot multi-channel diffusion weighted images, where a singular value decomposition of the composite sensitivity maps was used to approximate the latter in terms using a small number of basis functions (fig 1(c)&(d)). We extend this technique to the motion-compensated recovery of the diffusion ODF coefficients from high angular resolution diffusion data. Due to the huge dimensionality of this problem, we expect the simplified scheme to provide considerable acceleration compared to the traditional implementation.

Using a ball-and-stick model and set of pre-computed diffusion tensor basis functions ($e^{-bg^T\boldsymbol{D}_i g}$), we represent the diffusion data as a weighted linear combination of the basis functions: $S(b, g_q) = S_0(f_0 e^{-bd} + \sum_{i=1}^{N_b} \mathrm{f}_i\, e^{-bg_q{}^T\boldsymbol{D}_i g_q})$. The diffusion ODF for the above model can be written as $\psi(\hat{g}) = f_0 \frac{d}{4\pi} + \sum_{i=1}^{N_b} \mathrm{f}_i \frac{(\hat{g}^T\boldsymbol{D}_i{}^{-1}\hat{g})^{-3/2}}{4\pi\sqrt{\det(\boldsymbol{D}_i)}}$. The unknown coefficients, $\boldsymbol{f}$, completely define the diffusion-weighted images and the ODF. We can then formulate the motion-compensated reconstruction using the following optimization problem: $\widehat{\boldsymbol{v}} = arg\,\min_v \|\boldsymbol{E}(\boldsymbol{v}) - \boldsymbol{y}\|_2^2 + \lambda_1\|\boldsymbol{A}(\boldsymbol{v})\|_{\boldsymbol{TV}} + \lambda_2\|\boldsymbol{v}\|_{\mathbf{1}}$ where $\boldsymbol{v} = S_0\boldsymbol{f}$. The cost function imposes a minimum l_1 norm criterion on the ODF coefficients along the basis directions and a total-variation (TV) regularization on the diffusion weighted images $\boldsymbol{A}(\boldsymbol{v})$, enabling reconstructions from under-sampled k-space data also.

RESULTS: Diffusion data was collected on a Siemens 3T scanner using a variable density spiral sequence with the following parameters: 22 spatial interleaves, $\alpha = 8$ and readout duration of 18.6ms, FOV = 20cm, matrix size= 192x192, in-plane spatial resolution of 1.04 x 1.04 mm^2, slice thickness= 2.5 mm, 1 b_0 and 64 diffusion-weighted images at b= 1200 s/mm^2, TE/TR = 61/2500ms. The above data was retrospectively under-sampled to obtain an equivalent acceleration of R=8 using an incoherent k-q scheme (3). We reconstruct the diffusion ODFs corresponding to 256 angular orientations. Corresponding to 3 shots and 12 channels, there are 36 composite sensitivity maps per diffusion direction. The ODF reconstruction from 64 diffusion-weighted images using all 36 maps takes around 3 hours using the implementation in fig 1(b). We compare the reconstruction time and angular error in the reconstructed ODF as a function of the number of basis functions using the implementation of fig 1(d). Our results show that about 5-10 basis functions are good enough to approximate the 36 composite sensitivity maps per diffusion direction. The ODF reconstruction using 5 basis functions (fig 2) is almost 8 times faster compared to the implementation in fig 1(b), with very little loss in angular accuracy.

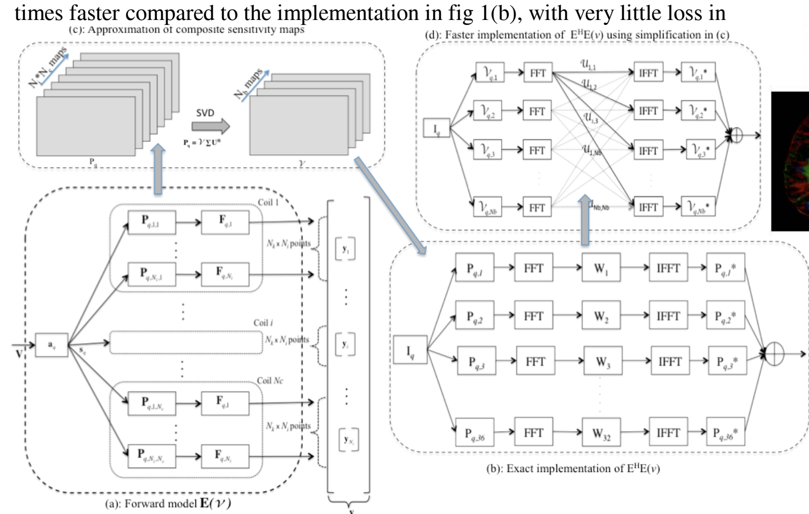

Figure 1: (a) forward model showing the computation of $\mathbf{E}(\mathbf{v})$. (b) Traditional iterative SENSE implementation of $\mathbf{E}^{\mathbf{H}}(\mathbf{E}(\boldsymbol{v}))$. (c) Approximation of composite sensitivity maps using singular value decompositions. (d) Simplification of (b) using the approximation in (c)

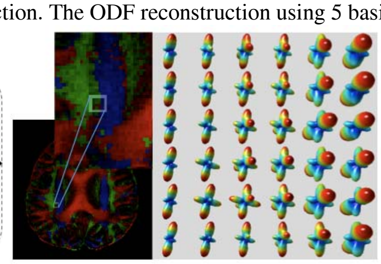

Figure 2: ODF reconstructed at angular resolution of 256, in-plane spatial resolution of 1mm^2. Reconstruction 7.5 times faster than traditional methods, with minimal angular error.

Number of basis functions	Acceleration(Time of computation in sec)	ODF average angular error
36	2.5 (4224 sec)	
18	4.2 (2557 sec)	2.9
10	5.7 (1874 sec)	3.2
5	7.5 (1438 sec)	3.2

DISCUSSION and CONCLUSION: The time savings come from reduced number of computations per diffusion direction as well as reduced memory requirements. This suggests that, equipped with a fast motion-compensated reconstruction, the non-Cartesian schemes have the potential to replace the Cartesian schemes for high spatial and angular resolution diffusion imaging applications.

REFERENCES: (1) Pruessmann et al, MRM,1999,42:952; (2) Liu et al, MRM, 2004, 52:1388 (3) Mani et al MRM, in press.