Diffusion Tensor Imaging Noise Removal for Tissue Fiber Tracking

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Introduction

Due to the large dataset size (minimum of seven images) and the intensity attenuation nature of diffusion encoding, diffusion tensor imaging (DTI), particularly at high resolution, has been hampered by long acquisition time and low signal to noise ratio (SNR). The noise level in the diffusion weighted images has a direct impact on the accuracy of diffusion tensor computation [1]. Noise removal techniques may be used to improve the SNR of diffusion tensor imaging without increasing the acquisition time. While noise removal techniques such as low-pass filtering can be readily used to improve the SNR, they necessarily incur blurring at tissue borders that may lead to errors in the diffusion tensor computation and fiber tracking. Partial differential equation based diffusion filter (PDE filter) has been used to remove image noise through anisotropic smoothing with edge preservation feature [2]. The challenges in extending scalar PDE filtering for DTI are (a) direct de-noise of eigenvector fields cannot be done accurately on a component-by component basis, and (b) the diffusion tensor eigenvector field is subject to both image noise and diffusion tensor goodness-of-fit errors. In this study, we developed a vector based PDE filter with norm conservation constrains and compared its performance with other widely used noise removal techniques.

Methods

Post-processing studies were performed on fixed mouse brain DTI datasets (256x128x128 data matrix, 100mm isotropic resolution, N=6) obtained in a separate study. We compared the denoising performance on these datasets among Fermi filter (fixed circular k-space low-pass filter), Wiener filter (adaptive k-space filter), image based PDE filter and vector based PDE filter with norm conservation constrains. The original data without filtering is treated as reference.

Image based PDE filter has been extended into vector space recently by introducing a unified parameter of vector geometry to couple the smoothing behaviors along three orthogonal directions of vector based PDE filter [3,4]. However, the fiber orientation in DTI represented by principle eigenvector of diffusion tensor is a unit vector. Without norm conservation constrain, the norm of vector will shrink quickly during numerical computation. The vector will lose orientation information when its norm goes to zero. Back projection to unit vector after each iteration could introduce errors of those vectors with very small norms. We designed a special diffusion term that its diffusion direction is always perpendicular to the orientation of eigenvector. Thus, we can denoise on eigenvector space while keeping the vector norm as a unit vector during the whole process.

In our study, Fermi, Wiener and image based PDE filter are implemented on diffusion weighted images. The vector based PDE filter directly acts on the original eigenvector field. One way to evaluate denoising performance is to compare diffusion tensor error represented by normalized magnitude of the nonlinear least square fitting covariance matrix (MN Covariance). For white matter fiber tracking, root mean square of deviation angle map with neighboring voxels (RMS value) is a good indicator to evaluate the noise removal effect since the white matter fiber is highly oriented to the same direction locally.

When performing denoising on mouse brain data, there is no noise-free and known vector field or gold standard for us to compare the performance of each method. Therefore, a Monte Carlo simulation on a uniform vector field combined with noise and fractional anisotropy (FA) variance is implemented to validate the denoising results in a more controlled way. The off-axis deviation distance after traveling same distance is used as an index of denoising performance.

Results

Table 1 shows the denoising results on mouse brains before and after noise removal. The noise level of diffusion tensor is indicated by normalized magnitude of the fitting covariance matrix. The image based PDE has better noise removal performance while the edges of FA map is also well protected (Fig 1) at the same time.

The RMS values in Table 1 demonstrate that the local fibers are more collimated after applying noise removal techniques in whiter matter region. The norm-conserved vector based PDE filter (NCVPDE) has better performance of reducing the incoherence of local neighboring pixels. One way repeated measurement ANOVA test on six datasets reveals that the norm-conserved vector based PDE filter is significantly better than all other denoising methods.

Table 1. Mouse brain: diffusion tensor noise level and fiber tracking deviation results (mean ± std)

	Original	Fermi	Wiener	Image PDE	NCVPDE
MN Covariance	0.056±0.006	0.049±0.004	0.045±0.004	0.031±0.003	N/A
RMS deviation	0.759±0.083	0.758±0.089	0.636±0.079	0.492±0.064	0.311± 0.030

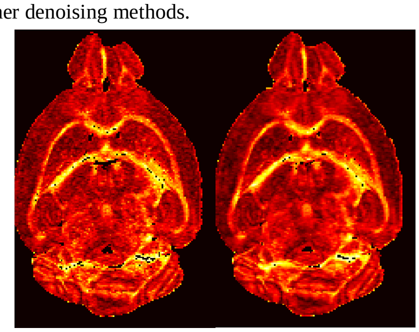

Fig 1. Fractional anisotropy (FA) map before after image based PDE denoising. The edges of white matter are preserved after PDE filtering.

Table 2 shows average off-axis deviation distance of streamline tracking on simulation after traveling 100 pixels. The smallest deviation distance after norm-conserved vector based PDE filter denoising means that the streamline can travel longer distance without strong deviation to reach the boundary or create erratic fiber fork after leaving current fiber trajectory.

Table 2. Monte Carlo simulation: deviation distance in pixels per 100 pixels traveled (mean ± std)

	Original	Fermi	Wiener	Image PDE	NCVPDE
Deviation distance	0.248±0.113	0.237±0.118	0.172±0.082	0.196±0.095	0.132±0.048

Discussion and Conclusion

In DT-MRI, the diffusion tensors are computed from diffusion weighted images and modeled as a rank two tensor. This widely used diffusion tensor computation model has its own limitations. It cannot reflect the real fiber orientation in the voxels under certain situations such as fiber crossing, or partial volume effect. Thus, the final long axis direction corresponding to the largest eigenvalues of diffusion tensor is subject to two error sources, the error from image noise and the model error at tensor computation stage.

By the comparison of all these noise removal techniques from the result of real data and simulation, regulation on vector space could be a better way to find more reliable trajectories because the error introduced by model can be reduced also. The noise can be further reduced when noise removal is implemented on both image space and vector space before and after diffusion tensor computation. The core technique of PDE filtering is the diffusion flow controlling. The diffusion process can be customized to favorite the white matter fiber tracking by integrating tissue information into PDE filters. The tissue property related regulation gives extra regulation information and it is independent to the regulation parameters computed from the image or tensor data. The noise removal becomes a data and anatomical information driven process for more accurate fiber tracking.

Reference

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