Local regularization of the diffusion tensor by means of independent component ananlysis and total variation - application to high resolution DTI

Gernot Reishofer[1], Karl Koschutnig[2], Christian Langkammer[3], Stefan Ropele[3], Stephen Keeling[4], Robert Merwa[5], and Franz Ebner[6]

[1]*Radiology, Medical University of Graz, Graz, Styria, Austria,* [2]*Psychology, University of Graz,* [3]*Neurology, Medical University of Graz,* [4]*Mathematics and Scientific Computing, University of Graz,* [5]*Medical Engeneering, Upper Austria University of Applied Sciences,* [6]*Radiology, Medical University of Graz*

INTRODUCTION:

Diffusion tensor imaging (DTI) has become one of the most important MRI techniques to study tissue micro-structures, specifically in white matter tissue of the brain. Advanced scan techniques, such as readout segmented EPI provide the basis for high resolution DTI with an in plane resolution of 1 mm and below. The low SNR in diffusion-weighted images (DWI), obtained by readout segmented EPI, requires long scan times and may prevent the use of this technique in a clinical setup. For shorter scan times, the noise results in uncertainties of the diffusion tensors (D) and their derived quantities, such as the fractional anisotropy (FA). To minimize uncertainty in D several regularization methods have been proposed, that focus on the regularization of DWI or D itself [1,2]. Giving the fact, that the SNR is not uniform in the whole image, the regularization procedure results in over regularized regions where small anatomical details are suppressed and under regularized regions with insufficient noise reduction. In this work we present a novel method for spatial regularization of D using local dependent total variation (TV) regularization. Information about the local noise distribution in D is obtained by separating DWI data into a signal term and a noise term by means of independent component analysis (ICA) and a separate projection into the orthogonal subspace.

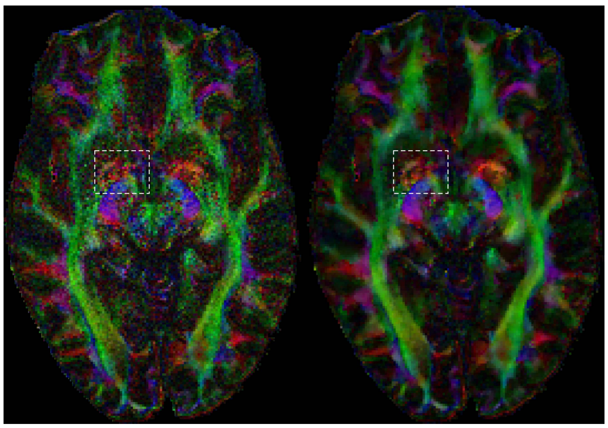

Figure 1: FA maps evaluated from the original diffusion tensor (left) and from the regularized diffusion tens minimize uncertainty or (right). The white dashed rectangle mark the region shown in Figure 2.

METHODS:

DWI data from a healthy volunteer was acquired using a readout segmented EPI sequence with the following parameters: TR = 4200 ms, TE = 81 ms, FOV = 220 mm, resolution = 1x1x4 mm^3, slices = 24, b = 1000 s/mm^2, directions = 20, number of shots = 11, acquisition time = 9.5 min. All measurements were carried out on a 3T Tim Trio system (Siemens Medical Systems, Erlangen, Germany) using a 12 channel head coil. Low SNR diffusion weighted images with b = 1000 s/mm^2 were processed using a complex ICA algorithm based on entropy bound minimization [3]. This linear transformation resulted in a subspace of six independent components representing independent diffusion directions and 14 components representing noise. By inverting the ICA transformation for the first six components, a denoised set of DWI images was obtained. The subtraction of the denoised DWI set from the original DWI data provided a set of images containing only noise. Using the Stejskal–Tanner relation, the six elements of the diffusion tensor (D_{xx}, D_{xy}, D_{xz}, D_{yy}, D_{yz}, D_{zz}) were evaluated from the denoised DWI data. The set of noise images was transformed into the same subspace resulting in six corresponding noise images. From these noise images the noise variance was evaluated using a 11x11 moving window to obtain a noise variance map for each tensor element (σ^2). Diffusion tensor elements and corresponding noise variance maps served as input for the total variation optimization problem which minimized the functional:

$$\min_{D} \left\{ \int_{\Omega} \left(\hat{D} - D\right)^2 d\Omega + \lambda(\sigma) \int_{\Omega} \left|\nabla \hat{D}\right| d\Omega \right\},$$

where Ω is the image domain, D is the diffusion tensor, $\hat{D}$ the restored diffusion tensor and $\lambda(\sigma)$ is the specially dependent regularization parameter. Total variation regularization was carried out using the algorithm proposed by Chambolle et al. [5] and the regularization parameter $\lambda(\sigma)$ was estimated according to [6]. All calculation and visualization was done with Matlab software (The MathWorks, Inc., MA, USA).

RESULTS:

Figure 1, comparing FA maps for a single slice obtained from the original diffusion tensor (left) and the regularized diffusion tensor (right) demonstrate the excellent noise suppression by our proposed method while small anatomical details are preserved. The visualization of the diffusion tensors in Figure 2 show that our local dependent regularization method applied on the diffusion tensor elements successfully minimizes uncertainties in both the eigenvectors (color and direction) and eigenvalues (shape of the tensors). This results in a more homogeneous tensor field which might improve further post processing steps such as fiber tracking.

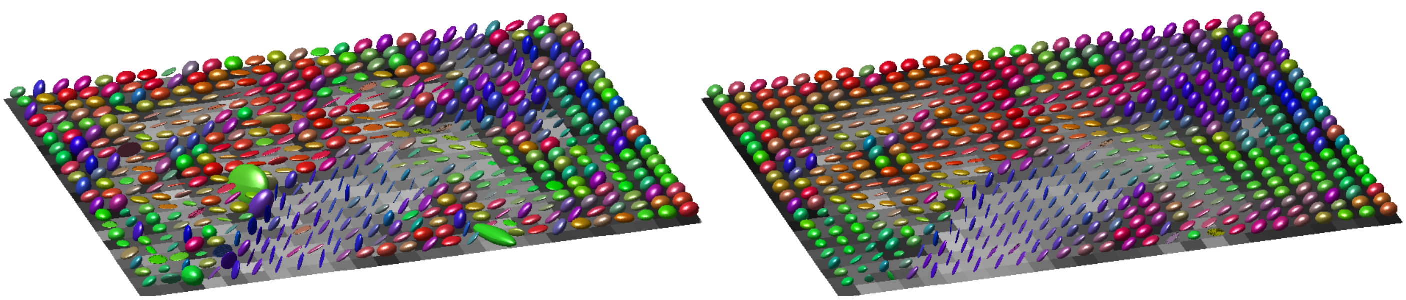

Figure 2: Diffusion tensor field from the original DWI data (left) and spatially TV regularized tensor field (magnified view from marked region in Figure 1).

CONCLUSION:

In this work we propose a novel method for the spatially dependent regularization of the diffusion tensor based on independent component analysis and total variation regularization. We demonstrate that diffusion tensors from noisy DWI data, acquired with a readout segmented EPI sequence, are successfully denoised while fine structural details are preserved. This technique enables the application of high resolution DTI in a clinically acceptable time.

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