DTI Crossing Fibers Estimation Using Fast Independent Component Analysis*

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***Abstract*—Tracing fibers in voxels containing multiple fiber tracts has been an important problem in white matter fiber tractography using Diffusion Tensor Magnetic Resonance Imaging (DT-MRI) data. In order to solve this problem, based on the fact that DTI signals have super-Gaussian pdf's, fast Independent Component Analysis (ICA) is applied to decompose the original DTI signal from voxels containing multiple fibers into its non-Gaussian components. Tractography is then done based on the eigenvectors of the new components. In this approach, the voxels with crossing fibers are identified based on the orientation difference, number of fibers coexisting in a voxel, and the C_p value. Results show more reconstructed fibers by the proposed method compared to the previous methods.**

I. Introduction

Diffusion Tensor Imaging (DTI) is a Magnetic Resonance Imaging (MRI) technique that provides information about the random motion of water molecules referred to as Brownian motion. The water diffusion is anisotropic in the brain white matter. In fact, water tends to diffuse predominately in a direction parallel to the axons, so this anisotropy can reveal microscopic properties of the anatomy of the nerve fibers. Therefore, DTI can be used to no-invasively assess white matter fiber pathways and also to build connectivity maps [1].

One of the major concerns in in-vivo white matter fiber tractography is the tracing of the fibers in voxels containing multiple fibers with different orientations. In conventional streamline tracking methods, the direction of the eigenvector corresponding to the largest eigenvalue of the diffusion tensor is considered to be the local direction of the fiber pathways [1]-[2]. However, this direction is not valid in voxels with multiple fibers.

In order to solve this problem, we should determine which voxels contain crossing voxels. It is known that in voxels containing non-parallel fibers, the linear anisotropy (C_l) is low but parallel anisotropy (C_p) is high. However, determination of an appropriate threshold for C_p is difficult. In addition, the position where fibers cross affects the C_p value [3].

As can be seen in Fig. 1, a crossing has occurred but the C_p value is low. So, using the C_p value will not be sufficient for accurate classification of crossing voxels.

In this paper, we consider a voxel to be a crossing voxel if: 1) multiple fibers coexist in that voxel; and 2) the C_p value is sufficiently high.

We employ conventional Independent Component Analysis (ICA) to decompose multiple tensors for the voxels identified as containing crossing fibers. This method is called "fast ICA" and finds multiple non-Gaussian sources from multi-channel data by maximizing their non-Gaussianity [4].

II. Methods and Materials

A. Determining Crossing Voxels

We identify a voxel with crossing fibers based on the following criteria: 1) multiple fibers coexist in the voxel; and 2) the orientation difference in the previous voxel exceeds a certain degree [3]; and C_p is larger than a threshold. According to the fact that white matter fibers have low curvatures, two fibers with large orientation differences in the previous voxel maintain their difference when they meet in the so called crossing voxels.

To this end, we ran the streamline tracking algorithm in the whole brain. Then, a Region of Interest (ROI) was selected and each of the voxels within this (ROI) was checked whether they were contained in multiple fibers or not. If yes, the fibers containing the selected voxels were

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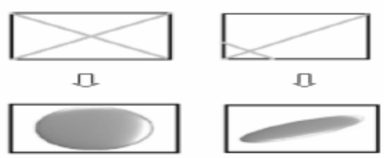
listed and the orientation difference between these fibers in a step before reaching the desired voxel was calculated.

When the maximum orientation difference between all possible pairs of fibers passing through a voxel exceeds a specified threshold, this voxel will be defined as a crossing voxel.

The orientation difference of the two fibers is calculated as [3]:

$$OD(r) = Max(\arctan(\frac{v_i^1}{v_3^1}) - \arctan(\frac{v_i^2}{v_3^2})) \qquad (1)$$

where v_i corresponds to the *i-th* eigenvector.



(a) High C_p value (b) Low C_p value

Fig. 1. Position of crossing fibers affects the value of C_p. For (b) we expect a high C_p value due to the crossing but this value is low [3].

Among the selected voxels, those having C_p value less than a selected threshold were discarded. In previous studies, the threshold was set at 0.3 [4], while in this work, the threshold is set at a lower level. The reasons for the above setting were consideration of the pervious two criteria and selection of crossing voxels with low C_p value.

Having identified the crossing voxels, it is time to decompose their DTI signals into non-Guassian components.

B. Decomposition of DTI Signal

According to the fact that the width of a fiber tract may be more than the dimension of a voxel, crossing fibers can cover several neighboring voxels [4]-[5]. In the proposed approach, it is assumed that it covers 19 adjacent voxels (see Fig. 2) [4].

The data matrix X was constructed for the cubic window described above. Each element of X, x_{ij}, correspond to *i-th* voxel and *j-th* gradient DTI signal and is defined by the logarithm of the division of the *j-th* gradient signal $s(g_j, b)$ by the *j-th* gradient signal $s(g_j, b=0)$ [4].

$$x_{ij} = \log\left(\frac{s(g_j, b)}{s(g_j, b=0)}\right) \qquad (2)$$

When we have 25 gradient DTI signals, matrix X will be 19 x 25.

	x_{1j}	
x_{2j}	x_{3j}	x_{4j}
	x_{5j}	

x_{6j}	x_{7j}	x_{8j}
x_{9j}	x_{10j}	x_{11j}
x_{12j}	x_{13j}	x_{14j}

	x_{15j}	
x_{16j}	x_{17j}	x_{18j}
	x_{19j}	

Fig. 2. The cubic window used for the construction of data matrix X. Left and right windows correspond to voxels located in a lower and upper slice in 3-D neighborhood of the central voxel [4].

After construction of the measured data matrix X, fast ICA was used to extract a new set of statistically independent vectors of Y called independent components [6]:

$$\mathbf{Y=WX} \qquad (3)$$

where **W** is the unmixing matrix whose columns contain unmixing weights corresponding to individual sources [6]. Here, it was assumed that the source signals were decomposed into two independent components using a deflationary orthogonalization method that finds the components sequentially. Each of the components corresponds to one of the crossing fibers.

C. Fiber Tracking

The two estimated independent components were first projected onto the data space. The first and second components of the central voxel (10-th component) were used to construct two diffusion tensors. In the next step, the eigenvectors and eigenvalues of the constructed diffusion tensors were calculated and then fiber tracking was performed using FACT (Fiber Assignment by Continuous tracking) algorithm.

In the FACT algorithm, the 3-D trajectories are reconstructed from a 3-D vector field by propagating a line from a seed point by following the local vector orientation. The propagation direction is alerted at voxel boundary interfaces. Line propagation is terminated according to the following 2 criteria: 1) The extent of anisotropy. In low anisotropy regions, such as gray matter, the fractional anisotropy is in the range of 0.1-0.2. In such regions the fastest diffusivity direction is not well defined and the largest principle axis is prone to noise error. So the FA threshold for propagation termination can be set to 0.2. 2) Large angular change. In diffusion tensor calculation, it is assumed that there is no sharp turn during line propagation. We have considered the angle-change threshold to be 45° [1].

The tractography was done twice, once selecting the ICA component corresponding to the larger primary eigenvalue and once for the other component.

III. EVALUATION OF FAST ICA

In order to evaluate the performance of fast ICA, DT-MRI data were simulated for two crossing fibers which cover five voxels with different mixing ratios in each voxel. The angle between the crossing fibers were considered to be 45 degrees.

The estimated fiber tracts can be seen in Fig. 3. The mixing ratio of the two horizontal (black bar) and diagonal (gray bar) tracts, considered in this estimation were 0.5:0.58 in the central voxel and 0:0.58, 0.5:0.06, 0.5:0.06 0:0.58, in four adjacent voxels [4]. ICA was applied to data matrix X constructed based on the estimated fiber tracts. The mean error in 100 trails was 12.8° which showed almost reliable performance of fast ICA.

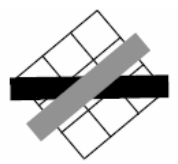


Fig. 3. Position and orientation of two horizontal (black bar) and diagonal (gray bar) crossing fibers [4].

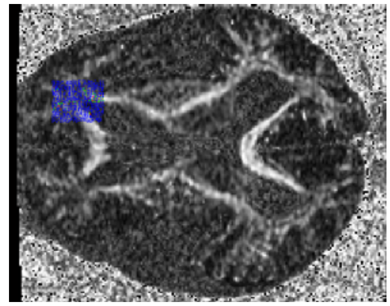
IV. DATA ACQUISITION

The DTI data used in this experiment were acquired using a 1.5 Tesla, 63.8859 MHz, GE Signa System (GE Medical Systems, Milwaukee, WI), 256x256 matrix, 29, 5mm thick slices, 25 gradient directions with $b=1000\, s/mm^2$ and one $b=0$ acquisition.

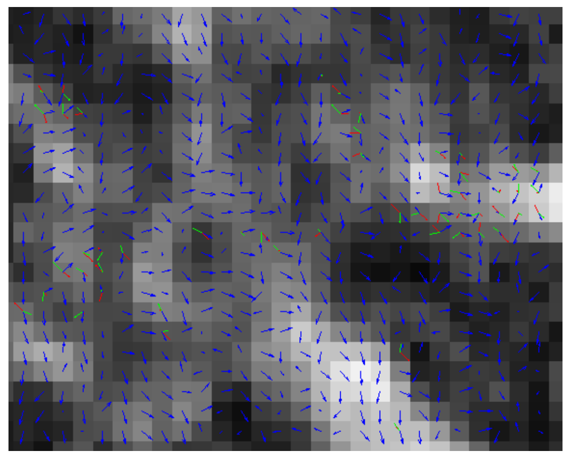
V. EXPERIMENTAL RESULTS

Results of the ICA decomposition are shown in Fig. 4. The selected ROI is indicated by a blue box in Fig. 4(a). This region is likely to contain several crossing fibers. The blue arrows in Fig. 4(b) correspond to the primary eigenvectors of voxels in the selected ROI. The red and green arrows represent the primary eigenvectors of the two independent components corresponding to the voxels identified as crossing voxels, with maximum angular difference > 20 degrees and C_p value > 0.08.

The fiber tractography results for the selected ROI are shown in Fig. 5. Fiber tracts represented in Fig. 5(a) and Fig. 5(b) are obtained using conventional FACT tracking algorithm where Fig. 5(c) and Fig. 5(d) are the reconstructed fibers using FACT algorithm by considering two independent components. As seen in the figures, the second method results in tracking of many more fibers. Table I illustrates the quantitative difference between the two methods.



(a)



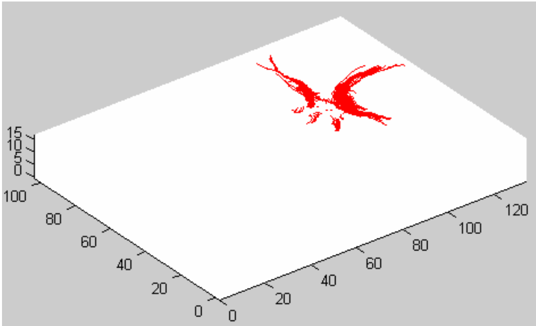
(b)

Fig. 4. Results of decomposition of the DTI signal. In (a) the blue box shows the selected ROI. In (b) the blue arrows indicate the eigenvectors calculated from the original DTI signal whereas red and green arrows represent the eigenvectors obtained from the independent components.

TABLE I

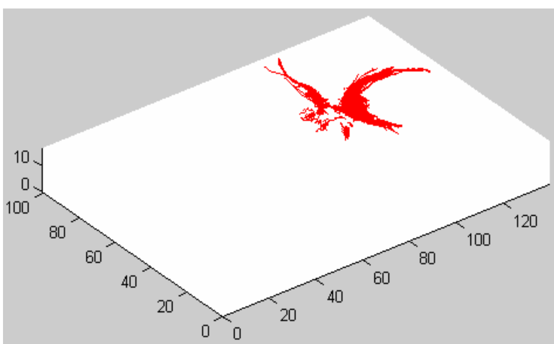
Quantitative Evaluation of Reconstructed Fibers.

Tractography Algorithm	Number of Reconstructed Fibers
Conventional FACT Tractography	169
Fast ICA +FACT Tractography	353

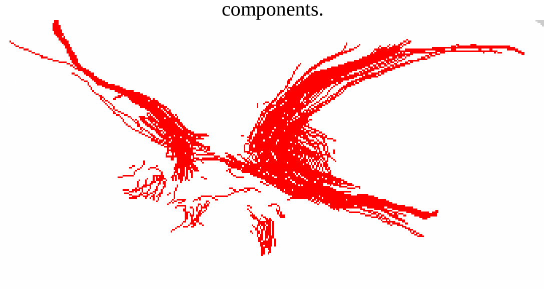


(a) Reconstructed fiber tracts using the conventional streamline tracking algorithm.

(b) Zoomed image of fibers in (a).



(c) Reconstructed fiber tracts considering the two independent components.



(d) Zoomed image of fibers in (c).

Fig. 5. Fiber tracking results

VI. CONCLUSIONS

White matter fiber tractography in voxels containing multiple fibers is a difficult problem. In solving the problem, the main concerns are: 1) How to identify the voxels containing the crossing fibers; 2) How to perform the fiber tractography.

In this work, for the identification of the crossing voxels, in addition to the C_p value, coexistence of multiple fibers and their orientation differences were considered as well. Then, fast ICA method was used to decompose the DTI source signals of the selected voxels into two non-Gaussian components. Next, a FACT tractography algorithm was preformed twice, once for each of the independent components. Although experimental results showed better reconstruction of fiber tracts, cross-validating the results are not yet possible via noninvasive methods.

In this study, we limited the number of crossing fibers to two and estimated two independent components each corresponding to one of the crossing fibers. However, since ICA works as long as the number of independent sources to be estimated is less than the number of input channels, and we have nineteen input channels in this study, additional fibers within a voxel can be detected in the future work.

ACKNOWLEDGMENT

In this work the code for fast ICA was obtained from http://www.cis.hut.fi/projects/ica/fastica.htm.

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