Estimation of Multiple Fibers per Voxel Using Fast Independent Component Analysis*

Ch. Khodaverdian, H. Soltanian-Zadeh, *Senior Member, IEEE*

***Abstract*—Estimation of multiple fiber tracts with different orientations within a voxel 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. In this paper, we present a new method for tractography, which considers the eigenvectors of the independent components simultaneously. The voxels with crossing fibers are identified based on the orientation difference, number of fibers coexisting in a voxel, and the high parallel anisotropy value. Results show more reconstructed fibers by the proposed method compared to the previous methods.**

***Key words*—Fiber tracking, Diffusion Tensor Imaging, Independent Component Analysis, FACT**

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].

Ch.Khodaverdian is with the Control and Processing Center of Excellence, Electrical and Computer Engineering Department, University of Tehran, Tehran 14395-515, Iran (email: christin_mkh@yahoo.com).

H.Soltanian-Zadeh is with the Control and Processing Center of Excellence, Electrical and Computer Engineering Department, University of Tehran, Tehran 14395-515, Iran and Image Analysis Laboratory, Radiology Department Henry Ford Health System, Detroit MI, 48202 USA (emails: hszadeh@ut.ac.ir; hamids@rad.hfh.edu).

*This work was supported in part by the Iran Telecommunication Research Center (ITRC), Tehran, Iran.

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, voxels containing crossing fibers should be determined. It is known that low linear anisotropy (C_l) value as well as high parallel anisotropy (C_p) value indicates intra-voxel orientation heterogeneity, but due to the lack of an accurate relationship between these values and fiber direction difference, determination of an appropriate threshold for them is difficult. Moreover, the position where fibers cross affects the C_p value [3].

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

In this paper, we consider a voxel to be a crossing voxel if: 1) multiple fibers coexist in that voxel; 2) the orientation difference in the previous voxel exceeds a certain degree; and 3) C_p is larger than a threshold.

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].

In the previous work [4], the eigenvectors calculated from the two decomposed diffusion tensors were classified into two classes, the ones corresponding to the larger primary eigenvalue and those corresponding to the smaller ones. Then, for the reconstruction of fiber tracts, tractography was done twice, each time considering one of the eigenvector classes [4]. But in this paper a new method is proposed in which during the tractography both eigenvectors of the crossing points are considered simultaneously. As a result, eigenvectors of two classes are combined and a fiber is reconstructed containing eigenvectors of the two classes.

II. METHODS

A. Determining Crossing Voxels

In this method, crossing voxels are identified based on the following criteria: 1) coexistence of multiple fibers in the voxel; 2) fiber orientation difference in the previous voxel exceeds a certain degree [3]; and 3) 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.

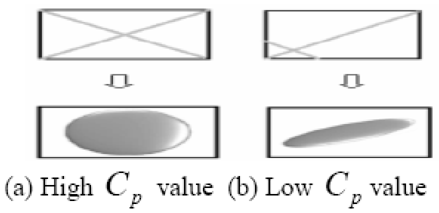


Fig. 1. Position of crossing fibers affects the value of C_p. For (b) we expect a high C_p value due to the crossing but this value is low [3].

To this end, we run the streamline tracking algorithm in the whole brain. For each of the voxels in a selected ROI we specify two signs: 1) a number-sign which stores the total number of tracts passing through that voxel; and 2) index-sign which specifies the fibers passing through the specified voxel. In the next step, the number-sign of the voxels is checked. If it is more than two, the fibers containing the selected voxels are listed according to the index-sign and the orientation difference between these fibers in a step before reaching the desired voxel is calculated. When multiple fibers enter the same voxel and also the maximum orientation difference between all possible pairs of fibers passing through a voxel exceeds a specified threshold, this voxel is defined as a crossing voxel.

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

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

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

Among the selected voxels, those having C_p value less than a selected threshold are discarded. In previous studies, the threshold was set at 0.3 [4], while in this work, the threshold is set at a lower level (0.08). The reasons for the above setting are consideration of the pervious two criteria and selection of crossing voxels with low C_p value.

After the identification of the crossing voxels, it is time to decompose their DTI signals into statistically independent, 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 is constructed for the cubic window described above. Each element of X, x_{ij}, corresponds 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].

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

When 25 gradient DTI signals are available for each of the voxels, dimension of data 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].

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

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

where **W** is the unmixing matrix whose columns contain unmixing weights corresponding to individual sources [6]. In fact, the main goal of fast ICA is to determine the unmixing matrix such that a representation, in which the transformed components are statistically as independent as possible, is found. This is done using a deflationary orthogonalization method that finds the components sequentially. Here, it is assumed that the source signals are decomposed into two independent components each corresponding to one of the crossing fibers.

C. Fiber tracking

First, the two independent components are projected on to the data space. Two diffusion tensors are constructed based on the first and second components of the central voxel (10-th component). In the next step, the eigenvectors and eigenvalues of the constructed diffusion tensors are calculated and then fiber tracking is 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 altered 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 50° [1].

In the previous study, in order to reconstruct fiber tracts, tractography is done twice once selecting the ICA component corresponding to the lager primary eigenvalue and once for the other component [4]. However, in this approach seed points, classified as crossing voxels are visited twice once for each of the components and also, during the tractography both eigenvectors of the crossing points are considered simultaneously and the fiber tracking is done as described below.

For each of the seed points, the FACT algorithm is performed. Whenever the fiber tract reaches a voxel containing two components, classified as a crossing voxel, the angular change between the previous step's eigenvector and the two eigenvectors of the current step are calculated. In this case, one of the following situations would occur:

1. The angular change for both of the eigenvectors exceeds the selected threshold.
2. The angular change for one of the eigenvectors satisfies the angular change criteria.
3. Both of the eigenvectors satisfies the angular change criteria.

In the first case the tractography is terminated while in the second case it continues, considering the eigenvector satisfying the angular change criteria. In the third case, both eigenvectors are considered. First a stack is created which stores information containing the coordinates of the crossing voxel and one of the two eigenvectors. Then, tractography continues in the direction of the remaining eigenvector. If the same situation occurs during the propagation of the tract, the above mentioned information is added to the stack and the tractography continues considering one of the eigenvectors. When the tracking is terminated, the information stored in the stack are taken respectively from up to bottom and each time the tractography is continued from the specified point in the direction of the stored eigenvector. This process continues until stack becomes empty. In the next step, tractography is performed for the next seed point.

The advantages of this approach over the previous one are:

1. Tracks originating from one of the classes can be continued by the eigenvectors of the other class.
2. The eigenvectors of two classes are combined and a fiber can be reconstructed containing eigenvectors of two classes.
3. More fibers are reconstructed.

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.

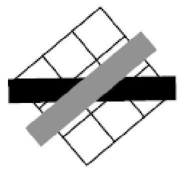
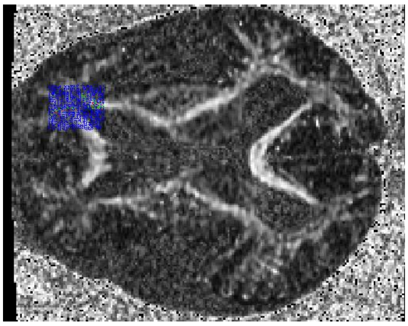


Fig. 3. Position and orientation of two horizontal (black bar) and diagonal (gray bar) crossing fibers [4].

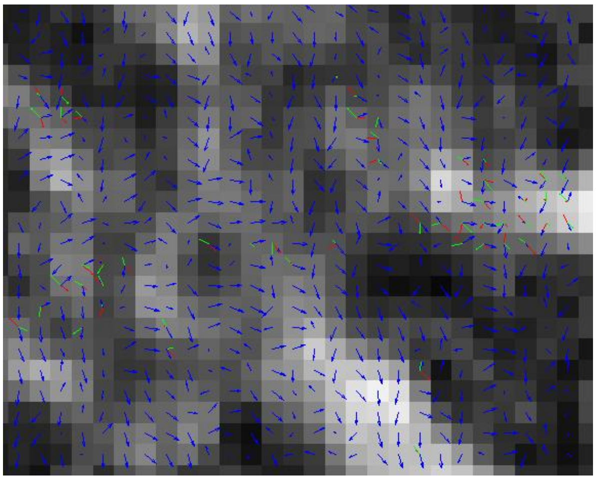
IV. Experimental Data and Results

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

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



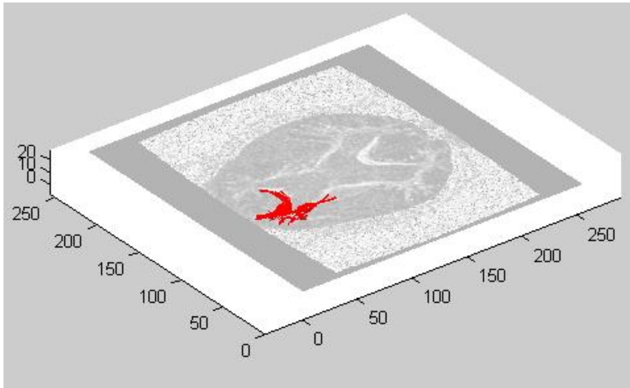
(a)



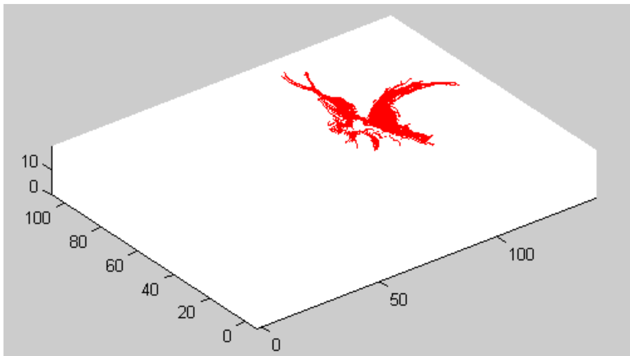
(b)

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.

Fig. 5 shows results of the fiber tractography for the selected ROI. Fiber tracts represented in Figs. 5(a), 5(b), and 5(c) are obtained using conventional FACT tracking algorithm. Figs. 5(d), 5(e), and 5(f) show the reconstructed fibers using FACT algorithm by considering two independent components separately. Finally, Figs. 5(g), 5(h), and 5(i) correspond to the reconstructed fibers using FACT algorithm by considering two independent components simultaneously. In Figs. 5(a), 5(d), and 5(g) the fiber tracts are overlapped on the FA map of the 14-th slice while, in the rest of them fibers are shown separately. Table I illustrates the quantitative differences between the three methods. As is apparent from the table and the figures, the largest number of reconstructed fiber tracts corresponds to the third method.



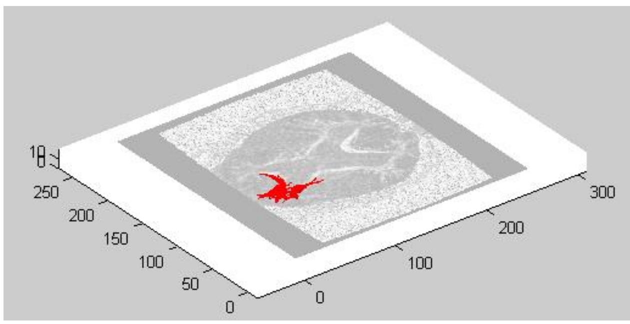
(a) Reconstructed fiber tracts using the conventional streamline tracking algorithm overlapped on the FA map of 14-th slice.



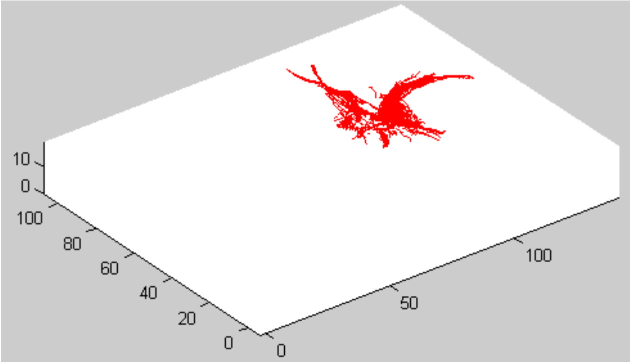
(b) Reconstructed fiber tracts using the conventional streamline tracking algorithm.

(

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

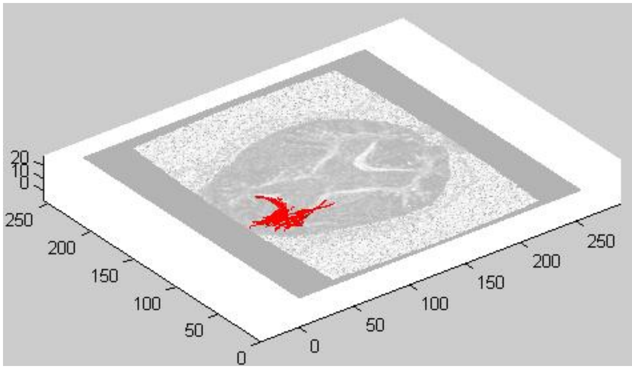


(d) Reconstructed fiber tracts considering the two independent components separately, overlapped on the FA map of 14-th slice.

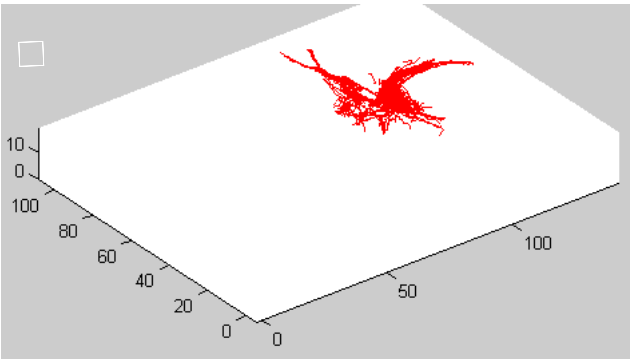


(e) Reconstructed fiber tracts considering the two independent components separately.

(f) Zoomed image of fibers in (d), (e).



(g) Reconstructed fiber tracts considering the two independent components simultaneously, overlapped on the FA map of 14-th slice.



.(h) Reconstructed fiber tracts considering the two independent components simultaneously.

(i) Zoomed image of fibers in (g), (h).

Fig. 5. Fiber tracking results.

TABLE I
Quantitative Evaluation of Reconstructed Fibers.

Tractography Algorithm	Number of Reconstructed Fibers
Conventional FACT Tractography	252
Fast ICA +FACT Tractography considering two IC's separately	386
Fast ICA +FACT Tractography considering the two IC's simultaneously	415

V. Summary and Conclusion

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 in the previous voxel were considered as well. Then, fast ICA method was used to decompose the DTI source signals of the crossing voxels into two non-Gaussian components. For the reconstruction of fiber tracts, a new tractography method using the FACT algorithm was performed. Although experimental results showed better reconstruction of fibers and visually enhanced continuity in white matter tracts through the ROI, cross-validating the results are not yet possible via noninvasive methods.

In this study, the number of crossing fibers was limited to two and each of the estimated independent components corresponds 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 19 input channels in this study, additional fibers within a voxel can be detected in the future work.

ACKNOWLEDGMENT

The code for fast ICA was obtained from http://www.cis.hut.fi/projects/ica/fastica.

REFERENCES

[1] S. Mori, P.V. Zijl, "Fiber tracking: principles and strategies- a technical review," MNR in Biomedicine. vol. 15, pp. 468-480, 2002.

[2] H. Jiang, P.V. Zijl, J. Kim, G.D. Pearlson, S. Mori, "DTI Studio: Resource program for diffusion tensor computation and fiber bundle tracking," Elsevier, Computation and Programming in Med. vol. 81, pp. 106-116, 2006.

[3] M. Wang, W. Gao, X. Zhao, H. Liu, D. Li, "Modified method for classifying crossing and non-crossing voxels in fiber reconstruction," 27th annual IEEE conference, Engineering in Medicine, pp. 3082-3085, 2005.

[4] J.W. Jeong, M. Singh, "Multiple fibers per voxel detection by fast independent component analysis," *IEEE International Symposium on Biomedical Imaging*, pp. 49-52, 2006.

[5] S.H. Kim, J.W. Jeong, M. Singh, "Estimation of multiple fiber orientation from diffusion tensor MRI using independent component analysis," *IEEE Trans*. Nuclear Science, vol. 52, no. 1, pp. 266-273, Feb. 2005.

[6] A. Hyvarinen, "Fast and robust fixed-point algorithm for independent component analysis," *IEEE Trans. Neural Networks,* vol. 10, no. 3, pp. 626-634, 1999.