An Improved Fiber Tracking Method for Crossing Fibers

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Abstract. Fiber tracking is a basic task in analyzing data obtained by diffusion tensor magnetic resonance imaging (DT-MRI). In order to get a better tracking result for crossing fibers with noise, an improved fiber tracking method is proposed in this paper. The method is based on the framework of Bayesian fiber tracking, but improves its ability to deal with crossing fibers, by introducing the high order tensor (HOT) model as well as a new fiber direction selection strategy. In this method, orientation distribution function is first obtained from HOT model, and then used as the likelihood probability to control fiber tracing. On this basis, the direction in candidates that has the smallest change relative to current two previous directions is selected as the next tracing direction. By this means, our method achieves better performance in processing crossing fibers.

Keywords: Fiber tracking · Crossing fibers · Diffusion tensor magnetic resonance imaging (DT-MRI) · High order tensor (HOT)

1 Introduction

Diffusion tensor magnetic resonance imaging (DT-MRI) is a widely used MRI method to investigate microscopic structures of living tissue. As a noninvasive technology in vivo, DT-MRI has the potential to trace trajectories of fiber tracks. Currently, this technology has been used for brain disease diagnosis [1, 2], where fiber tracking is a basic task, and takes an important role in deriving maps of neuroanatomic connectivity.

Many fiber tracking methods have been proposed in the last decades. Most of them can be classified into deterministic methods and probabilistic methods. Moreover, new signal processing techniques such as high angular resolution diffusion imaging (HARDI) [3] and compressed sensing (CS) [4, 5] also attract the interests of researchers in this area.

All deterministic fiber tracking methods [6–8] assume that white matter fiber paths are parallel to the principal eigenvector of the underlying diffusion tensors. When the measured signals are effected by noise, the tracing results could be wrong. Due to the noise and uncertainty in measurement, probabilistic fiber tracking methods were proposed in [9, 10]. This kind of methods can process the noise problem to some extent. But most of them have the assumption that there is only one fiber orientation in each voxel. When there are crossing fibers in a voxel, they often fail to trace the right ones.

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To deal with crossing fibers, high order tensor (HOT) model [11, 12] was proposed, where multiple fibers are allowed in a voxel. In this case, the direction with the maximum diffusion rate is often chosen as the fiber forward direction in fiber tracing. This simple selection strategy often leads to incorrect results in the crossing area of fibers, especially for noisy data.

In order to address the issue mentioned above, we propose an improved method to trace noisy crossing fibers. This method is based on the framework of Bayesian fiber tracking proposed by Friman et al. [9] and the high order tensor model [11]. In Friman's method, fiber direction is determined by the prior and likelihood probabilities of current voxel. In this paper, we replace the likelihood probability with orientation distribution function that is calculated from HOT model, and then control the fiber tracing with a new fiber direction selection strategy. By this means, we improved the performance of fiber tracking for noisy crossing fibers.

The remainder of this paper is organized as follows. In Sect. 2, we briefly review the related work. In Sect. 3, we describe our method and its implementation. Test results are included in Sect. 4. Section 5 is for conclusions and future work.

2 Related Work

As mentioned before, our method is based on the framework of Bayesian fiber tracking proposed by Friman et al. [9] as well as the high order tensor voxel model [11]. To help understand our method, we describe them briefly in this section.

2.1 Framework of Bayesian Fiber Tracking

In [9], Friman et al. proposed a novel probabilistic modeling method for white matter tractography that can deal with the noise problem to some extent. According to the Bayes' theorem, the probability density function of local fiber orientation $p(v_i \mid v_{i-1}, D)$ is defined as:

$$p(v_i \mid v_{i-1}, D) = \frac{p(D \mid v_i)p(v_i \mid v_{i-1})}{p(D)} \quad (1)$$

where D represents diffusion measurements with the underlying tissue properties and fiber architecture, v_i is the fiber direction of in the current voxel, and v_{i-1} is the prior fiber direction. The denominator $p(D)$ is a normalization factor given by

$$p(D) = \int_S p(D \mid v_i)p(v_i \mid v_{i-1})dv_i \quad (2)$$

where $p(v_i|v_{i-1})$ is prior probability and S is a set of unit vectors which can be obtained by several times tessellation of an icosahedron [9].

The likelihood probability $p(D|v_i)$ in Eq. (1) is calculated according to Eq. (3) for each predefined unit vectors v_k in S.

$$p(D \mid v_k) = \prod_{j=1}^{N} \frac{\mu_j}{\sqrt{2\pi\sigma^2}} e^{-\frac{\mu_j^2}{2\sigma^2}(z_j - \ln \mu_j)^2} \tag{3}$$

where

$$\mu_j = \mu_0 e^{-\alpha b_j} e^{-\beta b_j (g_j^T v_k)^2}, \tag{4}$$

$$z_j = \ln s_j, \tag{5}$$

and μ_j is the estimated intensity in gradient directions g_j $(j = 1, \cdots N)$, s_j is the corresponding observation intensity. σ^2 is the noise variance of the error between the estimated intensity and the observation intensity. As usual, μ_0 is the intensity without diffusion gradients applied. Parameters α and β are derived from standard DTI model. Supposed that the eigenvalues of DTI model are $\lambda_1 \geq \lambda_2 \geq \lambda_3$, then $\alpha = \frac{1}{2}(\lambda_2 + \lambda_3)$ and $\beta = \lambda_1 - \gamma$.

The prior density $p(v_i \mid v_{i-1})$ that defines prior knowledge about fiber regularity is simply given by

$$p(v_i \mid v_{i-1}) \propto \begin{cases} (v_i^T v_{i-1})^\gamma, & v_i^T v_{i-1} \geq 0 \\ 0, & v_i^T v_{i-1} < 0 \end{cases} \tag{6}$$

where γ is a positive constant.

2.2 High Order Tensor Imaging

Barmpoutis et al. [11, 12] proposed a unified framework to estimate high order diffusion tensors for DT-MRI data, and developed a robust polynomial solution to solve the computation in high order tensor estimation.

Given a set of diffusion-weighted MRI data, the signal of DT-MRI can be estimated by Stejskal-Tanner signal attenuation model:

$$S/S_0 = e^{-bd(g)} \tag{7}$$

where $d(g)$ is the diffusivity function, and S is the observed signal intensity with gradient orientation g and the diffusion weighting b. S_0 is the intensity without diffusion gradients applied.

The diffusion function $d(g)$ in Eq. (7) can be approximated by Cartesian tensor as follows

$$d(g) = \sum_{i=1}^{3} \sum_{j=1}^{3} \cdots \sum_{k=1}^{3} \sum_{l=1}^{3} g_i g_j \cdots g_k g_l D_{i,j,\cdots k,l} \tag{8}$$

where g_i is the i^{th} component of the three-dimensional unit vector g, and $D_{i,j,\cdots k,l}$ is the tensor coefficient. When the tensor is even order and in full symmetry, according to the theory in [11], the Eq. (8) can be rewritten as:

$$d(g) = \sum_{k=1}^{N_L} \rho_k D_k \prod_{p=1}^{L} g_{k(p)} \tag{9}$$

where N_L is the number of different elements, L is the order of the tensor, D_k is k^{th} different elements of the L-order tensor, ρ_k is the number of repetitions of the element, and $g_{k(p)}$ is the p^{th} component of the gradient direction specified by k^{th} unique element of the generalized diffusion tensor.

According to homogeneous polynomials conversion theory [13], any positive-definite polynomial can be written as a sum of squares of lower order polynomials. Equation (9) can be written as follows

$$d(g) = \sum_{j=1}^{M} p(g_1, g_2, g_3; c_j)^2 \tag{10}$$

where c_j is a vector that contains the polynomial coefficients. $p(g_1, g_2, g_3; c_j)$ is L-order homogeneous polynomials in three variables, M is number of polynomials terms.

As addressed in [11], the high order tensor model generalizes the two-order tensors and has the ability to detect multiple fiber orientations. With the measured DT-MRI data, we can compute the diffusion function $d(g)$, and further get the orientation distribution function.

3 Our Approach

3.1 Overview

The Bayesian fiber tracking in [9] can effectively reduce the impact of noise, but it often fails to get the right tracts when encountering crossing fibers due to assumption that there is only one fiber orientation in each voxel. High order tensor model can detect multiple fiber orientations, and has advantages in processing crossing fibers, but how to select a direction for a fiber approaching to the crossing area is still a problem. Improper selection may cause wrong results.

In this paper, we propose an improved method for fiber tracking. This method combines the advantages of the HOT model and Bayesian fiber tracking. We first compute orientation distribution function for each voxel, and then carry out probabilistic tracking in the framework of Friman's method where the likelihood probability is replaced by orientation distribution function. At last, we choose the fiber tracing direction based on the current direction and its change from the previous direction. Here, we assume that the fiber will not take a sharp turn during the tracing procedure. So the direction with the smallest change relative to the current direction will be chosen as the next forward direction. Finally, our method works as the flow chart shown in Fig. 1, including the following steps.

1. Initialization. Set parameters for fiber tracing, including step size, seed points, initial directions, fiber termination criteria, etc. In our experiments, we use fractional anisotropy as one of the termination criteria. And the initial fiber direction at the seed point is set to the main eigenvector of the local standard two-order tensor.
2. Start from the voxel where the seed point lies.
3. Calculate the orientation distribution function of the current voxel according to the HOT model, and use the distribution as the likelihood probability required by the Bayesian approach.
4. Calculate prior probability according to Firman's method.
5. Get posterior distribution by multiply prior probability and likelihood probability.
6. Draw N directions randomly from a predefined unit vector set S, and then choose the direction with the smallest change relative to the current tracing direction as the next forward direction.
7. Trace to the next point in the forward direction, and repeat steps 3–7 until the termination of the fiber.

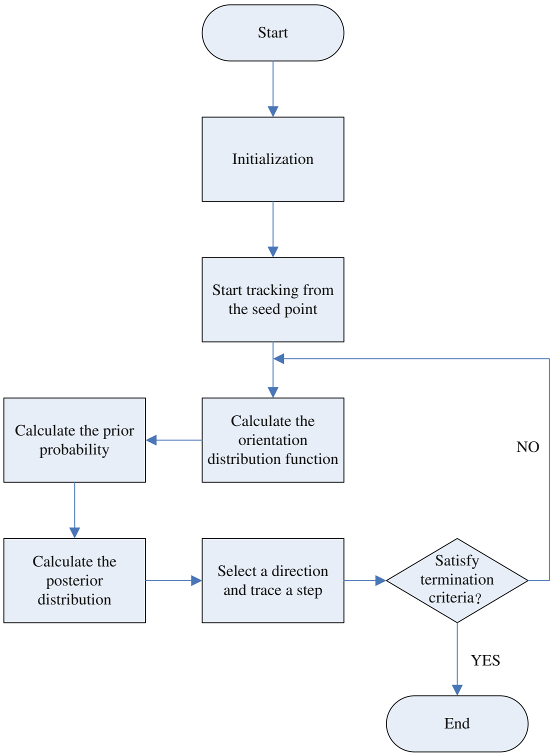


Fig. 1. Flow chart of our algorithm

3.2 Processing for Crossing Fibers

The step 6 in our method is specially designed for crossing fibers, which differs our method from existing ones. As shown in Fig. 2, when using HOT model to detect crossing fiber, we can get the directions of crossing fibers a and b. But, with traditional HOT-based method,when we start tracing from the red arrow, a is often be chosen, because the magnitude of a is bigger than b (here, the magnitude represents diffusion rate). In fact, b is the direction that should be followed in this case.

In order to deal with crossing fibers and get the right tracing results, we resample the unit vector space, get all directions with high probabilities, and select one from them to continue the tracing. As shown in Fig. 3, suppose $V1$ and $V2$ are already known vectors in the fiber. And candidates with high probabilities for next step are labeled with $V3$, which are the re-sampling results of the current voxel. We first compute the angle between $V1$ and $V2$, and then compute the angles between $V2$ and all $V3$ candidates. The one from $V3$ candidates that is in best consistency with $V1$ and $V2$ will be chosen. In other words, the angle between the selected $V3$ and $V2$ is the closest to the angle between $V1$ and $V2$. For the case in Fig. 3, the selected $V3$ is drawn in red. By this means, our method can avoid falling into wrong directions in most of cases, just as shown in the test results.

4 Test Results

In this section, we evaluate the performance of our method with tests on three synthetic dataset and a real DT-MRI dataset.

4.1 Synthetic Data

Two sets of synthetic data were created with the following parameters: $30 \times 30 \times 1$ voxels, $1 \times 1 \times 1$ mm, b = $1500\, s/mm^2$, 21 gradient directions, 10% noise, according to the simulation method in [14]. The first dataset contains two bundles of straight

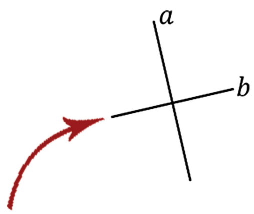


Fig. 2. Example of crossing fibers (Color figure online)

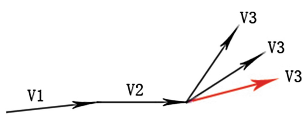
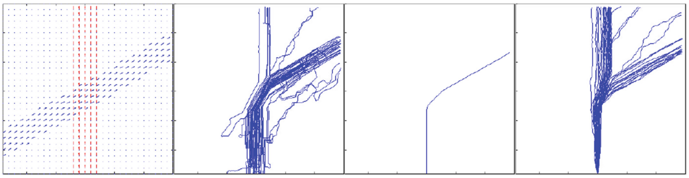
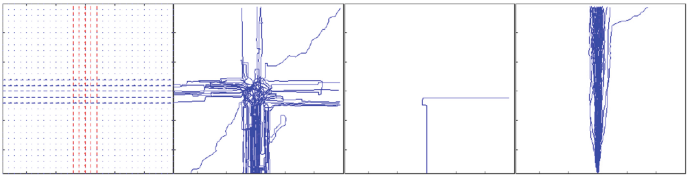


Fig. 3. Selection of fiber directions (Color figure online)



(a) 60° crossing fibers (b)Friman's method (c) HOT method (d)Our method

Fig. 4. Test results for 60° crossing fibers. The seed point is at (15, 1).



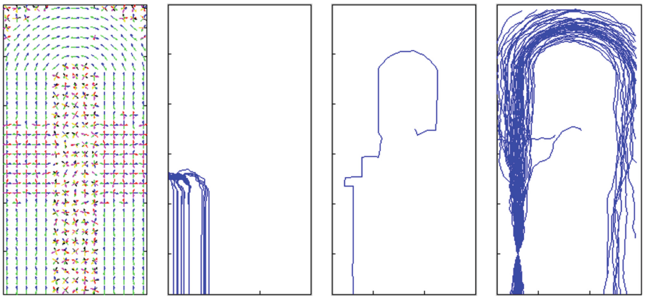
(a) 90° crossing fibers (b)Friman's method (c) HOT method (d)Our method

Fig. 5. Test results for 90° crossing fiber. The seed point is at (15, 1).

fibers that are 60° crossing, and the second has 90° crossing fibers, just as shown in Fig. 4 (a) and Fig. 5 (a), respectively.

We compared our method with Friman's method and HOT method. With the same seed point, we tracked 50 times for all methods. The results are given in Figs. 4 and 5. Obviously, our method improved the performance of crossing fiber tracking, because most of fibers traced along the right way in our method, while they deviated from the truth in Friman's method. Here, it should be noted that HOT method always get the same wrong result, because it is a deterministic method that traces along the direction with the largest diffusion rate.

The third synthetic data set was designed by Peter [15]. It contains $15 \times 30 \times 5$ voxels and 162 gradient directions with b = 1500 s/mm^2. The comparative results are shown in Fig. 6, where the ground truth of fiber directions is included in Fig. 6 (a).



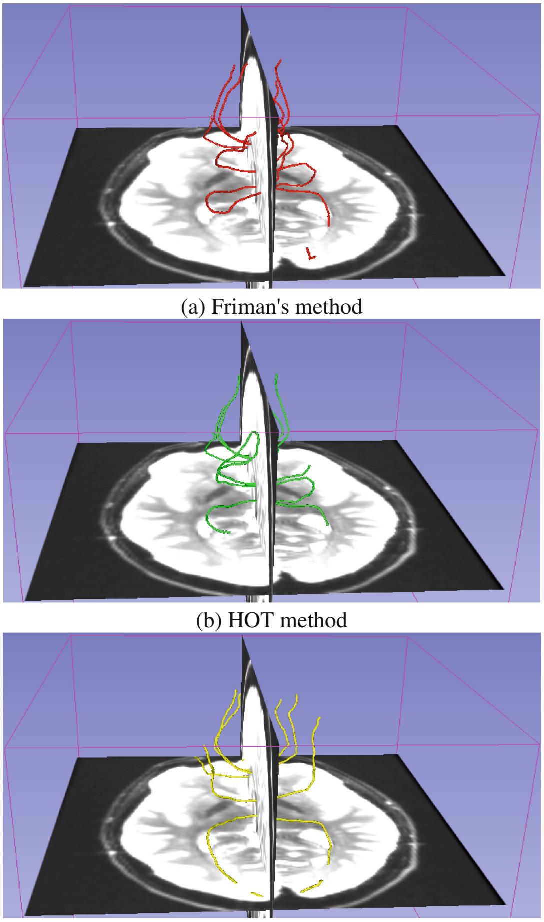
(a)peter's data (b)Friman's method (c)HOT method (d)Our method

Fig. 6. Test results for Peter's dataset. The seed point is at (3, 5).

For Friman's method, most of fibers ran out of the field when they encountered the crossing area, as shown in Fig. 6 (b). For HOT method, it also can not get the right tract. But, for our method, most fibers successfully went through the crossing areas, and disclosed the structure of fibers.

4.2 Real DT-MRI Data

We further tested our method with the DWI Volume dataset, which is a sample data of 3D Slicer [16]. In this test, the fiber step size was set to 0.4, fractional anisotropy was no smaller than 0.12, and the seed points were set on the Corpus Callosum structure. Figure 7 gives the test results of the DT-MRI data, where fibers generated by Friman's method, HOT method, and our method are drawn in red, green and yellow colors, respectively.



(a) Friman's method

(b) HOT method

(c) Our method

Fig. 7. Test results for the DWIVolume dataset. (Color figure online)

Comparing the fiber tracts in Fig. 7, we can see that our results in Fig. 7 (c) are consistent with the arcuate structure, showing the symmetrical features. For the Friman's method and the HOT method, the symmetry of fibers is broken, because some fibers turned around and changed their tracing directions. Although the ground truth is not available, we infer that the problem of turning around may be caused by something that is similar to crossing fibers. Our method is more robust in dealing with crossing fibers, so it got better results.

5 Conclusions

In this paper, we propose an improved fiber tracking method on the framework of Bayesian fiber tracking. This method replaces the likelihood probability with the orientation distribution function obtained from high order tensor model, and integrates a new fiber direction selection strategy. By this means, it achieves better performance in processing crossing fibers, just as shown in test results. In future work, our method would be further evaluated on more real datasets and extended to process more complicated fiber structures.

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References

1. Warach, S., Gaa, J., Siewert, B., Wielopolski, P., Edelman, R.R.: Acute human stroke studied by whole brain echo planar diffusion-weighted magnetic resonance imaging. Ann. Neurol. **37**(2), 231–241 (1995)
2. Amlien, I., Fjell, A.: Diffusion tensor imaging of white matter degeneration in alzheimers disease and mild cognitive impairment. Neuroscience **276**, 206–215 (2014)
3. Du, J., Goh, A., Qiu, A.: Diffeomorphic metric mapping of high angular resolution diffusion imaging based on riemannian structure of orientation distribution functions. IEEE Trans. Med. Imaging **31**(5), 1021–1033 (2012)
4. Lustig, M., Donoho, D., Pauly, J.M.: Sparse MRI: The application of compressed sensing for rapid MR imaging. Magn. Reson. Med. **58**(6), 1182–1195 (2007)
5. Kuhnt, D., Bauer, M.H., Egger, J., Richter, M., Kapur, T., Sommer, J., Merhof, D., Nimsky, C.: Fiber tractography based on diffusion tensor imaging compared with high-angular-resolution diffusion imaging with compressed sensing: initial experience. Neurosurgery **72**(0 1), 165–175 (2013)
6. Mori, S., Crain, B.J., Chacko, V.P., Van Zijl, P.C.M.: Three-dimensional tracking of axonal projections in the brain by magnetic resonance imaging. Ann. Neurol. **45**(2), 265–269 (1999)
7. Lazar, M., Weinstein, D.M., Tsuruda, J.S., Hasan, K.M., Arfanakis, K., Meyerand, M.E., Badie, B., Rowley, H.A., Haughton, V., Field, A., Alexander, A.L.: White matter tractography using diffusion tensor deflection. Hum. Brain Mapp. **18**(4), 306–321 (2003)

8. Weinstein, D., Kindlmann, G., Lundberg, E.: Tensorlines: Advection diffusion based propagation through diffusion tensor fields. In: Proceedings of the Conference on Visualization 1999: Celebrating Ten Years. pp. 249–253. VIS 1999, IEEE Computer Society Press, Los Alamitos, CA, USA (1999)
9. Friman, O., Farneback, G., Westin, C.F.: A bayesian approach for stochastic white matter tractography. IEEE Trans. Med. Imaging **25**(8), 965–978 (2006)
10. Zalesky, A.: DT-MRI fiber tracking: a shortest paths approach. IEEE Trans. Med. Imaging **27**(10), 1458–1471 (2008)
11. Barmpoutis, A., Vemuri, B.: A unified framework for estimating diffusion tensors of any order with symmetric positive-definite constraints. In: IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2010, pp. 1385–1388 April 2010
12. Barmpoutis, A., Zhuo, J.: Diffusion kurtosis imaging: robust estimation from DW-MRI using homogeneous polynomials. In: IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2011, pp. 262–265 March 2011
13. Rudin, W.: Sums of squares of polynomials. Am. Math. Mon. **107**(9), 813–821 (2000)
14. Barmpoutis, A., Jian, B., Vemuri, B.C.: Adaptive kernels for multi-fiber reconstruction. In: Prince, J.L., Pham, D.L., Myers, K.J. (eds.) IPMI 2009. LNCS, vol. 5636, pp. 338–349. Springer, Heidelberg (2009)
15. Savadjiev, P., Rathi, Y., Malcolm, J.G., Shenton, M.E., Westin, C.-F.: A geometry-based particle filtering approach to white matter tractography. In: Jiang, T., Navab, N., Pluim, J.P., Viergever, M.A. (eds.) MICCAI 2010, Part II. LNCS, vol. 6362, pp. 233–240. Springer, Heidelberg (2010)
16. 3D Slicer. http://www.slicer.org/