Wavelet Thresholding of Diffusion Tensor Images

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Introduction:

White matter tractography in Diffusion Tensor Imaging (DTI) is an emerging imaging technique that enables non-invasive visualization of white matter fibers. For example, the ability to map white matter fibers in patients with brain tumors provides an unprecedented view of fiber changes due to the presence of tumors and consequently the ability to predict cognitive impairment. However, noise from DTI introduces errors in fiber orientation estimation, which affect fiber tracking, segmentation and clustering. The errors are reflected by the large number of negative eigenvalues calculated, which are physically meaningless. Therefore, fast and effective denoising technique is critical. Acquisition of a single average DTI dataset of the whole brain takes about 2 minutes. Due to the low SNR of the basic EPI acquisition, even images acquired with a large number of averages may still suffer from low SNR. Non-linear adaptive approaches such as the wavelet method are local in nature and play an important role in image processing areas such as denoising. In this paper, we extend a fast and effective denoising technique for multivalued images to DTI, exploiting interband/interscale correlations. Previous wavelet denoising approaches have been applied to scalar images, but DTI contains one baseline image and images with diffusion sensitization along 6 directions, which have strong correlations to each other. Therefore, we propose a specific wavelet function to separate the signal and noise probability density functions (pdf) based on products of coefficients at adjacent scales and products of coefficients from different bands (images). We make use of the high correlation of useful signals between bands to separate noise from clean signals. Here, we examine real DTI data using the image volumes acquired at high magnetic field (3.0 T). Our denoising scheme is evaluated with selective ROI analysis at homogeneous regions. We also compare our results with other wavelet denoising schemes.

Method:

The correlation between signals and noise at different wavelet scales had been researched in [1]. We make use of the signal interscale and interband correlation to separate noise from signal pdf by multiplying coefficients of adjacent scales. Multivalued noise can be decorrelated and modeled as a Gaussian random vector with independent components of equal variance. We extend the method in [2] to denoise the acquired baseline image and images with diffusion sensitization along 6 directions. We use an undecimated Discrete Wavelet Transform (DWT) which is shift-invariant. The wavelet basis is based on Mallat [3] which is good for edge detection. After the wavelet coefficients are computed at each level, the coefficients in adjacent scales are multiplied at each special location to separate signal from noise. The product of real edge data is large because it is closely correlated along the scales. The products of noise correlation is low due to small correlation across scales. BayesSrink [4] is then performed onto the wavelet coefficients to threshold the small values. Data is acquired at 3.0 T (Magnetom Trio®, Siemens Medical Solutions, Erlangen, Germany) with a 8-element head coil array, using spin-echo single shot EPI with parallel acquisition (GRAPPA; acceleration factor of 2). The spatial resolution is 1.3 mm x 1.3 mm x 2 mm. We compare our denoised images from 2 averages with images from 18 averages which takes over 40 minutes to acquire for the whole brain. The images from 18 averages have a high SNR which can be served as ground truth.

Results and Discussions:

The images are denoised using multi-scale products. Fig. 1 illustrates the concept: A profile through the diffusion weighted image is shown in the middle column, after wavelet transform at three levels. Clearly it is difficult to distinguish signal from noise to set an appropriate threshold. However, the far right column shows the product of multiple scales, where clearly the noise is suppressed and the real edges are enhanced. The wavelet coefficients appear to have less oscillations after the product of scale is performed. Fig. 2 shows the noisy and denoised DTI image. We compared the image with classic soft thresholding on scalar image and the results are visually superior while having a lower mean square error at several ROIs placed in homogeneous regions.

A further evaluation was performed checking the number of negative eigenvalues which is a reflection of the noise in the image. In Table 1, the threshold of wavelet denoising versus number of negative eigenvalues on slice 35 of the brain volume is shown. There is a reduction in the noise as shown by the reduction in negative eigenvalues on denoising with the proposed algorithm. However, there are no significant improvements beyond a threshold of 100. Currently, we are focused on integrating the criterion of positive definite within the multiscale/mutiband wavelet denoising algorithm.

Threshold	Number of -negative eigenvalues		Threshold	Number of –ve eigenvalues
0 (original)	21707		300	11538
50	16686		400	11357
100	14009		500	11310
200	12208			

Table1. Threshold of wavelet denoising vs. number of negative eigenvalues

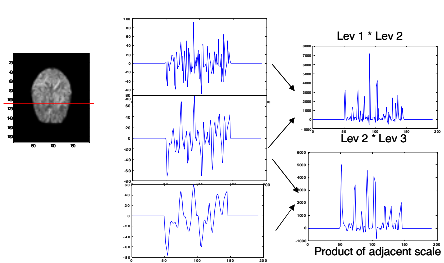

Fig.1. Left to right: location of line profile, wavelet coefficients of line profile at adjacent scales, product of wavelet coefficients at adjacent scales.

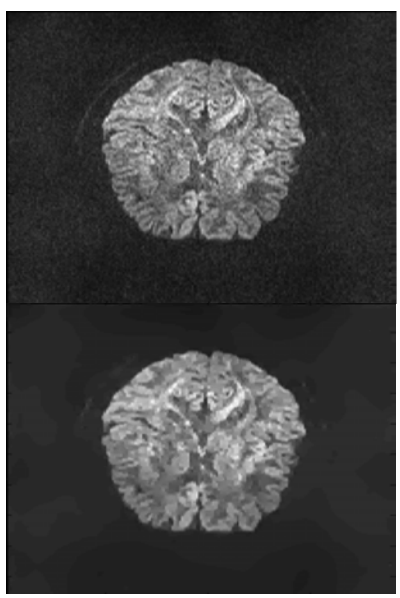

Fig.2. Above: Noisy image. Below: Denoised image.

Conclusions:

The wavelet denoising scheme utilizing signal correlation along scales is an effective and fast method to suppress noise. The visual and quantitative analysis justified our results.

References:

1. Y. Xu et. al., IEEE Transactions on Image Processing, vol.3, (6), 747-758, 1994.
2. P. Scheunders, IEEE Transactions on Image Processing, IEEE Transactions on Image Processing, Vol. 13, (4), p. 475-483, 2004.
3. S. Mallat and S. Zhong, IEEE PAMI, vol. 14, 710-732, 1992.
4. S. Grace Chang, B. Yu and M. Vetterli, S. Zhong, IEEE Transactions on Image Processing, vol. 9, (9), 1522-1531,2000.