Tensor Field Regularization for Diffusion Tensor MR Images using Nonlinear Smoothing

W. Li[1], J. Tian[1], J. Dai[2]

[1]Institute of Automation, Chinese Academy of Sciences, Beijing, China, People's Republic of, [2]Department of Neuroradiology, Beijing Tiantan Hospital, Beijing, China, People's Republic of

Introduction

Diffusion tensor magnetic resonance imaging (DT-MRI) allows the investigation of diffusion differences between tissues in vivo, which reflect the physiological and structural properties of tissues[1]. However, DT-MRI measurements are sensitive to noise levels [2]. The level of noise depends on parameters such as acquisition time or voxel size. There is an interest in providing post-processing denoising techniques that would relax the acquisition constraints. Some work has been presented for regularization of DT-MR images, either for the whole data, or only the principal diffusion direction (PDD) [3]. We propose here a technique that regularizes the whole tensor to reduce both the random errors normally associated with noise, and the systematic errors in subsequently calculated values of anisotropy.

Materials and Methods

Diffusion Data

The images used for this study were acquired with a 3.0T clinical MRI scanner (General Electric Medical Systems, Milwaukee, WI, USA). Diffusion tensor imaging was performed using a single-shot SE-EPI pulse sequence with 24cm×24cm field of view, 35 axial slices, TE/TR 87/8499ms, b value of 1000s/mm^2, 13 directions. The diffusion tensor eigenvalues (λ_1, λ_2, λ_3) and eigenvectors (ε_1, ε_2, ε_3), and fractional anisotropy (FA) maps were calculated from DT-MRI data.

Data Processing

Nonlinear anisotropic diffusion scheme, named PM filter developed by Perona and Malik [4], is adopted in our method of tensor field regularization. There are three problems which we resolved: firstly, nonlinear smoothing is performed on tensor fields other than on scalar images; secondly, sorting eigenvalues (principal diffusivites) by magnitude introduces a bias in their sample mean within a homogeneous region of interest (ROI); thirdly, magnitude sorting also introduces a significant bias in the variance of the sample mean eigenvalues [5].

Because the sign of eigenvectors are indeterminate, arithmetically operation of eigenvectors within an ROI produces a poor estimate, Here we represent each eigenvector as a second order dyadic tensor [5], allowing us to calculate a non-linear weighted mean eigenvector unambiguously. So the regularized eigenvector is defined as follows:

$$\frac{\partial\left\langle \varepsilon_{i,1}\varepsilon_{i,1}^{T}\right\rangle}{\partial t}=div\left[g\left(\left\|\nabla\left\langle \varepsilon_{i,1}\varepsilon_{i,1}^{T}\right\rangle\right\|\right)\cdot\nabla\left\langle \varepsilon_{i,1}\varepsilon_{i,1}^{T}\right\rangle\right],\quad \text{where}\quad g\left(\left\|\nabla\left\langle \varepsilon_{i,1}\varepsilon_{i,1}^{T}\right\rangle\right\|\right)=e^{-(C/K)^2}$$

C represents the "overlaps" between corresponding eigenvalue-eigenvector pairs or dyadics in two different voxels. To account for the three-dimensional character of anisotropy diffusion, C are summed by the interaction of three eigenvalue-eigenvector pairs in two voxels respectively, and normalized using its global maximal value. So $C_{i,j}$ between two diffusion tensors (i and j) are obtained:

$$C_{i,j}=\frac{\sum_{m=1}^{3}\sum_{n=1}^{3}\lambda_{i,m}\lambda_{j,n}^{'}\cdot\left(\varepsilon_{i,m}\varepsilon_{j,n}^{'}\right)^{2}}{\sum_{m=1}^{3}\sum_{n=1}^{3}\lambda_{i,m}\lambda_{j,n}^{'}}$$

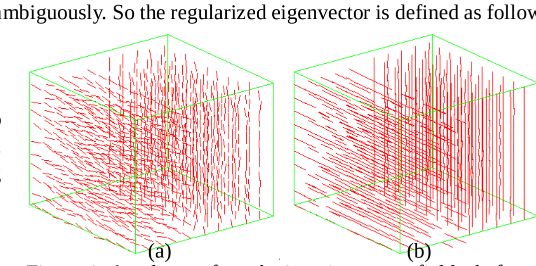
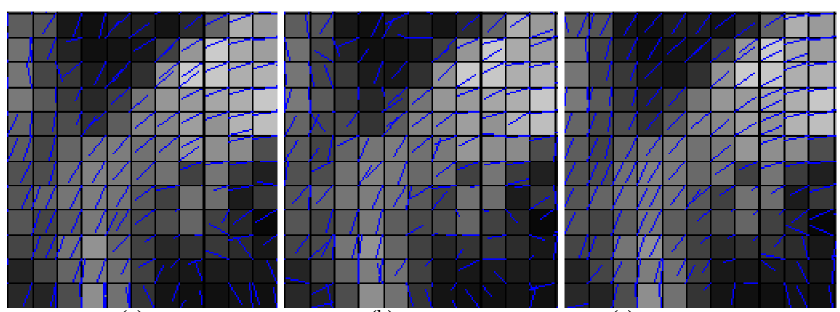


Figure 1. A volume of synthetic noisy tensor fields, before (a) and after regularization of tensor field.

By construction, 0<$C_{i,j}$<=1, where 0 indicates no overlap and 1 indicates complete overlap. After recalculated for the principal eigenvector of each tensor in the DT-MRI images, we get the regularized PDD map $\varepsilon_1^{\,r}$. The second eigenvector $\varepsilon_2^{\,r}$ is projected on the plane orthogonal to $\varepsilon_1^{\,r}$, and we get $\varepsilon_3^{\,r}$ which orthogonal to $\varepsilon_1^{\,r}$ and $\varepsilon_2^{\,r}$. Then the whole tensor fields are all regularized.

Results

Tensor field regularization was experimented on both synthetic and real data. A volume composed of two orthogonal bundles with anisotropy equal to 1 was created. Noise was added to the directions. Figure 1 shows a part of this volume before (a) and after (b) regularization. One can see that directions are properly restored; moreover, restoration is efficient even at the borders of the bundles. At their interface, the two bundles stay orthogonal, showing good improvement in terms of discontinuity preservation. Some real DT-MRI dataset was used as gold standard data set, show in Figure 2 (a). Figure 2 (b) shows the principle eigenvectors with tensor field corrupted by noise, and (c) is the regularized diffusion tensor. The filtering process reduced both random and systematic errors, and the orientation of eigenvectors are more coherent between neighboring voxels.



(a) (b) (c)

Figure 2. Tensor field regularization on real DT-MRI data. The directions of principal eigenvectors are colored in blue and displayed on FA map, acquired from original diffusion tensor data as gold standard (a), noisy tensor data (b), and the regularized tensor data (c).

Discussion and Conclusion

Nonlinear anisotropic smoothing is promising in tensor field regularization. Sorting eigenvalues by magnitude introduces a bias and magnitude sorting also introduces a significant bias, which can be quantitatively evaluated by the calculation of the "overlap" between eigenvalue-eigenvector pairs. Using the interaction of whole eigenvalues and eigenvectors can perform better than only using largest eigenvalue and principal eigenvector. With regularized tensor field, we can get more accurate fiber tracts with a simple tractography method. In summary, we presented a regularization process for DT-MRI images that restores the whole tensor field using nonlinear anisotropic diffusion scheme. Results demonstrate that tensor field regularization using nonlinear smoothing is satisfied and reproducible. These effects are of particular importance when DT-MRI is used for connectivity analysis of fiber tracts[6].

References

[1] Parker GJM, J. Magn. Reson. Imag. 2000; 11:702-710. [2] Jones DK, Magn Reson Med. 2003; 49:7-12. [3]Tench CR, Magn Reson Med. 2002; 48:677-683.
[4] Perona P, Malik J, IEEE Trans PAMI,1990; 12:629-639. [5]Besser PJ, Magn Reson Med. 2000; 44:41-50. [6]Hagmann P, NeuroImage 2003; 19:545-554.