Adaptive Bayesian Tracking of Neuronal Fiber Pathways from Diffusion Tensor Images

Y. Lu[1], Z. Ding[1], J. C. Gore[1], A. W. Anderson[1]
[1]Vanderbilt University Institute of Imaging Science, Nashville, TN37232-2675, United States

Introduction

Fiber tractography based on diffusion tensor imaging (DTI) allows structural characterization of the human brain *in vivo* (1). A major issue of this technique is tracking accuracy, which may suffer significantly from the effect of noise and partial volume averaging. The purpose of this study was to develop a novel tracking algorithm that is robust to these artifacts. To achieve this objective, we designed a statistical tracking method by extending the classical Bayes decision theory. Tests with simulated and *in vivo* human brain data demonstrate that this method can effectively reconstruct fiber pathways in the presence of noise and partial volume effect.

Theory

The framework of this algorithm is based on the extension of classical Bayesian decision theory (2). According to this theory, a decision with minimum error rate can be reached by maximizing *a posteriori* probability $p(A|B)$ that is expressed as the product of *a priori* probability $p(A)$ and conditional probability density $p(B|A)$, i.e.: $p(A|B) = p(A) * p(A|B) / p(B)$. In the context of fiber tracking, if we set A to be a candidate outgoing fiber direction, B the incoming fiber path direction, $p(A)$ will be the probability of a fiber pathway in the direction A, and $p(B|A)$ the probability of incoming fiber pathway belong to a fiber with direction A. We model both $p(A)$ and $p(B|A)$ with Gaussian functions:

$$p(A) = \frac{1}{\sqrt{2\pi}\sigma_1}\exp(-\frac{\theta_1}{\sqrt{2}\sigma_1})^2, \quad p(B|A) = \frac{1}{\sqrt{2\pi}\sigma_2}\exp(-\frac{\theta_2}{\sqrt{2}\sigma_2})^2$$

Where θ_1 — the angle between fiber direction and main eigenvector, σ_1 — the angular standard deviation of main eigenvector within a certain neighborhood.
θ_2 — the angle between fiber direction and incoming direction, σ_2 — the angular standard deviation along fiber pathway.

Basically, $p(A)$ encourages fibers to go along the direction of the main eigenvector while $p(B|A)$ enables smooth transition of fiber pathways. These two constraints are equally taken into account in the classical Bayesian decision rule. To selectively emphasize *a priori* or conditional terms, different weighting factors can be applied. We employ an adaptive weighting scheme that allows the weighting factors to be tunable to local fractional anisotropy (FA): $p(A|B) = p(A)^w * p(A|B)^{1-w} / p(B)$, $w = FA^n$.

When the local FA is high, $p(A)$ carries more weight in determining path direction; when the FA is low, $p(A|B)$ weighs more thus allowing fiber to penetrate region of low anisotropy due to partial volume averaging. It is interesting to see that when n = 0, the tracking method becomes a streamline approach, whereas n = ∞, only straight lines can be tracked. We empirically set n = 1 in this study.

Methods

Simulated and in-vivo human DTI data are used to test the performance of this algorithm. Simulated data contain two sets of fibers with axes perpendicular to each other, generating a region of crossing fibers (see Figure 1). These data are corrupted with different levels of Gaussian noise (stdev = 0, 0.05, 0.1). Human data were obtained on a 3T GE MR scanner with original data matrix of 128 x 128 x 30 and voxel size of 2 x 2 x 4 mm^3, but interpolated into 256 x 256 x 30 and 1 x 1 x 4 mm^3. Eigenvectors and eigenvalues are derived from the diffusion tensor. Variance σ_1 of each voxel is calculated from its 26 neighbor voxels, and σ_2 is a measure of fiber rigidity which is fixed to be 15° in this study. Three different tracking algorithms, including streamline, classical and adaptive Bayesian methods, are used for comparison with simulated data. The streamline method is defined as the adaptive method with n = 0, and the classical Bayesian method is the adaptive method without weighting factors. The tracking procedure starts from a seed point, which propagates with a certain step size (0.05mm) until one of the termination criteria is reached.

Results

Figure 1 shows the results from the simulated data obtained with three tracking methods and at three different levels of noise. At 0% noise level, both the classical Bayesian and streamline methods fail to follow the correct pathway in the crossing region (shown as the overlapped red and blue lines in Figure 1(a)), only the adaptive method gives the faithful pathway. At other noise levels, the streamline method cannot penetrate the crossing region, while the classical and adaptive method can traverse the cross region, but the adaptive method performs better (as observed in Figure 1(b) and 1(c)). Figure 2 displays the results of healthy in vivo human data using the adaptive method. Portions of corpus callosum and descending motor pathway are shown in 2-D (Figure 2(a), 2(c)) and 3-D (Figure 2(b), 2(d)) views.

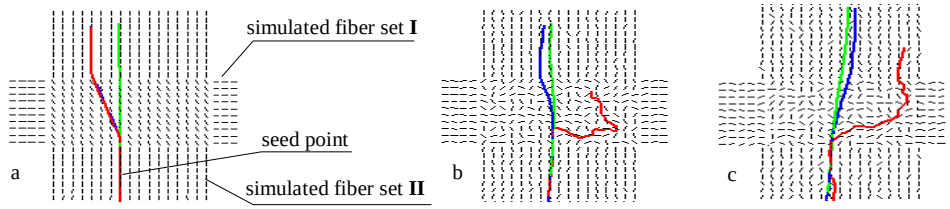

Figure 1. Results of simulated data with different methods at noise level of (a) stdev = 0 (b) stdev = 0.05 (c) stdev = 0.01 (Red line — streamline method, blue line — Bayesian method, green line — adaptive Bayesian method).

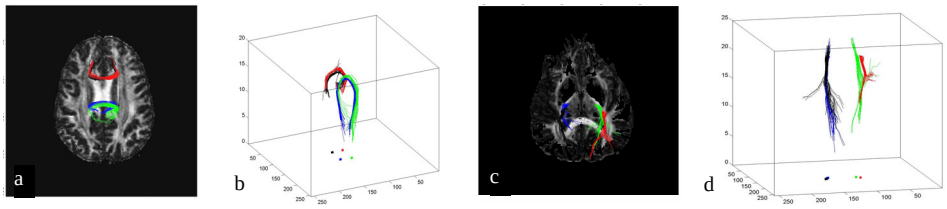

Figure 2. Results of *in vivo* data with adaptive Bayesian method at (a) and (b): portion of corpus callosum. (c) and (d): portion of descending motor pathway.

Discussion and conclusions

Our initial results demonstrate the adaptive Bayesian method to be a promising new approach for fiber tracking. We are currently making efforts in improving this method by employing mathematically more rigorous models of *a priori* probability and conditional probability, and determining optimal parameters involved.

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