NEURORADIOLOGY

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Improvement of White Matter Fiber Tracking Based on Diffusion-Tensor MR Imaging Data Using Modified Speed Functions

Background/Objective: White matter tractography is a non-invasive method, which reconstructs three-dimensional trajectories of the brain tracts using diffusion-tensor imaging (DTI) data. Due to the partial volume effect of DTI data, some of tractography algorithms are unable to follow the correct pathways after the crossing and branching regions. The main challenge for tractography methods has been the ability to detect these regions. Fast marching techniques are capable of tracking the fibers with wide spreading.

Materials and Methods: In order to detect true fibers, an adaptive functional anisotropy (FA) weighted function is proposed to modify the speed function of these algorithms. The performance of the proposed tractography method is assessed using synthetic data and its feasibility is showed by extracting some well-known tracts using healthy human DTI datasets.

Result: The percentage of the length of whole tracts extracted by our proposed method is above 85% even for a signal to noise ratio (SNR) level equal to 16. The ability of this method to detect the fiber crossing in simulation data is above 90%. Furthermore, the tractography results of some well-known tracts demonstrate the ability of the proposed methods to extract the correct pathways from the anatomical point of view.

Conclusion: This method has led to great impact on the fast-marching fiber-tracking method in propagating the tractography front in an adaptive manner. The suggested speed function can make the speed of front propagation adapted to the type of brain's environments such as isotropic and anisotropic regions.

Keywords: Diffusion Tensor Imaging, White Matter Tractography, Fast Marching Algorithm, Fractional Anisotropy, Fiber Crossing

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Introduction

Diffusion-Tensor Imaging (DTI) is a non-invasive tool used for measuring the diffusion of water molecules and estimating the orientation of white matter neural fibers based on Magnetic Resonance Imaging (MRI). Diffusion is a random physical phenomenon, which may be observed microscopically in any material with a temperature above zero degree Kelvin. Due to this thermal energy, molecules are propagated in all directions in space. In isotropic environments, the molecules spread out equally in all directions, whereas in anisotropic regions, diffusion is restricted by some macromolecules or cell membranes. The white matter of the brain is an anisotropic tissue containing axons of neurons with myelin sheaths restricting the motion of water molecules. Diffusion in directions parallel to the white matter tracts is at least twice faster than perpendicular directions.[1,2] Thus, the directions of the white matter tracts may be found by finding the direction of the maximum diffusion in brain voxels.

Diffusion properties of the neural pathways may be obtained by the DTI technique, where a symmetric 2nd-order tensor is assigned to each image voxel. The principal eigenvector of each voxel's tensor represents the direction of white

matter fiber bundles. Measurements of the diffusion tensor may be used to investigate white matter pathways in the brain and to help neurosurgical planning methods. This information can also be used to assess white matter diseases like Multiple Sclerosis, Schizophrenia, Alzheimer, and Epilepsy.[2]

White matter fiber tracking methods are one of the most important applications of DTI data which are used non-invasively to reconstruct the three-dimensional trajectories of fiber pathways. Several tractography algorithms have been used to reconstruct the neural pathways and connect the brain regions. Due to the limitation of the diffusion tensor model, i.e., intra-voxel orientation heterogeneity (IVOH), some of these tractography algorithms are unable to detect correct pathways in the crossing and branching fibers.

Assessing the strategies of the proposed fiber tracking algorithms, the current tractography methods are categorized into three groups: (1) line propagation methods, (2) probabilistic fiber-tracking algorithms, (3) global energy minimization techniques. The simplest line propagation method is called the principal diffusion direction method (PDD) which propagates a line along the direction of the principal eigenvector of each voxel's tensor. In this method, tracking starts from a user defined seed voxel and follows its main eigenvector direction to enter the next voxel with a fractional anisotropy value higher than the predefined threshold.[3-5] FACT,[6] Streamline,[7] EZ-Tracing[8] and TEND[9] algorithms are the other methods following this approach.

Probabilistic techniques are hybrid methods in which probabilistic diffusion estimates are merged with the deterministic line propagation methods. In these algorithms, a probability distribution function (PDF) is assigned to each voxel to describe the uncertainty and multiple fiber orientations.[10,11] In another approach, Behrens et al. (2003) used the information of the tensor model to estimate a maximum likelihood solution for the fiber orientation in each voxel.[12] The probabilistic methods are more time consuming than the deterministic methods, but they can generate better results in the branching regions.

The energy minimization algorithms are classified as the third category. The fast marching, FM,[14] is one of these algorithms in which a front spreads out from a seed point or area. The evolution of the front is controlled by a speed function based on the co-linearity of principal eigenvectors. In another attempt, Campbell et al. performed the fast marching algorithm using the HARDI data[15-17] as well as DTI data. In this algorithm, which is called flow-based fiber tracking, the orientation density function (ODF) of HARDI data was utilized to obtain a good performance in the fiber crossing regions. Jackowski et al. (2005) defined a speed function based on the distance between the diffusion ellipsoid center and the point wherein the normal direction is calculated.[18] The advanced fast marching (AFM) is another modification of fast marching tractography where four different speed functions are used according to the tensor shapes.[19,20] This algorithm had better results in fiber crossing detection than the standard fast marching.

In the previous front propagation algorithms, the direction of eigenvectors determines the speed value for the entrance to the next voxel. These methods consider fractional anisotropy (FA) threshold for selecting the front voxels. Thus, the correct detection of fibers depends on the correct selection of the FA threshold. If a low FA threshold is selected, several false pathways may be extracted and if a high value is selected, the front may not enter the low anisotropy crossing regions such as the oblique crossing regions.

The method presented in this paper considers the effect of anisotropy strength of tensors as well as the directions of eigenvectors in a modified FA weighted fast marching speed function. This modification makes the speed function change adaptively according to the diffusion anisotropy of the brain environments (i.e., isotropic and anisotropic regions). The performance of the anisotropy weighted front evolution method is assessed using synthetic data and its feasibility is shown by extracting some well-known tracts using healthy human DTI datasets.

Materials and Methods

In the fast marching (FM) tractography algorithm, the speed function changes according to co-linearity of the eigenvectors of the two neighboring voxels, whereas all three eigenvalues of each tensor are important since they define anisotropy strength and therefore have a role in forming the ellipsoidal shape
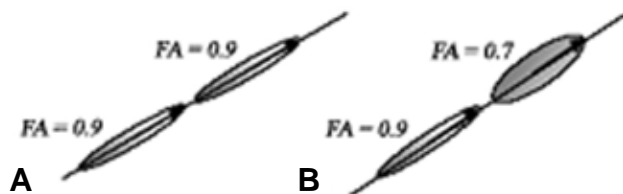
Fig. 1. Local connection samples of two neighboring voxels with the same diffusion orientation but different FAs.

of the tensor.[14] The ordinary FM speed value becomes maximal for the connection between two voxels with full co-linearity without considering the strength of anisotropy. Figure 1 schematically shows two samples of local connections, where the speed values are equal for these two samples. The local connection shown in Figure 1A is stronger and the second voxel may be added to the front.

Since the original FM speed function is only based on the diffusion orientation without considering the role of diffusion anisotropy, it is valuable to take into account the effect of the diffusion anisotropy as well. Fortunately, a latest algorithm called advanced fast marching (AFM) does this job by considering different speed functions based on tensor shapes.[19] Figure 2 shows the defined connections of AFM (Figs. 2A-D) along with some other possible connections (Figs. 2E-K) which may happen. Although the diffusion orientation in each pair of voxels is co-linear, the eigenvalues are different.

In our proposed method, we applied the product of FA values of the two neighboring voxels to adapt the speed function based on the strength of tensors. This speed function is computed by the following equation, which we call, FA weighted fast marching

(FAW-FM) speed function:

$$S_{FAW}(q) = W(p,q).S(q)$$

where $W(p,q) = FA(p)FA(q)$ is called the adaptive FA weighted function[21] and S(q) is the speed function computed by Parker et al. (2002) in FM.[14] In the FAW-FM algorithm; based on $W(p,q) \leq 1$, this new speed function may be viewed as a function of the percentage of the speed value computed in the FM ($S_{FAW} \leq S$). In this approach, the effect of the anisotropy for any type of connection between every pair of voxels as well as their diffusion co-linearity may be considered. This also gives more weighting to the higher values of FA specifying how strongly the diffusion is directed along the principal eigenvector orientation.

In order to implement our proposed method to the AFM algorithm,[19] we multiplied the adaptive FA weighted function to its speed functions and called it FAW-AFM. The wide narrow band of the AFM method is also considered in this modification. Unlike the AFM, the FA threshold is not considered for selection of the front voxels, therefore the front may be entered into the low anisotropy regions with an adaptive manner.
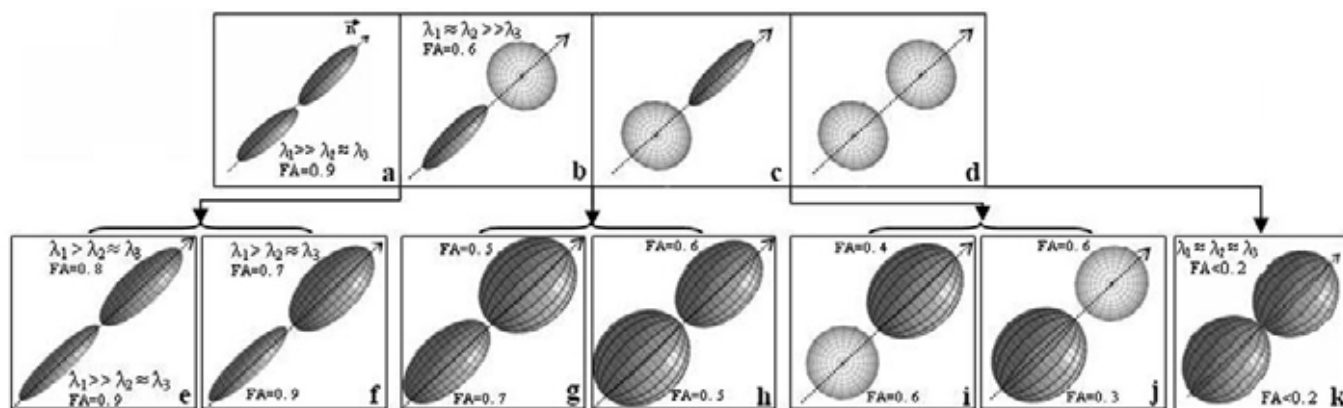

Fig. 2. (A-D) Four defined connections in the advanced fast marching algorithm and (E-K) samples of other possible conditions.

Evaluation process

Synthetic Fibers: In order to evaluate the proposed methods in the fiber tracking detection, some synthetic fibres were generated. For this purpose, some known tracts were extracted from a normal human brain DTI data. These tracts were simple fibers without crossing in their pathways but with different bending angles. In addition, some crossing fibres extracted from the same DTI dataset were used for evaluation of crossing detection. An image sample of these fibres is shown in Figure 3A. In this method, the tensors of the extracted fibres were computed and placed in their corresponding locations. Then, in order to generate the desired random FA values less than 0.25, the background tensors were calculated with random orthogonal eigenvectors and the selected eigenvalues. Therefore, realistic fibers were generated in this synthetic DTI dataset. Figures 3B & C shows a region of interest of DTI data and the simulated data which has been reconstructed from it.

To investigate the ability of the FAW-FM and the FAW-AFM algorithms to detect the fibers in the presence of noise, the simulated DTI datasets containing 10 images with simple fibers and 10 images with fiber crossing were used. Gaussian noise[22] with different standard deviation was added to these images. This stage was repeated 10 times for each image and finally 200 simulated DTI data were reconstructed.

Real Data: The raw datasets of DTI data were provided by the Oxford Centre for Functional Magnetic Resonance Imaging of the Brain [FMRIB]. The diffusion weighted data were acquired using echo planar imaging with a 256×208 mm^2 field of view, 128×112 matrix size, 72 slices with 2 mm thickness. The diffusion-weighted images with b-value equal to 1000 s/mm^2 were disseminated along 60 directions. Eddy current and head motions were corrected using affine
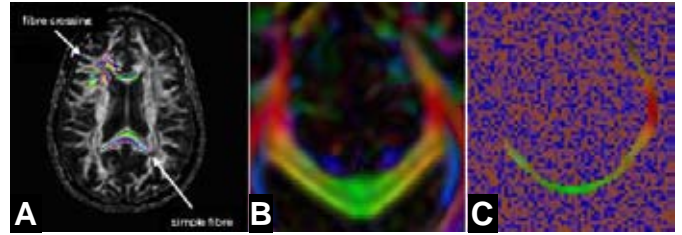

Fig. 3. A. 2D display of extracted fibers.
B. A cropped image from real DTI.
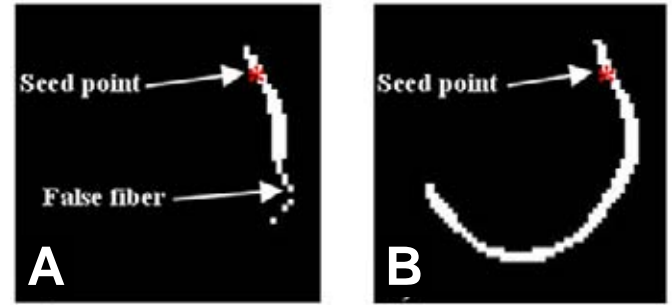**C.** Simulated DTI data.

Fig. 4. Fiber tracking results
A. Using FM.
B. Using FAW-FM methods.

registration to a reference volume using FSL software. The diffusion tensors were then computed for each voxel and the DTI data was then constructed.

In order to investigate the performance of the algorithms, three well-known tracts were selected and the seed areas were located on them. The corticospinal tract was chosen as a projection connecting fibers with a seed area located in the brain stem. The second seed placed in a sagittal plane was used for tractography of the corpus callosum as a commissural connection. Furthermore, a seed point was selected in the right cingulum that is one of the association fibers.

Results
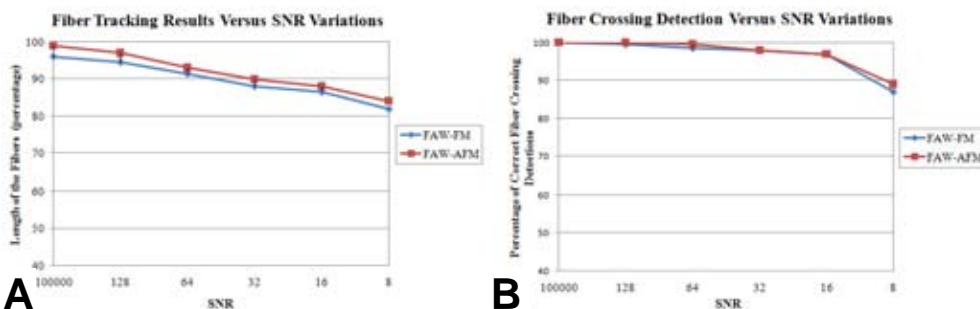
Fiber Tracking Using Simulated Data

Fig. 5. A. Percentage of the length of extracted fibers.

B. Percentage of correct fiber crossing detections using the FAW-FM and FAW-AFM algorithms versus SNR variations.

The results of implementing the FM and the FAW-FM algorithms on one of our proposed realistic shape simulated data are shown in Figure 4 (A&B). For this set of data, the standard FM failed to follow the correct tract because of the incorrect utilized FA threshold. This is due to the fact that FM only uses the similarity of the principal eigenvector's directions. If the next voxel in the tract has a co-linearity in the principal eigenvector directions with the previous voxel, it becomes a candidate for entering the propagation front. If the FA threshold is wrongly selected this makes the algorithm unable to follow the correct pathways. Since the proposed FAW-FM algorithm considers the strength of tensors as well, it is likely to detect the correct pathway in the tract.

The fiber tracking was implemented on 200 simulated data at different signal to noise ratio (SNR) levels with the same seed point using both modified methods. In order to investigate the tractography results, first the voxels selected correctly in the pathways were counted. Then the length of the extracted fibers which was above 85%, even for an SNR level equal to 16, was computed based on the percentage of the length of all tracts (Fig. 5A). Therefore, it reveals that the modified algorithms are robust to noise and provide good fiber tracking results in all SNR levels.

Assessment of Fiber Crossing Detection

In order to investigate the ability of the FAW-FM and FAW-AFM algorithms to detect fiber crossing of white matter fiber pathways, the simulated DTI dataset was used. The percentage of crossing regions de-tected correctly is plotted versus SNR variations in Figure 5B for both algorithms. Although the percentage of correct fiber-crossing detection is reduced by decreasing the SNR level below 16, our suggested speed functions are shown to be robust in relation to SNR reduction.

Tractography Results Using Real Data

The FAW-FM and the FAW-AFM methods were also implemented on three well-known tracts of real DTI datasets to assess the feasibility of these methods in extracting the white matter pathways from human DTI data. The results of the corticospinal tractography (Fig. 6. A&D) using both methods show the wide spreading of this projection tract. Figure 6 (B&E) shows the fiber tracking results of the corpus callosum, while the right cingulum tractogram is shown in Figure 6 (C&F) for the FAW-FM and FAW-AFM methods, respectively. The results demonstrate the ability of the proposed methods in extracting the correct pathways from the anatomical point of view.[23] The divergence of fibers obtained by FAW-AFM is more than the FAW-FM. This result is due to the fact that FAW-AFM used the tensor shape information in their speed functions on a wider narrow band area.[19]

Discussion

The influence of the FA values was reflected in the fast marching tractography methods as a modification to make them able to propagate into the regions with lower FAs in an adaptive manner.[14,19] In order to as-
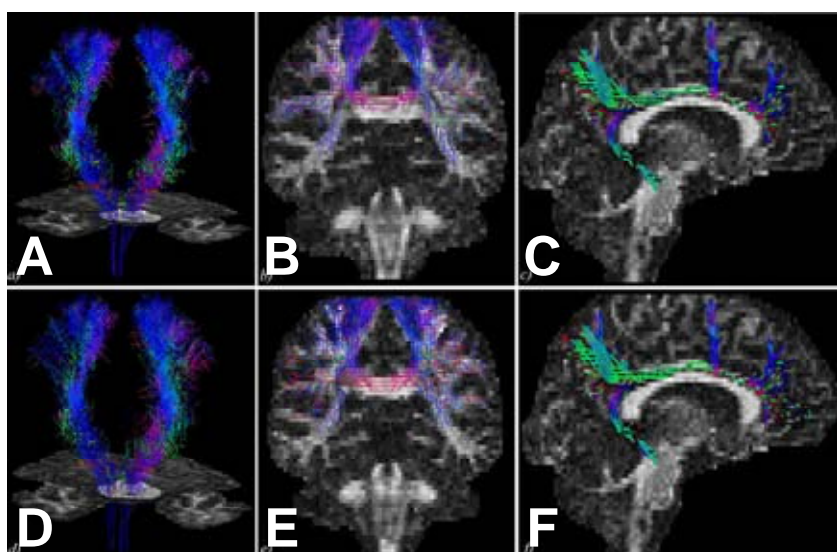

Fig. 6. A-C. Tractography results of the corticospinal tract with a seed area in the brainstem, the corpus callosum seeded in the sagittal plane and the right cingulum using the FAW-FM algorithm.

D-F. The same results using the FAW-AFM method. The tractography results have been overlaid on the FA image.

sess the ability of the FA weighted FM based algorithms in finding fibers and detecting fiber crossing, simulated DTI datasets containing both simple and crossing fibers were used. As shown in Figure 5, the percentages of correct fiber crossing detection were high and fairly constant for both the FAW-FM and FAW-AFM methods in SNR levels over 16. Since the effect of noise is high in changing the direction and shape of the tensors, the crossing detection affects more considerably in an SNR value equal to 8. It also should take into account that the SNR level in real DTI data is about 32.[22] In addition to the noise robustness, the tractography strategy of the proposed methods are different compared to the other conventional ones.

Unlike the line propagation methods,[6,7,24] which only consider the beginning and the end of the propagated trajectory as points for pathway length growth, the front propagation methods[10,14,19] take all the neighboring voxels into account in order to include them in the front. Our proposed method as an adaptive front propagation technique selects the best connections between voxels. Therefore, the FA weighted front evolution methods have a wide spread tractography result since their propagation speeds adapt with the principal eigenvector direction and the FA strength as well.

Acknowledgment

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