4D WAVELET NOISE SUPPRESSION OF MR DIFFUSION TENSOR DATA

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ABSTRACT

Diffusion tensor imaging (DTI) is known to be promising for providing anatomical information about white-matter fiber bundles that cannot be obtained by other non-invasive in vivo imaging methods. However, its application is limited because of its low signal-to-noise ratio and significant imaging artifacts. To improve the accuracy of tissue structural and architectural characterization with diffusion tensor imaging 4D wavelet denoising technique is used to improve the signal to noise ratio (SNR) of diffusion tensor images. To evaluate the proposed method, a high SNR data set is built by repeating and averaging the data acquisition several times and is compared to the denoised data. Our results revealed that wavelets would effectively reduce the noise in DTI data with less blurring of tissue types, especially in the white matter. It would suggest that by using the 4D wavelet noise suppression, one could decrease the acquisition time and still have an acceptable SNR.

Index Terms— Diffusion Tensor Imaging, Fiber Tracking, Noise Suppression, Wavelets

1. INTRODUCTION

Diffusion tensor imaging (DTI) is a growing application of magnetic resonance imaging (MRI) technique that allows the in vivo estimation of water diffusion. Estimating the local diffusion of water provides unique information about the structure of brain bundles. Because of this unique ability, DTI has evolved into a main technique for noninvasive evaluation of white matter structure and is used in a variety of applications, from diagnosis of disease conditions such as schizophrenia, multiple sclerosis, stroke, and Alzheimer to microstructural characteristics of the brain.

In the human brain which is an anisotropic environment the diffusion is characterized by a symmetric tensor D [1]. This tensor is called diffusion tensor and contains six independent coefficients which describe the mobility of water molecules along each direction and correlation between these directions [2,1]. In DTI, these diffusion coefficients of water molecules are measured using diffusion-weighted MR measurements in at least six noncolinear directions.

One of the most promising applications of DTI is reconstructing the pathways of white matter structures in the brain, known as Tractography. Considering that, the axonal fibers are myelinated and consequently the diffusion in the direction of fibers is faster than in the perpendicular direction [2], dominant direction of water diffusion at each voxel represents the local direction of the fibers. So the eigenvector of diffusion tensor D associated with its largest eigenvalue (principal diffusivity) defines the tissues' local fiber-tract (principal direction). Based on this fact, tractography algorithms connect image voxels using the directional similarity of their principal directions [3].

Despite its promising applications, typical in vivo diffusion-weighted MR data suffers from low signal-to-noise ratio and harmful effects of experimental noise and imaging artifacts due to effects such as magnetic field inhomogeneities and eddy currents which make DTI highly sensitive to noise.

At low SNRs the eigenvalues of the diffusion tensor D diverge rapidly from their original values. Pierpaoli *et al.* [4] using a monte carlo simulation show that the background noise generates bias in the eigenvalues of diffusion tensors. They show that the sample mean of the largest sorted eigenvalues is always larger than its true value and the smallest one is smaller than its true value. This would result in a significant overestimation in of the degree of diffusion anisotropy within each voxel. This will cause cumulative errors which propagate to parameters calculated from the eigenvectors such as diffusion and tractography maps.

To obtain reliable tractography maps, it is necessary to have data with a high SNR at small voxel sizes. To achieve an appropriate SNR, one solution is multiple data acquisition and signal averages but this has the obvious drawback of increasing the total scanning time of the study which is undesirable. Due to the rigorousness of noise problem, one should trade off between the number of averages (SNR), quality of maps (Voxel size and number of slices), and the scanning time. In this paper, it is shown that using the noise suppression technique, one can reduce the severity of noise level in the DTI data and decrease its effect on tractography maps.

Different postprocessing algorithms have been employed by other investigators to improve the SNR of DTI data. Parker *et al.* [5] use a nonlinear diffusion filtering technique to reduce noise and show that applying filtering to calculated images of fractional anisotropy, fails in reducing the errors. In this paper, we apply the proposed denoising method to the diffusion-weighted MR images. Ding *et al.* [6] use anisotropic smoothing to reduce the noise in DTI.

The wavelet transform is an analysis tool that projects signals onto orthogonal and semi-orthogonal bases. Using wavelet transform, the energy of a signal is partitioned through a wavelet expansion to express simultaneous time (space) and frequency local information. Wavelets, due to their known advantages such as localization in space and frequency, have shown their ability for noise suppression. Wavelet methods have been previously used to enhance specific features and reduce noise in medical images [7]-[8] [9]. Considering these facts, compared to other methods previously used to smooth DTI images [5]-[6], wavelet-based noise reduction offers unique theoretical advantages for identifying a signal from noise; this was our intial motivation for using wavelet s for denoising.

In this research, we apply a 4D wavelet signal expansion along with the well-established wavelet shrinkage [10] for suppressing the noise. The proposed denoising method is applied to the diffusion-weighted MR images used to calculate the diffusion tensor. Our results reveal that applying the proposed method to raw data, leads to reduction in the propagation of noise related errors in calculation of diffusion tensors and DTI maps.

We evaluate the denoising method by analyzing a normal volunteer's DTI data and comparing it to the high SNR data obtained by several acquisitions and averaging of the DTI data. We compare the FA maps derived from high SNR data to that of denoised data. A comparison is also made by comparing the tractographs of the Fornix area (which is used as the standard index) of these datasets.

2. METHODS AND MATERIALS

2.1. Diffusion Data

Diffusion weighted images were acquired from a healthy human subject using a 3T GE MRI scanner (General Electric, Milwaukee, WI). Images were scanned using 25 noncolinear weighting directions and a single shot echo planar imaging (EPI) sequence with b value of 1000 sec/mm2. Each volume covers a 240 mm x 240 mm field of view with 0.9375 mm x 0.9375 mm in-plane resolution and 3 mm slice thickness. To generate a high SNR data, we repeated the above experiment 5 times for each subject and averaged the acquired data.

2.2. Wavelet Denoising

Step 1: 4D wavelet transform is applied to the noisy data. The wavelet basis may be chosen based on various factors including computational burden, and ability to compress the L2 energy of the signal into a very few, very large coefficients. In this study, different wavelet coefficients were examined and coifelet3 wavelet which revealed the best performance was used.

Step 2: Wavelet coefficients underwent a soft thresholding operation [10]-[12]. A threshold (λ) was determined according to the sampling number (*n*) and local statistics of the wavelet coefficients (Eq. 1). Then, a "soft thresholding" process reduced the amplitudes of the coefficients by λ. (Eq. 2)

$$\lambda = \sigma \times sqrt(2 \times \log(n)) \tag{1}$$

$$\eta_\lambda(x) = \begin{cases} x - \lambda; x >= \lambda \\ 0; |x| < \lambda \\ x + \lambda; x <= \lambda \end{cases} \tag{2}$$

Step 3: The shrunken set of coefficients obtained from step 2 were then padded with zeros to produce a legitimate wavelet transform. The result was inverted to obtain the estimate of the actual signal.

In this manner, the noise is largely suppressed while features in the original signal remain sharp after denoising in contrast with traditional linear methods of smoothing which trade-off noise suppression against a broadening of the signal.

2.3. Fiber Tracking

DTI provides a unique tool for investigating brain structures and assessing axonal fiber architectures in vivo. A conventional fiber-tracking algorithm is based on the Fiber Assignment by Continuous Tracking (FACT) approach, by which tracking is performed using a continuous coordinate system rather than a discrete voxel-based matrix grid.

First, for each voxel, three eigenvalues λ1, λ2, and λ3, which correspond to the three eigenvectors of the diffusion tensor at that voxel are calculated. These eigenvalues represent the magnitudes of diffusivity in three orthogonal directions. Based on these three diffusivities and the mean diffusivity, λ, (Eq 3) the fractional anisotropy (FA) is calculated using Eq 4 [13].

$$\lambda = \frac{\lambda_1 + \lambda_2 + \lambda_3}{3} \quad (3)$$

$$FA = \frac{\sqrt{3}}{\sqrt{2}} \frac{\sqrt{(\lambda_1 - \lambda)^2 + (\lambda_2 - \lambda)^2 + (\lambda_3 - \lambda)^2}}{\sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}} \quad (4)$$

FA value represents the degree of anisotropic diffusivity at each voxel. The fiber tracking starts at the center of each voxel having a fractional anisotropy (FA) value greater than a user-defined threshold (0.2 in our experiment), and proceeds along the principal eigenvector direction. At the point where the track intercepts the voxel's boundary, the tracking direction changes to that of its neighbor. Applying this tactic iteratively, a continuous fiber trajectory is obtained. Tracking is stopped at voxels where FA is lower than the threshold (FA threshold) or the angle between the two eigenvectors is greater than a user-defined threshold (angle threshold). DtiStudio software package is used in this work for the implementation of this method [13].

3. EXPERIMENTAL RESULTS

To evaluate the denoising method, a high SNR dataset is built by repeating the data acquisition 5 times and averaging the results. This high SNR dataset is used as the gold standard. Wavelet denoising and Gaussian filtering [14] were applied to diffusion-weighted images. FA maps were generated using the denoised DWIs and high SNR DWIs and effects of the denoising methods on the FA maps were evaluated. The error at each voxel was quantified as the root mean square error between the high SNR FA map and the denoised data FA map. The performance of the methods was evaluated by computing the Root Mean Square Error (RMSE) in the brain tissues and white matter alone. The estimated values for the brain tissues are compared in Fig. 1.

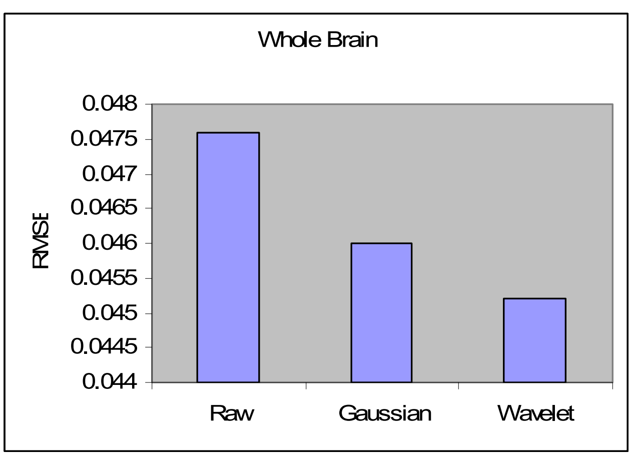

Fig. 1. The effect of denoising on FA map of the whole brain.

Note that the wavelet denoising considerably decreases the error. Since in the DTI tractography we are more interested in regions with anisotropic diffusion, we also made comparison of the FA values in the white matter. The estimated errors in the white matter are plotted in Fig. 2. It can be seen that wavelet denoising again generates the lowest error.

The effect of the denoising methods on the tracking of the fibers is also evaluated. The Fornix fibers have been chosen as an index. For reconstruction of the Fornix, we placed a single ROI at the level of the column of the Fornix as it becomes vertical in its most anterior segment. The 3D reconstructed fibers after denoising (Fig. 3) demonstrate white matter connections between the hippocampal region and the septal region and the mamillary bodies. The reconstructions also include fibers of the mamillo-thalamic tract. As can be seen without noise suppression, the fornix fibers could not be reconstructed properly. The result of the Gaussian filtering was very similar to that in Fig 4.a and is not shown due to page limitations.

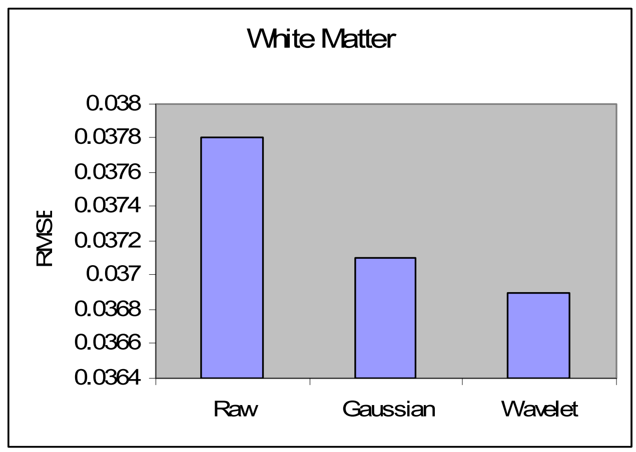

Fig. 2. The effect of denoising on FA map of White Matter.

4. DISCUSSION AND CONCLUSION

In this paper, wavelet shrinkage was investigated for suppressing the noise in diffusion tensor image data. To evaluate the effect of the wavelet denoising on in-vivo DTI data, diffusion weighted images were acquired from a healthy human subject. FA maps of the whole brain and white matter was compared to that of our gold standard which was generated by repeating the acquisition several times. The effect of wavelet denoising on tractography maps was also investigated. Fiber tracts were estimated using the dominant eigenvector field obtained from the diffusion tensor image. According to our results, wavelet denoising would reduce the noise of the FA maps more effectively compared to the Gaussian filtering. However, in the white matter which is pretty homeogenious, the difference is less compared to the whole brain.

(a)

(b)

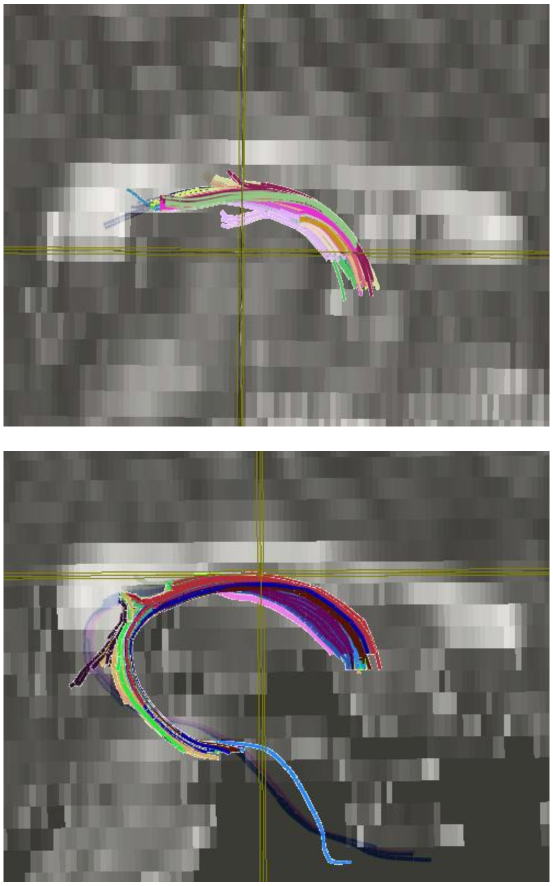

Fig. 3. Reconstructed fibers (Fornix): a) without denoising b) with wavelet denoising.

An interesting point is that although the improvement in the FA maps is not very large but an obvious improvement in the fiber tract maps is resulted. Errors in the fiber tract maps are due to the propagation of errors induced by noise and confounding effects and are very sensitive to noise. Therefore, a small improvement in the FA maps quality will often lead to a considerable improvement in the fiber tracts. Results of white matter fiber tract mapping after wavelet denoising revealed that the fiber tracts are quite accurate when validate visually and correspond well with known anatomical structures such as the Fornix. It seems that using wavelet denoising, it is possible to decrease the acquisition time by avoiding multiple acquisitions and still be able to reconstruct acceptable fiber tracts.

6. REFERENCES

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