Fractional Anisotropy Weighted Front Evolution Algorithm for White Matter Tractography Based on Diffusion Tensor Imaging Data

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| Keywords: | Diffusion Tensor Imaging, White Matter Tractography, Front propagation, Fractional Anisotropy, Fiber Crossing |
Fractional Anisotropy Weighted Front Evolution Algorithm for White Matter Tractography Based on Diffusion Tensor Imaging Data

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Abstract—Tractography is one of the most important applications of diffusion tensor imaging (DTI) which non-invasively reconstructs three dimensional trajectories of the white matter tracts. Due to the intra-voxel orientation heterogeneity (IVOH) of DTI data, some of tractography algorithms are unable to follow the correct pathways after the crossing and branching regions. Front propagation techniques are efficient methods in tracking the crossing fibers. A key parameter influencing the performance of these algorithms is the cost function which is mainly based on the co-linearity of tensors eigenvectors. The effect of the eigenvalues on the anisotropy strength of tensor has not been previously addressed in the definition of the speed function. In this paper, a new speed function, based on the effect of diffusion anisotropy and the co-linearity of eigenvectors is proposed. The performance of the suggested method on fiber tracking and crossing fiber detection has been evaluated using synthetic datasets and the feasibility of the proposed method was shown by fiber tracking implemented on real DTI data.

Keywords: Diffusion Tensor Imaging, White Matter Tractography, front propagation, Fast Marching algorithm, Fractional Anisotropy, adaptive FA weighted speed function, fiber crossing.
Introduction

Diffusion tensor imaging (DTI) is a non-invasive tool for measuring the random motion of water molecules. In isotropic environments, the molecules spread out equally in all directions, whereas in anisotropic regions, diffusion is restricted by some macromolecules or the membrane of cells. Brain’s white matter is an anisotropic tissue containing axons of neurons which their myelin sheaths restrict the motion of water molecules. Diffusion in parallel directions of the white matter tracts is at least twice faster than in the perpendicular directions (Pierpaoli et al. 1996; Melhem et al. 2002). Thus, the directions of the white matter tracts can be estimated by finding the maximum diffusion direction.

White matter tractography methods use DTI datasets to non-invasively reconstruct the three dimensional trajectories of the 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 can be categorized into three groups: (1) line propagation methods, (2) probabilistic fiber tracking algorithms, (3) global energy minimization techniques. The simplest line propagation method called the principal diffusion direction method (PDD) 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 fractional anisotropy value higher than the predefined threshold (Westin et al. 1999; Conturo et al. 1999; Jones et al. 1999). FACT (Mori et al. 1999), Streamline (Basser et al. 2000), EZ-Tracing (Nakada et al. 2002) and TEND (Lazar et al. 2003) algorithms are the other methods that follow this approach.

Besides, 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 (Parker et al. 2002; Hagmann et al. 2003). 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. The bootstrap method is also used to estimate the effect of noise on fiber tracking results.
this method, diffusion weighted imaging is repeated and bootstrap samples are reconstructed from these collected datasets. This method can help one to estimate the uncertainty of DTI data in each voxel (Lazar et al. 2005; Jones et al. 2005). DTI data acquisition for implementing bootstrap sampling takes a lot of time which is hard for a patient to bear with it. The wild bootstrap method (Jones 2006, 2007) solves this problem and generates wild bootstrap samples from one raw dataset. The probabilistic methods are more time consuming than the deterministic methods, but they can generate better results in the branching regions.

The last category named the energy minimization algorithms are front propagation methods. The fast marching, FM, (Parker et al. 2002) is one of them 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, Compbell et al. (2005) performed the fast marching algorithm with extension to use the HARDI data (Tuch et al. 2002, 2003) as well as DTI data. In this algorithm, 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. The advanced fast marching, AFM, (Staempfl et al. 2006, 2007) is another modification of fast marching tractography where four different speed functions according to the tensors shapes are used. This algorithm had better results in fiber crossing detection than the standard fast marching. Jbabdi et al. (2008) recently utilized and improved the fast marching method implemented in path planning and vessel extraction 3D angiography images in order to be used in the diffusion field of DTI data.

In the previous front propagation algorithms, the direction of eigenvectors determines the speed value for the entering 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 can be extracted and if a high value is selected, the front may not enter into the crossing regions having low anisotropy 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 to change adaptively according to the diffusion anisotropy of the brain environments (i.e., isotropic and anisotropic regions). Furthermore, it utilizes the advantage of fuzzy approach in the selection of the best connectivity between each pair of voxels with maximal co-linearity and higher anisotropy. It is theorized that the proposed algorithm can pass the crossing regions with low anisotropy because it does not consider the FA threshold. 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.

Methods

The fast marching, FM, algorithm proposed by Parker (Parker et al. 2002) was used in this study as the basic front propagation method. In this algorithm, the speed function changes only according to co-linearity of the eigenvectors of the two neighboring voxels, whereas all three eigenvalues of each tensor are important since they define its anisotropy strength and therefore playing an important role in forming the ellipsoidal shape of the tensor. The ordinary FM speed value becomes maximal for the local connection between the two voxels with full co-linearity, but without considering the strength of anisotropy. Fig. 1 schematically shows two samples of local connections, where the speed values are equal for these two samples. The local connection shown in Fig. 1a is stronger and the second voxel in this connection can 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 in computing the speed function. Fortunately, an algorithm called advanced fast marching, AFM, (Staempfli et al. 2006) does this job by considering different speed functions based on tensor shapes. The defined connections of AFM are shown in Fig. 2a-d along with some other possible connections which can happen (Fig. 2e-k). 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 the FA values of the two voxels, the front voxel, $FA(p)$, and one of its neighbors in a narrowband, $FA(q)$ to adapt the speed function based on the strength of tensors. Narrowband is defined as a set of neighbor voxels around the front (Parker et al., 2002). This speed function is named FA weighted fast marching (FAW-FM) which is computed by the following equation:

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

(1)

where $W(p, q) = FA(p) \cdot FA(q)$, $W(p, q) \leq 1$ is called the adaptive FA weighted function (Darki et al. 2007) and $S(q)$ is the ordinary speed function as defined by Parker et al. (2002). This new speed function can be viewed as a function of the percentage of the speed value as computed in conventional FM methods; thus, $S_{FAW} \leq S$. Since FA has a value in $[0, 1]$, this modification assigns a fuzzy value for each local connectivity. In this approach, the effect of the anisotropy for any type of connection between each pair of voxels along with their diffusion co-linearity is considered. This modification in the speed function gives more weighting to the higher values of FA and specifies how strongly the diffusion is directed along the principal eigenvector orientation. Fig. 3 shows the plots of speed values obtained using the FM and the FAW-FM algorithms. This figures show how the FA weighted adaptive function modifies the FM speed, which changes along a curve, into a surface of FAW-FM speed function which is obtained by multiplying FA weighted adaptive function by the ordinary speed function.

As shown in Fig. 3, the FM speed function only takes one speed value for each angle difference of the principal eigenvectors, whereas the FAW-FM speed function takes the proper value according to the values of FA of two neighboring voxels. This varied speed function decreases with decreasing the FA value of the first voxel, and can be increased simultaneously for the second voxels when the FA value becomes close to one. Therefore, it is anticipated that this adaptive behavior adjusts the speed function according to the anisotropy type of brain environments. To show this, suppose that the front voxel is in the anisotropic environment and the FA value is close to one, the speed value tends to enter a voxel in the same environment rather than the isotropic one with FA value close to zero. So the voxel in the isotropic environment which has co-linearity with the first one and also higher FA value is selected for entering into the front.
In order to implement our proposed method to the AFM (Staempfli et al. 2006) algorithm, we multiplied the adaptive FA weighted function to its speed functions and called it FAW-AFM. The wide narrowband of the AFM method is also considered in this modification. But unlike the AFM, the FA threshold is not considered for selection of the front voxels by which the front can be entered into the low anisotropy regions in an adaptive manner.

The process of extracting the fibers from the front voxel is mainly based on two connections namely local and global as explained below. The local connectivity is used for front propagation and global connectivity is utilized for the fiber trajectory reconstructions. For local connectivity, front evolution of the FAW-FM and FAW-AFM algorithms is implemented using the dynamic programming method in which a cost function based on arrival time is calculated for all the narrowband voxels. Using the speed value, $S_{FAW}(q)$, and the distance, $|q-p|$, the arrival time is computed as a cost function using the following equation:

$$t_q = t_p + \frac{|q-p|}{S_{FAW}(q)}$$

(2)

where $t_p$ and $t_q$ are the arrival times for voxels p and q, respectively. In each iteration step, a voxel with minimum arrival time is added to the front and the connection between the new and previous voxels generates the local connectivity. Continuing this process leads to connect all voxels satisfying the minimum arrival time criteria with respect to the other neighbors. In cases that an ending region is defined, the front evolution is stopped when it reaches to the ending area.

Moreover, global connectivity is implemented in order to extract 3D trajectories from the local connections. Since front propagate faster along the white matter tracts rather than the other directions, the voxels that minimize the arrival time function, $T(.)$, are put in a tract as follows:

$$\int_{t_q = \gamma(0)}^{t_q = \gamma(L)} T(\gamma(\tau)) d\tau .$$

(3)

The arrival time function in equation (3) is minimized along a defined path $\gamma(\tau)$ starting from the seed point, $t_0 = \gamma(0)$, to any point with total length of, L, $r = \gamma(L)$. There are generally many paths connecting the seed points to front voxels with different arrival times. In order to extract the suitable pathways
from all possible tracts, the overall speed, $S(.)$, is first computed by the following equation for all the tracts:

$$S(y(\tau)) = \frac{\int_{0}^{\tau} y(\tau) d\tau}{\int_{0}^{\tau} T(y(\tau)) d\tau}$$ (4)

Then, using the Max-Min algorithm, all the global connections can be described by the following equation:

$$S_{a_{m+1}} = \min(t(o_{m}, o_{m+1}), t(o_{m}, o_{m+2}), \ldots, t(o_{m}, L))$$ (5)

$$\gamma(o, L) = \max(S_{a_{m+1}}, S_{a_{m+2}}, \ldots, S_{a_{N}})$$

where $o, o_{m}, o_{m+1}, \ldots, L$ is the sequence of the voxels placed in the $i$th pathway and $t(o_{m}, o_{m+1})$ is the arrival time computed for the local connections between the $m$th and the $(m+1)$th voxels. $S_{a_{m+1}}$ is the overall speed for the $i$th path and $N$ is the number of all possible global pathways. The greater speed value means the more diffusion in the white matter tracts. Therefore, pathways with higher speed value are more reliable from the anatomical point of view. Furthermore, in cases that the tracking is expected to end up by reaching to the target region; backtracking is applied to find the connecting pathway to the seed area. The best candidate voxels for connecting back to the seed are the neighbor voxels with minimal cost values.

**Evaluation process**

**Synthetic Fiber Crossing:** In order to generate the synthetic fibers, some tracts were extracted from human brain DTI datasets using the streamline fiber tracking technique and then saved as binary mask. Tensors with randomly selected FA values, between 0.5 and 0.9, were assigned to the corresponding voxels. Accordingly, eigenvalues of each tensor were set by the suitable FA values. First, the principal eigenvector of each tensor was laid along the connecting vector to the next voxel. Then, the second and third eigenvectors were created in the perpendicular directions to the main eigenvector. Using the computed eigenvalues and eigenvectors the desired tensors were formed. Background tensors were also calculated with random orthogonal eigenvectors and eigenvalues to generate desired random FA values less than 0.2. This FA value was selected based on the fact that most of the fiber tracking algorithms use
the threshold of 0.2 to stop the tracking when the fibers meet this criteria (Westin et al. 1999; Conturo et al. 1999).

To construct the crossing fibers, a synthetic fiber was rotated around its third eigenvector at an arbitrary angle. As shown in Fig. 4a, if two fibers have linear shapes and the rotation takes place around the third eigenvector, the total tensor of the crossing voxels become ellipsoidal. The rotation angle approaching zero leads to a linear tensor and when the rotation angle approaches to 90° it forms a tensor with a lower anisotropy. On the other hand, if the rotation takes place around the third eigenvector and then follows by another rotation around the second eigenvector, the average tensor will be a spherical tensor with a low FA value. Fig. 4b shows schematically two tensors in a crossing region with their corresponding total tensors shapes.

The simulated crossing fibers include various pathways, FA values and crossing angles, to create the crossing regions having different FA values. Fig. 4c, d show samples of the synthetic crossed fibers constructed from various rotations together with the FA values of the corresponding crossing regions.

The evaluation of the fiber crossing detection was performed on 10 different artificial datasets, in which 6 DTI datasets were prepared as the crossed tracts rotated in plane and the rest were used as oblique crossing fibers. Table 1 lists the parameters used for the simulation of crossed tracts. In order to generate the simulated datasets with various SNR values, the Gaussian noise of zero mean with different standard deviations was added to these simulated datasets (Kingsley 2006). This process was repeated 20 times making the total number of the generated data from all datasets as 200.

Real Data: The raw datasets used in this study 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 field of view 256 × 208 mm², matrix size 128 × 112, 72 slices with 2 mm thickness. The diffusion weighted images with b-value equal to 1000 s/mm² were disseminated along 60 directions. Eddy current and head motions were corrected using affine 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 FAW-FM and FAW-AFM 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. Also, the seed placed in a sagittal plane is 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

The results of implementing the FM and the FAW-FM algorithms on one of our proposed realistic shape (Fig. 5a) simulated data are shown in Fig. 5b, c. For this set of data, the standard FM method 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. That is, if the next voxel in the tract shows a co-linearity with previous voxel in the principal eigenvector directions, then it becomes a proper candidate for entering into the propagation front. This makes the algorithm unable to follow the correct pathways if the FA threshold is wrongly selected. This inefficiency has been removed in the proposed FAW-FM algorithm by considering the strength of tensors to detect the correct pathway in the tract more precisely.

The proposed tractography methods, FAW-FM and FAW-AFM, were implemented on the similar simulated datasets containing fiber crossings. The percentage of correct fiber crossing detections was calculated for both simple and oblique crossing fibers. The tracking started from one end of the crossing fibers (two crossed fibers have four end points) and reached to the other end points. This tracking was considered as a criterion for correct detection of a crossing. The percentages of the true detected crosses containing various SNR for FAW-FM and FAW-AFM algorithms are shown in Fig. 6. A reasonably high percentage values were obtained for both simple crossing sample (FAW-FM: 93.3%, FAW-AFM: 95%) and the oblique (FAW-FM: 82.5%, FAW-AFM: 85%) even in the lowest SNR of 8. Moreover, the percentages of total true detected crosses were found to be 97% for both algorithms provided that the noise is not effectively high (i.e. SNR above 16). In general, the FAW-AFM method was found to
be a little superior comparing to the FAW-FM for detecting both the simple and oblique crossing regions.

**Tractography Results Using Real Data**

In another experiment the FM and AFM methods were implemented on the real DTI data for the tractography of the corticospinal tract and corpus callosum both with the FA threshold equal to 0.2 and 0.05. As shown in Figs. 7 b, h and Figs. 7e, k, these algorithms perform well with the FA threshold equal to 0.2. When the FA threshold reduces to 0.05, more fiber spreading was detected but the fiber tracking appears to have false pathways (as shown with red arrows in Figs. a, d, g, and j). These incorrect fibers are obtained due to the wrong selection of the FA threshold.

The FAW-FM and FAW-AFM methods were also implemented on three well-known tracts of real DTI datasets to assess the feasibility of these methods to extract the white matter pathways from human DTI data. The results of the corticospinal tractography (Fig. 7c, f) using both methods show the wide spreading of this projection tract. Fig. 7i, l show the fiber tracking results of the corpus callosum. The results demonstrate the ability of the proposed methods to extract the correct pathways from the anatomical point of view (Krieg 1969). The divergence of fibers obtained by the FAW-AFM is more than the FAW-FM. This is due the fact that the FAW-AFM utilizes the tensor shape information in their speed functions on a wider narrow band area (Staempfli et al. 2006).

**Discussion**

In this study a new speed function is defined to extend the two well-known front propagation tractography methods, namely the fast marching (Parker et al. 2002) and the advanced fast marching algorithms (Staempfli et al. 2006. The main objective was to improve the above existing and frequently used methods in a way that they will be able to propagate more effectively into the regions with lower FAs with an adaptive manner. In order to evaluate the ability of the proposed FA weighted FM based algorithms to detect fiber crossing, simulated DTI datasets containing both simple and oblique crossing fibers were used. As the results of applying FAW-FM and FAW-AFM clearly show, the percentages of
the correct fiber crossing detection were appeared high and fairly constant for both the simple and oblique crossings having SNR levels over 16.

This modification to the algorithms leads to reduce their sensitivity to noise. Since eigenvectors directions are sensitive to noise, the speed functions of the FM based algorithms can be easily affected by the noise. The principal eigenvectors directions of higher FA values are less sensitive to noise. Therefore, by relatively increasing the weight of the co-linearity of the eigenvectors in tensors with high FAs, the noise sensitivity of the speed functions decreases. As the results of applying FAW_FM method showed, the percentage of correct fiber crossing detection remains more than 97% for the SNR level of above 16.

Unlike the line propagation methods (Mori et al. 1999; Basser et al. 2000; Bammer et al. 2003) which only consider the start and the end points of the propagated trajectory for growing the length of the pathway, the front propagation methods (Parker et al. 2002; Staempfli et al. 2006) take into account all the narrowband voxels in the favour of adding them into the front. The FAW-FM as an adaptive front propagation technique selects the best local connections that have minimum time of arrival. These local connections can be from a crossing region, in which the global pathways are formed. Therefore, the FA weighted front evolution methods perform a wide spread tractography result due to the adaptation of their propagation speeds with the principal eigenvector direction and strength of FA value.

Furthermore, the implementation of the proposed methods was done by dynamic programming that can help to extract the fibers by considering the target regions. The idea of backtracing is also utilized in order to find the voxels with minimal arrival time for participating in pathway reconstruction. This technique would be very useful for finding the brain connectivity network in combination with fMRI data to use the brain functional areas as seed and target regions.

However, there are some limitations to mention in front propagation based methods. The main problem is due to the inherent nature of DTI. The tensor model and intra-voxel orientation heterogeneity (IVOH) of the DTI limits this imaging method to find some directions of diffusion in volume voxels. Besides, the front propagation methods obtain branches like pathways for both crossing and branching regions (Staempfli et al. 2007). These two drawbacks make the front propagation DTI based tractography techniques unable to detect the small high curvature fibers such as U-fibers. This
problem may be resolved by using the information of high angular diffusion tensor imaging (HARDI),
q-ball imaging and spectral decomposition methods (Frank et al. 2001; Zhan et al. 2003). In addition,
since the proposed FA weighted front propagation methods do not consider the FA threshold; they are
more time consuming than the FM methods because all the volume voxels should be checked out. Thus,
in cases where the tractography time is important, it is suggested to use the standard methods with
properly selected FA threshold.

Conclusion

In our study, the influence of the FA values was considered in the speed functions of fast marching
based algorithms. We called the modified type of the FM and AFM algorithms as FAW-FM and FAW-
AFM. Since the FA value shows how the direction of the diffusion tensor is aligned with the principal
eigenvector, by this modification, the strength of the anisotropy of a tensor is also considered in the cost
function. Because the FA value varies between zero and one, it can be said that the new speed function
makes a fuzzy strategy for finding the local connections with minimal arrival time. Consequently, the
new algorithms do not rely on the FA threshold, since their adaptive speed functions set the speed
values according to the types of brain environments (isotropic and anisotropic regions).

The modified algorithms yielded high percentage of correct fiber crossing detections when passing
the crossing regions simulated with low FA values such as oblique crossing regions. The new methods
also found to be relatively more robust to noise. This robustness is because of the fact that their speed
functions reduce the effect of uncertainty in finding the diffusion direction by giving more weight to
high FAs.

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**FIGURE LEGENDS:**

Fig. 1. Local connection samples of two neighboring voxels with the same diffusion orientation but different FAs.

Fig. 2. (a-d) Four defined connections in the advanced fast marching algorithm and (e-k) samples of other possible conditions.

Fig. 3. (a) Representation of the FM speed function versus the angle differences. (b) Adaptive FA weighted function plotted versus FA values of $p$ and $q$ voxels. (c) Representation of the FAW-FM speed function for FA=0.8.

Fig. 4. Synthetic fibers rotated (a) around the third eigenvector, and (b) around the third eigenvector followed by another rotation around the second eigenvector (oblique fiber crossing). (c) Crossing fibers rotated 45° around third eigenvector, (d) Crossing fibers rotated 45° and 60° respectively around third and second eigenvectors. Note to the difference of FA values obtained in each crossing region.

Fig. 5. (a) Sample of realistic shape simulated data. Fiber tracking results using the (b) FM, (c) FAW-FM methods.

Fig. 6. Percentage of correct fiber crossing detections using (a) the FAW-FM and (b) FAW-AFM algorithms versus SNR variations.

Fig. 7. Corticospinal and corpus callosum tractography using (a, g) FM algorithm with FA=0.05, (b, h) FM algorithm with FA=0.2, (c, i) FAW-FM, (d, j) AFM algorithm with FA=0.05, (e, k) AFM algorithm with FA=0.2, and (f, l) FAW_AFM. The seed areas are in the brainstem and in the sagittal plane of the corpus callosum. The tractography results have been overlaid on the FA image. The red arrows show the false pathways.
Fig. 1. Local connection samples of two neighboring voxels with the same diffusion orientation but different FAs.
Fig. 2. (a-d) Four defined connections in the advanced fast marching algorithm and (e-k) samples of other possible conditions.
Fig. 3. (a) Representation of the FM speed function versus the angle differences. (b) Adaptive FA weighted function plotted versus FA values of p and q voxels. (c) Representation of the FAW-FM speed function for FA1=0.8.
Fig. 4. Synthetic fibers rotated (a) around the third eigenvector, and (b) around the third eigenvector followed by another rotation around the second eigenvector (oblique fiber crossing). (c) Crossing fibers rotated 45° around third eigenvector, (d) Crossing fibers rotated 45° and 60° respectively around third and second eigenvectors. Note to the difference of FA values obtained in each crossing region.

86x51mm (300 x 300 DPI)
Fig. 5. (a) Sample of realistic shape simulated data. Fiber tracking results using the (b) FM, (c) FAW-FM methods.
Fig. 6. Percentage of correct fiber crossing detections using (a) the FAW-FM and (b) FAW-AFM algorithms versus SNR variations.
Fig. 7. Corticospinal and corpus callosum tractography using (a, g) FM algorithm with FA=0.05, (b, h) FM algorithm with FA=0.2, (c, i) FAW-FM, (d, j) AFM algorithm with FA=0.05, (e, k) AFM algorithm with FA=0.2, and (f, l) FAW_AFM. The seed areas are in the brainstem and in the sagittal plane of the corpus callosum. The tractography results have been overlaid on the FA image. The red arrows show the false pathways.

148x198mm (300 x 300 DPI)
Table 1

List of the parameters used for fiber crossing simulation.

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