Quantitative Performance Comparison of Reconstruction Methods for Multi-Coil DTI Data

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Introduction: Diffusion Tensor Imaging (DTI) [1] is useful for characterizing tissue microstructure, allowing determination of, for example, structural changes in brain white matter caused by stroke that are not evident in conventional MRI. Because the diffusion tensor is a rank 2 symmetric tensor, DTI requires a minimum of seven scans of the same image to fully solve the diffusion tensor. The low temporal resolution and the associated low spatial resolution and SNR present a significant challenge for the practical utility of the technique in clinical settings. To accelerate the acquisition time, a model-based approach to reconstruct undersampled DTI data has been proposed [2]. Rather than first reconstructing the diffusion weighted images then fitting the tensors, the diffusion tensor fields are directly estimated from k-space data via model-based reconstruction. The rationale is that better performance might be achieved by estimating fewer unknowns in the reconstruction and by providing a platform in which multiple practical considerations, such as phase error and field inhomogeneity, can be addressed in a single step. Here, the previous model-based approach is extended to multi-coil, EPI DTI data, which is more common in clinical applications, and its performance is compared against traditional compressed sensing reconstruction [3] as well as the parallel reconstruction techniques, GRAPPA [4] and SENSE [5].

Methods: Model-based reconstruction of undersampled data is performed by fitting the diffusion tensor, **D**, directly to the acquired data via minimizing the cost function in Eq. (1), where F_u is the undersampled Fourier operator, d_{nl} is the undersampled DTI k-space data, TV is the total variation operator with a regularization weight, α. N is the total number of diffusion weighted images and L is the number of coils used to acquire the data. The new signal model, m_{nl}, is defined in Eq. (2), where S_l is the estimated coil sensitivity of the lth coil. I_0 is the non-diffusion weighted reference image, b is the diffusion weighting factor, $\mathbf{g}_n$ is the diffusion encoding directional vector, φ_{nl} is the image phase due to imperfections in acquisition. Minimization is accomplished via gradient descent, requiring the derivative, $\delta C(\mathbf{D})/\delta D_{\xi\rho}$, of Eq. (1) with respect to the $\xi\rho^{th}$ element of the tensor (where $\xi, \rho \in \{x,y,z\}$). The process is repeated until all parameters have converged, in which Eq. (1) has reached a minimum.

$$C(\mathbf{D}) = \sum_{n=1}^{N} \sum_{l=1}^{L} \left(\left\| F_u\{m_{nl}\} - d_{nl} \right\|_2^2 + \alpha TV\{|m_{nl}|\} \right) \quad (1) \qquad\qquad m_{nl} = S_l I_0 e^{-b\mathbf{g}_n^T \mathbf{D}\mathbf{g}_n} e^{i\varphi_{nl}} \quad (2)$$

To test the performance of the proposed approach, fully-sampled Cartesian k-space DTI data (64 encoding directions, b = 800 s/mm^2, one b = 0 image, coils = 5) was acquired with a stroke patient on a Siemens 1.5T scanner with an EPI readout and TR=5.7 s, TE=138 ms, pixel size=1.8x1.8 mm^2, slice thickness=2.5mm.. The acquired k-space was retrospectively undersampled to simulate an acceleration factor, R, of 2. The coil sensitivity, S_l, was estimated using the fully-sampled non-diffusion weighted image, I_0. The image phase, φ_{nl}, was estimated using the fully sampled central k-space, low-passed using a Hann window. Therefore, all the terms in Eq. (2) are fixed, except for **D**. The performance of the proposed model-based approach was assessed by comparing fiber orientation deviation angle ($\Delta\theta$, in degrees) and fractional anisotropy difference (ΔFA, dimensionless) with respect to the fully-sampled "gold standard". The results of the proposed model-based approach are then compared against other common reconstruction methods: traditional compressed sensing, SENSE and GRAPPA. The acceleration techniques presented here are valuable in EPI because they effectively shorten TE, thus boosting the measured signal. Here, the GRAPPA and SENSE reconstructions were adapted from code posted online [6].
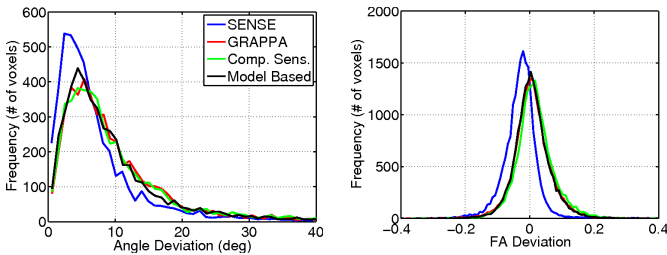

Figure 1: Left, distribution of $\Delta\theta$ for the different reconstruction methods. Right, distribution of ΔFA. SENSE performs the best in terms of $\Delta\theta$, while the proposed model-based approach estimates FA the best. There is a bias towards overestimation of FA in the case of SENSE.

Results and Discussion: Figure 1 shows the error distributions of the reconstruction methods mentioned above. Table 2 reports the average values and SEM of the error metrics for each case. In terms of $\Delta\theta$, SENSE performs the best, while the other three methods have similar distributions and means. The proposed model-based approach performs the best in terms of FA estimation, as seen in Fig. 1 and Table 1. There is a clear bias towards overestimation of FA in the case of SENSE, as seen in Fig. 1. This may be because of the different sampling patterns employed in the different cases. There has been previous work in comparing the results of GRAPPA and SENSE in DTI [7]. The proposed model-based reconstruction technique is shown to be a promising reconstruction technique for FA estimation, lacking the bias seen in SENSE reconstruction. Future work will include acquiring data from more patients and investigating why SENSE outperforms the other methods. These results may help form a basis when deciding which technique to use when reconstructing accelerated DTI data.

Table 1: Performance of reconstruction methods in terms of fiber orientation and FA measurement errors. (Mean ± SEM)

Method	Mean $\Delta\theta$ (deg)	RMS ΔFA (10^{-2})
Model-Based	10.77 ± 0.17	5.58 ± 0.04
Compressed Sensing	11.31 ± 0.18	6.31 ± 0.04
SENSE	7.79 ± 0.12	7.09 ± 0.05
GRAPPA	11.16 ± 0.18	6.33 ± 0.05

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