

Noise Analysis and Filtering for Diffusion Tensor Imaging

M. O. Irfanoglu¹, S. Sammet¹, R. M. Koch¹, R. Machiraju², and M. V. Knopp¹

¹Department of Radiology, The Ohio State University, Columbus, OH, United States, ²Department of Computer Sciences and Engineering, The Ohio State University, Columbus, OH, United States

Introduction: Diffusion Tensor Imaging (DTI) is a Magnetic Resonance Imaging (MRI) method for characterizing molecular diffusion and for extracting fibers of brain. DTI is prone to numerous artifacts and noise coming from different sources. These artifacts and low signal-to-noise ratio (SNR), limit the correctness and reliability of the extracted fibers. Once the noise is modeled with a suitable probability distribution function (pdf), it is possible to filter the image and increase SNR to obtain better fiber tracts. In this work, we investigate the distribution of noise for regions with low and high signal and analyze the performance of five different PDE (Partial Differential Equations) noise filtering techniques.

Materials: Diffusion Tensor Images from five subjects, were acquired with a 7T whole body MR-scanner (Achieva, Philips Medical Systems) using a prototype 8 channel SENSE head coil, and a T/R head coil with the following acquisition parameters: TR=5200ms, TE=87ms, FOV=230, matrix=128x128, axial slices=30, slice thickness=4mm, NSA=2, b=1000. To analyze noise distribution, 25 scans 2 volunteers were with the same parameters. To reduce motion artifacts, the images are registered with Diffusion Registration Rel-0.4 of Philips' Research Imaging Development Environment (PRIDE) software. Then tensors extracted from the Diffusion Weighted Images (DWI) are registered with 3D SLICER software. Nerve fibers were reconstructed with both applications. Noise filtering algorithms were implemented using MATLAB 7 (Mathworks, Boston, MA).

Methods: For noise distribution analysis, we used bootstrapping [6] method to resample the data and to build a pdf. For noise processing, the performances of 3 anisotropic diffusion image space filters: Perona-Malik (PM) filter [1], Rician correction filter [2], and Wang variational estimator [3]; and 2 tensor space filters: edge preserving regularization filter [4], and Riemannian space filter [5] were evaluated. We compared the convergence rates of these filters with and without SENSE. Also the quality of DWIs in regard to artifacts and edge sharpness were compared. The quality of fractional anisotropy (FA) maps by the presence of undesired discontinuities (negative eigenvalues) and the changes in the FA values for high and low diffusion regions was determined. For fiber tracking, we considered the correctness, lengths and densities of the fibers in the corpus callosum region.

Results: The basic Perona-Malik filter is able to clean the images but also alters essentially anisotropic features and produces non-positive definite tensors. The noise distribution analysis shows that the assumption of Rician noise for DTI is valid because the distribution is biased when the signal strength is low and becomes close to Gaussian distribution for higher signal values. For this reason, Rician bias corrector filter, performs well on lower signal regions, but suffers from the same problems as PM. Wang's filter guarantees the positive definiteness of the extracted tensor so it is suitable for images, which result in a considerable amount of negative eigenvalues. However, the filter also decreases the FA values in highly anisotropic regions. Tensor regularization method performs better than the Riemannian manifold approach but they both depend on the correct extraction of tensors. For all methods, using SENSE improves the convergence.

Discussions: This study shows that it is necessary to post-process DTI data in order to get correct fibers for clinical purposes. The filtering results indicate that DWI space based filters perform better than tensor space filters. If the FA map of the uncorrected data has a high proportion of negative eigenvalues, it is better to use a method (e.g. Wang variational estimator) that guarantees tensor positive definiteness.

References:

- [1] P. Perona, J. Malik: Scale-space and edge detection using anisotropic diffusion. IEEE Transactions on Pattern Analysis Machine Intelligence 17(4) (1990) 629-639
- [2] S. Basu, P. T. Fletcher, R.T. Whitaker: Rician Noise Removal in Diffusion Tensor MRI. MICCAI2006.
- [3] Z. Wang, Z. A constrained variational principle for direct estimation and smoothing of the diffusion tensor field from complex DWI. IEEE Transactions on Medical Imaging, 23(8), 2004, 930-939.
- [4] K. Hahn, S. Prigarin, B. Putz: Edge Preserving Regularization and Tracking for Diffusion Tensor Imaging, MICCAI 2001.
- [5] X. Pennec, P. Fillard, N. Ayache: A Riemannian framework for tensor computing. International Journal of Computer Vision 66(1) (2006) 41-66.
- [6] B. Efron, Bootstrap methods: another look at the jackknife. Ann. Stat. 1979;7:1-16.

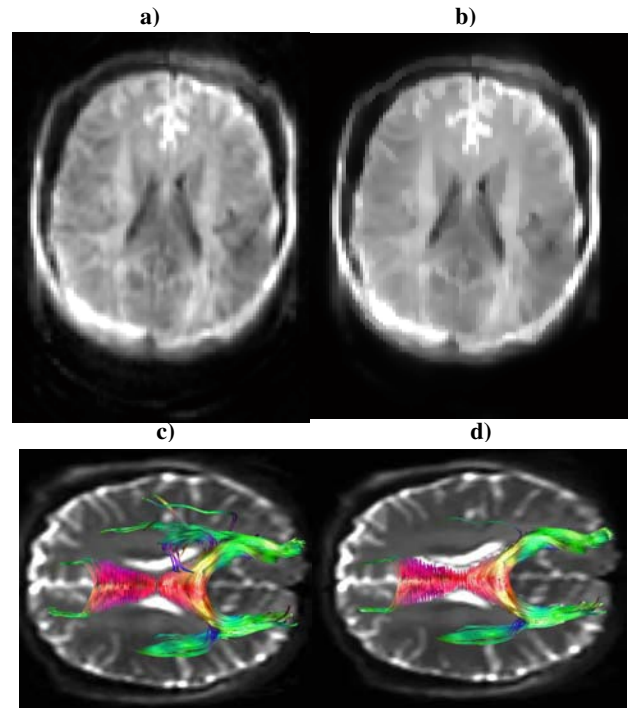


Figure 1. a) Uncorrected Diffusion weighted image (DWI) b) Cleaned DWI with Rician bias filter c) Fiber tracking based on a. d) Fiber tracking based on b.

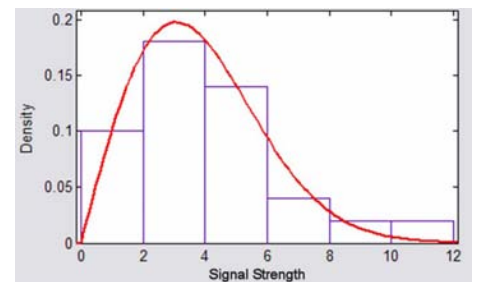


Figure 2. Histogram of the pixel values for low signal values and fitted Rician distribution.