Improved Probabilistic Tractography Using Atlas-Based Fiber Tracking

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Introduction

Magnetic resonance diffusion tensor imaging (DTI) is an established non-invasive technique for studying neuronal fiber pathways *in vivo*, particularly in the brain white matter (1). At each voxel, DTI provides a diffusion profile that describes the local Brownian motion of water molecules. By further processing the DTI data, a probabilistic fiber tracking algorithm generates a set of fibers that reflect the distribution of underlying neuronal pathways. As imaging artifacts such as random noise and partial volume averaging usually render reconstructed fibers unreliable, typically certain prior knowledge is used to regularize the fiber tracking process. A variety of regularization mechanisms have been proposed, most of which are based on heuristic assumptions about the fiber structure (2, 3, 4). In this contribution, we propose a novel atlas based probabilistic fiber tracking algorithm that incorporates prior knowledge from a white matter fiber atlas, thereby eliminating the need for the commonly used heuristic priors.

Methods

1) Probabilistic white matter tractography based on a fiber atlas

Our probabilistic tracking algorithm first constructs a posterior probability distribution of fibers given a DTI dataset and a fiber atlas and then samples a set of fibers from this distribution. Let a fiber y be composed of a sequence of linked unit vectors $v_1,...,v_{i-1},v_i,...,v_n$. The probability of y conditioned on DTI data D and a transformed fiber atlas $T(A)$ can be expressed as Equation (1), where T is a transformation that maps the atlas to the space of D and $v_{1:i-1}$ represents a set of vectors $\{v_1,...,v_{i-1}\}$. Using a Bayesian rule and assuming the atlas is independent of DTI data, $p(v_i|v_{1:i-1},D,T(A))$ is expressed as Equation (2). Given Equations (1) and (2), a fiber y can be sampled by first drawing v_1 from $p(v_1|D,T(A))$ and then sequentially drawing random vectors from $p(v_i|v_{1:i-1},D,T(A))$. The computation of $p(D|v_i)$ is based on a classical observational model (see Reference 2 for details), so the focus of this work is on the prior $p(v_i|v_{1:i-1},T(A))$, which is typically simplified as a heuristic function such as $(v_i^T v_{i-1})^\alpha$ in the literature.

$$p(v_{1:n}|D,T(A)) = p(v_1|D,T(A))\prod_{i=2}^{n} p(v_i|v_{1:i-1},D,T(A)) \tag{1}$$

$$p(v_i|v_{1:i-1},D,T(A)) = \frac{p(D|v_i)p(v_i|v_{1:i-1},T(A))}{p(D)} \tag{2}$$

2) Prior probability $p(v_i|v_{1:i-1},T(A))$

Construction of a fiber atlas: To demonstrate the proposed algorithm, a fiber atlas is constructed for the neuronal fibers that pass the splenium of the corpus callosum. First, a streamline fiber tracking algorithm (5) is used to generate the splenium fibers for eight different DTI datasets with seed points manually placed in a mid-sagittal slice. With one dataset as a reference, the fibers from the remaining datasets are then transformed into the reference space by coregistering their fractional anisotropy (FA) images using the affine registration function in SPM2 (6). The resulting aligned fibers are pooled together to serve a fiber atlas for the splenium bundle.

Computation of T: The FA image of a testing dataset is registered to the reference FA as above, so that the fiber atlas can be mapped to the testing data space.

Modeling $p(v_i|v_{1:i-1},T(A))$: Non-parametrically, $p(v_i|v_{1:i-1},T(A))$ can be modeled by counting the frequency or probability of each distinct vector $v_{1:i}$ in the atlas. However, due to the high dimension of vector $v_{1:i}$ especially for a large i, the atlas does not contain sufficient data for reliably training such a large distribution. To reduce the dimensionality of this problem, we assume each vector v_i is independent of previous vectors, so that $p(v_i|v_{1:i-1},T(A))$ is reduced to $p(v_i|T(A))$, which has only two dimensions and thus can be modeled reliably. In this work, the prior $p(v_i|v_{1:i-1},T(A))$ is computed by first uniformly resampling each fiber in the atlas into n consecutive points $x_1,...,x_{i-1},x_i,...,x_n$, and then counting the frequency of normalized $(x_i - x_{i+1})$ and $(x_i - x_{i-1})$. The resulting distributions for several selected points are shown in Figure 1d.

Experiments and Results

DTI of nine healthy human subjects was performed on a 3T Philips Achieva MR scanner with 32 non-collinear weighting directions (b=1000 s/mm^2). An image volume of 128×128×60 with a resolution of 2×2×2 mm^3 was generated for each subject. Eight DTI datasets were used as training data for constructing the fiber atlas. For the remaining dataset, which was used as testing data, two different priors that included the atlas based prior and a heuristic prior $(v_i^T v_{i-1})$ were used for probabilistic fiber tracking. Without prior knowledge, it is difficult to track this bundle reliably due to imaging noise and its close proximity to other white matter pathways. The experimental results from probabilistically sampling 250 splenium pathways are shown in Figure 1, which demonstrates that the atlas-based tractography (a-b) generates a larger number of coherent fibers than the method with the heuristic prior $(v_i^T v_{i-1})$.

Figure 1 Superimposition of tracked fibers and the atlas onto a slice of axial FA map. (a) Fibers sampled with the atlas-based prior. (b) Enlarged view of (a). (c) Fibers sampled with heuristic prior $(v_i^T v_{i-1})$. (d) Example distributions of prior $p(v_i|T(A))$.
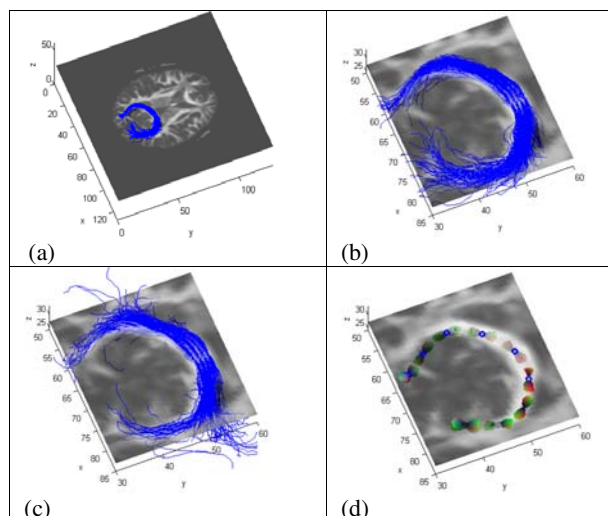
Conclusion

In summary, a novel framework is proposed to model the fiber prior from a fiber atlas and then utilize the prior to guide the process of fiber tracking. The proposed method can be embedded in any Bayesian fiber tracking algorithm. Preliminary experiments demonstrate that the atlas-guided method improves probabilistic tractography over methods with heuristic priors.

Reference

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