3D locally dependent regularization of the diffusion tensor using ICA and TGV

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Purpose: Readout-segmented echo planar imaging (rs-EPI) with 2D navigator-based reacquisition enables the sampling of high-resolution DWI with reduced susceptibility artifacts[1,2]. However, the poor SNR for shorter scan times limits the clinical applicability of this sequence. It has been shown recently that a user-independent approach for spatially dependent regularization of the diffusion tensor by means of independent component analysis (ICA) and total variation (TV) significantly improves fractional anisotropy maps and tractography[3] allowing for high-resolution diffusion imaging with shorter scan times. In this work we present two novel improvements for the diffusion tensor regularization. Firstly, the regularization is performed for all three dimensions simultaneously in contrast to the previously used 2D approach. Secondly, the concept of total generalized variation (TGV)[4] has been applied that uses a less restrictive assumption of piecewise constant signal compared to TV regularization. ICA is still used to evaluate the spatially dependent noise distribution of the diffusion tensor allowing for an automated estimation of the regularization parameter without a priori knowledge.

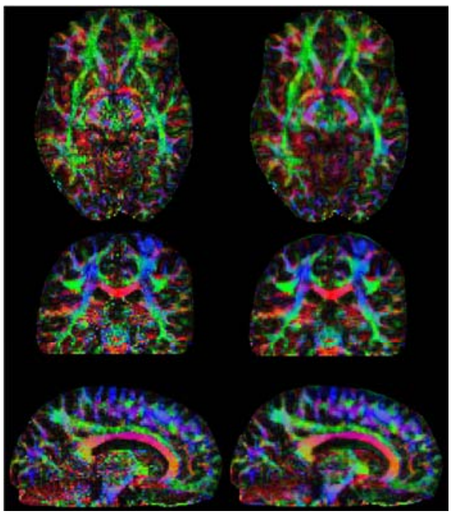

Figure 1: Fractional anisotropy (FA) maps without regularization (left column) and with spatially dependent 3D TGV regularization (right column) in transversal (first row), coronal (second row), and sagittal (third column) view.

Methods: Data from a healthy volunteer were measured using an rs-EPI sequence with the following parameters: TR = 9045 ms, TE = 67 ms, FOV = 240 mm, resolution = 1.5x1.5x1.5 mm^3, slices = 70, b = 1000 s/mm^2, diffusion directions = 12, number of readout segments = 11, GRAPPA =3. Measurements were carried out on a clinical 3T system using a 32-channel head coil. ICA based on entropy bound maximization[5] was applied on the 12 directions with an active diffusion gradient to separate diffusion-related components from noise components. Using the Stejskal-Tanner relation for the denoised DWI data and for the noise separately the diffusion tensor f_{ICA} and its corresponding noise tensor f_{noise} can be obtained. The 3D TGV regularization was performed by minimizing the cost function:

$$\min_{\substack{u:\Omega\to Sym^2,\\ w:\Omega\to Sym^3}} \frac{1}{2}\|\sigma^{-1}(u-f_{ICA})\|_2^2 + \alpha_1\|\varepsilon u - w\|_1 + \alpha_0\|\varepsilon w\|_1$$

where Ω is the 3D domain of computation, u is the denoised tensor data, σ a local estimate on the variance obtained from f_{noise}, w a third-order tensor field arising from tensor TGV^2 regularization[6], ε denotes the symmetrized derivative and α_0, α_1 are fixed parameters. An iterative primal-dual first-order optimization algorithm[7] was used to compute solutions numerically. The noise estimate σ was updated during the iteration using the following rule:

$$\sigma \leftarrow \sigma\frac{\|u-f_{ICA}\|_2}{\tau\|f_{noise}\|_2}$$

where τ is a factor compensating a potential underestimation of the noise level in f_{noise}. All calculation and visualization was done with Matlab software (The MathWorks, Inc., MA, USA) on a PC equipped with i7-2600 CPU with 3.4GHz and 24 GB RAM.

Results: 3D Regularization of the high-resolution diffusion tensor provides fractional anisotropy (FA) maps that are much more homogeneous and less noisy compared to the unregularized FA maps. Specifically central regions that suffer from low SNR are denoised successfully while small anatomical details are preserved. Due to the three-dimensional approach of the proposed regularization algorithm, the excellent denoising properties can be observed for arbitrary slice orientation (see Figure 1). The visualization of the diffusion tensors in Figure 2 shows that our 3D locally dependent regularization method applied on the entire diffusion tensor successfully minimizes uncertainties in both the eigenvectors (color and direction) and eigenvalues (shape of the tensors) resulting in a more homogeneous tensor field.

Discussion & Conclusion: In this work we present a new approach for automated locally dependent regularization of the diffusion tensor. Our algorithm utilizes TGV regularization that has been shown advantageous compared to TV regularization[8]. Staircasing artifacts, often observed when using TV regularization, can be avoided with TGV. The regularization in three dimensions simultaneously is a natural choice for denoising a three-dimensional structure such as white-matter fibers. Uncertainties of eigenvectors and eigenvalues of the diffusion tensors can be reduced within slices. The incorporation of the noise distribution, estimated by ICA, into the regularization procedure allows for a spatially varying regularization parameter that is evaluated automatically.

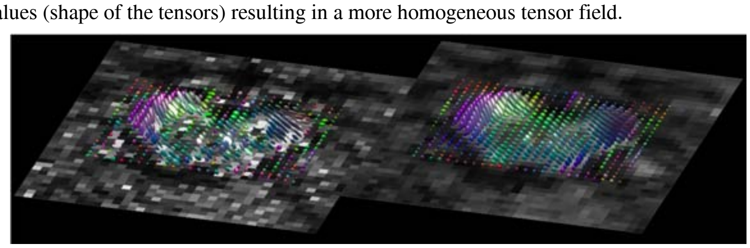

Figure 2:Tensor field of the brain stem obtained from the unregularized diffusion tensor (left) and for the spatially dependent 3D TGV regularized

References: [1]Porter DA et al. High Resolution Diffusion-Weighted Imaging Using Readout-Segmented Echo-Planar Imaging, Parallel Imaging and a Two-Dimensional Navigator-Based Reacquisition. Magn Reson Med. 2009;62:468–475; [2]Holdsworth SJ et al. Robust GRAPPA-Accelerated Diffusion-Weighted Readout-Segmented (RS)-EPI. Magn Reson Med. 2009;62:1629-1640; [3]Reishofer G et al. Time-Optimized High-Resolution Readout-Segmented Diffusion Tensor Imaging. PLoS ONE. 2013;8(9): e74156; [4]Bredies K et al. Total Generalized Variation. SIAM J. Imaging Sci. 2010; 3(3):492-526; [5]Li XL, Adali T. Complex Independent Component Analysis by Entropy Bound Minimization. Ieee Transactions on Circuits and Systems I-Regular Papers. 2010;57:1417-1430; [6]Valkonen T et al. Total Generalized Variation in Diffusion Tensor Imaging. SIAM J. Imaging Sci. 2013; 6(1) 487-525; [7]Chambolle A et al. A First-Order Primal-Dual Algorithm for Convex Problems with Applications to Imaging. J. Math. Imaging Vision 2011; 40(1):120-145; [8]Knoll F et al. Second order total generalized variation (TGV) for MRI. Magn Reson Med. 2011; 65(2):480-491.