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A Hough transform global approach to diffusion MRI tractography

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Introduction

Tractography in Diffusion-Weighted MRI provides a unique quantitative measurement of the brain’s anatomical connectivity using information not available from other imaging techniques. Many tractography algorithms are based on local fiber orientation estimates, such as streamline methods, and are vulnerable to noise and partial volume effects; fiber crossing and kissing are also difficult to distinguish. This led to the development of probabilistic techniques [1] and global approaches relying on front propagation [2, 3] or simulation of the diffusion process [4]. In this work, we present a global approach based on the voting process provided by the Hough transform [5]. Our proposed tractography algorithm essentially tests all possible 3D curves in the volume, assigning a score to each of them, then selecting the curves with the highest scores, and returning them as the potential anatomical connections. We present experimental results on both artificial and real diffusion tensor images (DTI) and high-angular resolution diffusion images (HARDI).

Methods

We first randomly generate a sufficiently high number of initial seed points inside a mask/ROI of the brain. The spatial probability distribution of the seed point is set to be proportional to its fractional anisotropy (FA). From each initial point, all possible curves passing through this location are estimated. A score is computed for each possible curve, and the curve with the maximum score is then chosen as the best fiber passing through that point. Curves are parameterized by the arc length s, and the (unit) tangent vector of the curve is identified at each point by standard polar coordinates \( \theta(s), \phi(s) \): 
\[
\mathbf{t}(s) = (\sin \theta(s) \cos \phi(s), \sin \theta(s) \sin \phi(s), \cos \theta(s)) T.
\]
In our proposed model, we consider polynomial approximations of these two angles with respect to the arc length, 
\[
\theta(s) = \sum_{k=0}^{N} a_k s^k \text{ and } \phi(s) = \sum_{k=0}^{N} b_k s^k,
\]
where the order \( N \) was chosen to be 4 in the experiments. In addition, two extra parameters \( L_+ \) and \( L_- \) determine the partial lengths of the curve at each side of the seed point \( (L_-, L_+) \leq L_{\text{max}} \), where \( L_{\text{max}} \) is a constant. Each curve initiated from the point \( \mathbf{x}_0 \) is then represented using 
\[
2N + 2 \text{ parameters } [a_0, \ldots, a_{N-1}, b_0, \ldots, b_{N-1}, L_-, L_+], \text{ and the curve itself can be computed by integrating the tangent vector, } \mathbf{t}(s) = \mathbf{x}_0 + \int_0^s \mathbf{t}(s') ds', \ s \in [-L_-, L_+].
\]
The score of each possible curve passing through a seed point \( \mathbf{x}_0 \) is given by 
\[
S_{\mathbf{x}_0} = \sum_{\theta, \phi} \mathcal{P}(\theta, \phi) |a + \cdots + a_{N-1} s^N| + \lambda |a + \cdots + a_{N-1} s^N|,
\]
where the \( \mathcal{P}(\theta, \phi) \) is the orientation distribution function (ODF) [6] at each voxel in the volume. For example, in the DTI case, it is computed by integrating the 3D normal distribution function in a cone (with constant solid angle) which yields the probability of diffusion in the direction specified by the unit vector \( \hat{\mathbf{t}} \) : 
\[
P(\hat{\mathbf{t}}) = \int_{-\pi/2}^{\pi/2} \int_{-\pi}^{\pi} e^{-\frac{(x^2+y^2)}{2\sigma^2} + \frac{(z^2)}{2\gamma^2}} d\gamma d\phi.
\]
The vector \( \mathbf{D}(\hat{\mathbf{t}}) \) is the diffusion tensor. In the case of HARDI, the ODFs were approximated by 4th or 8th order spherical harmonic series. This allows for their sampling in any desired direction \( \hat{\mathbf{t}} \). At each seed point, the curve with the highest score is chosen in a multi-resolution approach, discretizing the \( \mathbb{R}^{3N+2} \) space of parameters and computing the score for each set of parameters.

Results and Discussion

Fig. A shows an artificial DTI volume used to test our algorithm on a region with fiber crossing. We generated 200 random seed points, and the algorithm computed the best curve for each point. The top 100 curves are shown in Fig. B. We also ran the algorithm on real human brain data. Diffusion-weighted images were acquired on a 4T Bruker/Siemens MRI scanner using an optimized diffusion tensor sequence. 30 images were acquired, 3 with no diffusion sensitization and 27 computed the best curve for each point. The top 100 curves are shown in Fig. B. We also ran the algorithm on real human data. Diffusion-weighted images were acquired on a 4T Bruker/Siemens MRI scanner using an optimized diffusion tensor sequence. 30 images were acquired, 3 with no diffusion sensitization and 27 computed the best curve for each point. The top 100 curves are shown in Fig. B.

References

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