

# Model-based DTI reconstruction with sparsity constraints on the diffusion tensor

Florian Knoll<sup>1</sup>, Jos'e G Raya<sup>1</sup>, Rafael O Halloran<sup>2</sup>, Steven Beate<sup>1</sup>, Eric Sigmund<sup>1</sup>, Roland Bammer<sup>2</sup>, Tobias Block<sup>1</sup>, Ricardo Otazo<sup>1</sup>, and Daniel K Sodickson<sup>1</sup>

<sup>1</sup>Bernard & Irene Schwartz Center for Biomedical Imaging, Department of Radiology, NYU School of Medicine, New York, New York, United States, <sup>2</sup>Radiology, Stanford University, Stanford, California, United States

**Purpose:** Diffusion-tensor imaging (DTI) provides quantitative measurements of tissue microstructure that no other technique can reveal [1]. However, particularly for its advanced variants, data acquisition time is critical because many measurements are required with different diffusion encoding gradients. When using undersampling strategies to accelerate the acquisitions, such as compressed sensing (CS) or parallel imaging (PI), image reconstruction can be challenging because of the inherently low SNR of diffusion-weighted images (DWIs). Low SNR compromises the ability of CS to separate between true object structures and incoherent aliasing. However, a simple and well-defined signal model exists for DTI making it a good candidate for model-based methods [2]. The use of a model is expected to increase sparsity and therefore performance with respect to noise. This work describes a new combination of CS and model-based DTI reconstruction, which applies sparsifying transformations directly in the domain of the diffusion tensor element maps. It is shown how the method can be used for acceleration of in-vivo exams on a conventional clinical system, which to our knowledge has not been demonstrated previously.

**Methods: Image reconstruction:** The basic DWI signal model is  $x_n = I_0 e^{-b_n \tilde{g}_n^T D \tilde{g}_n}$ . Here,  $I_0$  is the non-diffusion-weighted image,  $x_n$  is the diffusion-weighted image for diffusion-sensitizing direction  $n$  with  $b_n$  being its diffusion weighting and  $\tilde{g}_n$  its unitary direction vector.  $D$  is the diffusion tensor. With  $c_n$  and  $e^{i\phi_n}$  being coil sensitivity maps and phase error due to macroscopic motion, respectively, an extended forward operator  $E_n(D)$  that maps  $D$  to the k-space data  $y_n$  can be written as:

$$y_n = E_n(D) = FT_n(I_0 e^{-b_n \tilde{g}_n^T D \tilde{g}_n} c_n e^{i\phi_n}).$$

$FT_n$  denotes the non-uniform Fourier transformation associated with the k-space sampling used for the direction  $n$ . Zero and first order phase correction is performed. A model-based optimization problem with regularization of the elements of  $D$  can therefore be formulated as:

$$S(D) = \sum_{n=1}^N \|E_n(D) - y_n\|_2^2 + \alpha \sum_i |\Psi(D)|.$$

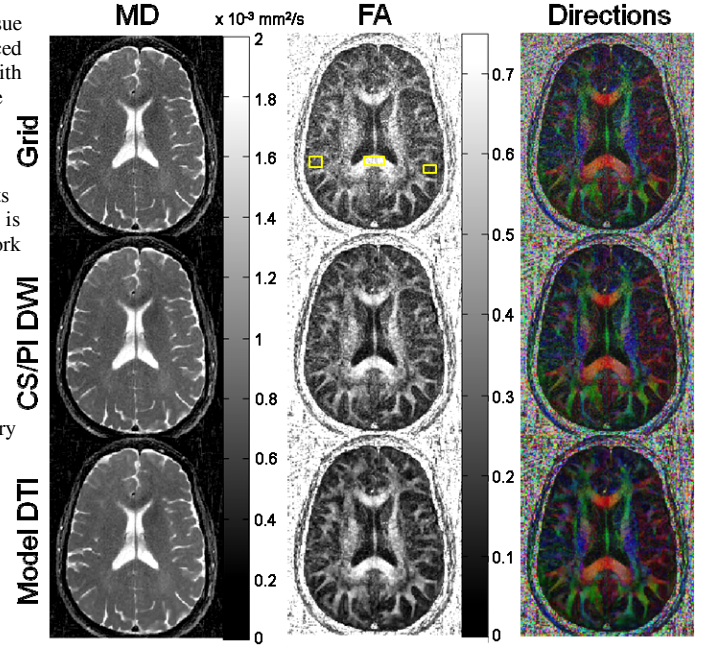
The indices  $i$  and  $n$  indicate the corresponding elements of the diffusion tensor  $D$  ( $N_D$ ) and the number of DWIs ( $N$ ). The total-variation seminorm was used as sparsifying transform  $\Psi$  and was applied individually to each tensor element. Gradient descent (GD) was used as numerical optimizer to find a minimum of  $S(D)$ . 100 iterations with identical step size ( $10^{-4}$ ) were used for all experiments. The regularization parameter was chosen heuristically for both reconstruction methods but was kept constant for the data sets of all experiments in order to test the robustness of the different methods.

**Data acquisition and evaluation:** MR measurements of the brain and knee of healthy volunteers were performed using a clinical 3T system (Siemens MAGNETOM Skyra) with a radial diffusion-weighted spin-echo sequence (RAISED) [3]. It includes a 2D EPI motion-correction navigator and alternates the diffusion gradients in different slices to avoid cross-talk. Each diffusion-weighted image is acquired using a different set of radial views to provide optimal sampling of the outer part of the k-space, and the readout polarization is changed between successive spokes. Sequence parameters were TR=1500ms, slice thickness 3mm, 11 slices, BW=300Hz/pixel and 6 diffusion-encoding directions. For brain acquisitions, TE=60ms, b-value 1000s/mm<sup>2</sup>, matrix=196x196, resolution=1x1mm<sup>2</sup>, and 75 radial spokes were used ( $t_{\text{acq}}=13:11$ min). Knee measurements were performed with TE=39ms, b-value 300s/mm<sup>2</sup>, matrix=208x208, resolution=0.74x0.74mm<sup>2</sup> and 114 radial spokes ( $t_{\text{acq}}=19:50$  min). Reconstructions were performed with conventional gridding and sum-of-squares combination of the coil elements, a combined compressed-sensing and parallel-imaging method [4] for the individual DWIs and the proposed model based approach with direct application of the sparsifying transform on the tensor elements.

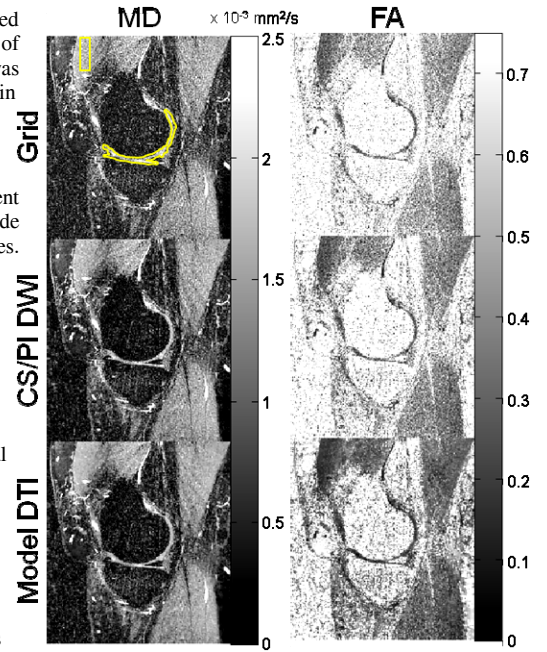
**Results:** The results of brain (Figure 1) and knee experiments (Figure 2) show a reduction of noise and residual streaking artifacts with both nonlinear reconstruction methods. The proposed model based method shows clearly improved contrast in the FA maps combined with the same detectability of fine structures in the MD maps. This is also represented in the quantitative analysis in Table 1. Values of MD are very consistent and are close to values reported in the literature [5]. In contrast, a reduction in FA is observed that is strongest for the model-based approach. The standard deviation within the ROI, mainly influenced by noise and streaking artifacts, is also reduced for both MD and FA with the proposed approach in comparison to the other methods.

**Discussion and Conclusion:** This observed reduction in FA likely reflects the lower residual streaking artifacts and noise in compressed-sensing reconstructions because MD is robust to noise while FA is easily biased in the presence of noise. One challenge of the model-based approach is that the nonlinearity of the forward operator results in non-convex optimization problems. This makes the numerical solution challenging and sensitive to initial values. In the current work, we used the gridding SOS reconstruction to initialize the optimizer. It is expected that improved numerical performance can be achieved with second order methods like the iteratively-regularized Gauss-Newton method [6], which is the subject of ongoing research. In summary, the results presented in this work demonstrate high performance of model-based reconstruction for truly accelerated in-vivo DTI on conventional clinical MR systems.

**References:** [1] Tournier et al., MRM 65: 1532-1556 (2011), [2] Welsh et al., MRM 70: 429-440 (2013), [3] Raya et al., ISMRM 3530 (2013), [4] Block et al., MRM 57: 1086-98 (2007), [5] Raya et al., Radiology 262: 550-559 (2012), [6] Uecker et al., MRM 60: 674-682 (2008).



**Figure 1:** MD, FA, and color coded directions of the principal eigenvector for the brain experiments, using gridding & sum-of-squares combination of coil elements (Grid), combined CS & PI (CS/PI DWI), and model-based reconstruction with sparsity constraint on tensor elements (Model DTI).



**Figure 2:** MD and FA for the knee experiments.

**Table 1:** Quantitative evaluation of ROIs indicated in Figs. 1 and 2. MD values are given in units of  $\mu\text{m}^2/\text{ms}$ ; FA values are unitless.

	Splenum CC	Grey Matter	Cartilage	Muscle
MD gridding	$0.76 \pm 0.11$	$1.02 \pm 0.27$	$1.65 \pm 0.45$	$1.74 \pm 0.23$
MD CS DWI	$0.76 \pm 0.09$	$1.02 \pm 0.26$	$1.65 \pm 0.44$	$1.74 \pm 0.18$
MD Model DTI	$0.76 \pm 0.06$	$1.01 \pm 0.25$	$1.59 \pm 0.38$	$1.74 \pm 0.11$
FA gridding	$0.70 \pm 0.09$	$0.24 \pm 0.09$	$0.46 \pm 0.21$	$0.33 \pm 0.10$
FA CS DWI	$0.68 \pm 0.07$	$0.21 \pm 0.08$	$0.43 \pm 0.20$	$0.30 \pm 0.09$
FA Model DTI	$0.66 \pm 0.06$	$0.18 \pm 0.07$	$0.28 \pm 0.14$	$0.25 \pm 0.04$