Probabilistic diffusion-tensor fiber tractography in a Bayesian framework with an atlas prior

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Introduction: Streamline tractography methods [1] aim to trace the path of white matter fiber tracts using the local fiber-orientation estimates derived from diffusion-weighted MRI (DWI). Uncertainty in DWI fiber tracking comes from several sources, including noise, partial volumes within voxels, and complex fiber architecture that cannot be modeled by the diffusion tensor (DT) [2]. Heuristic priors on the local fiber orientation, such as a restriction on the curvature of the fiber pathway, or spatial regularization of diffusion tensors in local neighborhoods [3], are often used to reduce erroneous streamline traces. This work leverages an atlas of diffusion-tensor images to inform the prior probability of the local fiber orientation. The prior is evaluated as part of a Bayesian framework for probabilistic tractography [4].

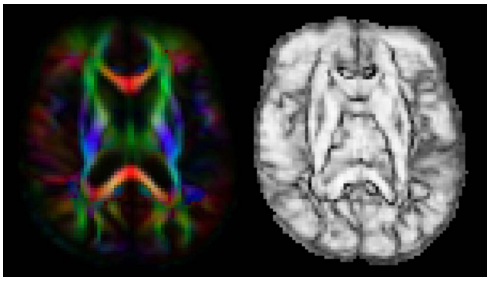

Fig. 1: Anisotropy of the atlas after transformation into subject space (left) and the first eigenvalue of the dyadic tensor.

***Methods*: Diffusion weighted data acquisition**: Eleven subjects were scanned in a Siemens Trio 3T scanner. Reconstructed voxel dimensions were 2.2 mm isotropic on a grid of 112×112, with 57 contiguous slices. The DWI protocol was 12 measurements at b=0 and 30 at b=1000 s/mm^2, each at independent gradient orientations spread isotropically on the sphere. The b=1000 measurements were repeated three times, giving a total of 102 DW images including those at b=0. A multi-channel head coil was used with Siemens GRAPPA parallel imaging (factor 2.5). Ethical approval was obtained for the scanning protocol.

Atlas construction: The white matter atlas is generated from the DT images of 11 healthy adult subjects using an iterative procedure [5] that leverages a high-dimensional tensor-based registration algorithm to explicitly optimize tensor orientation [6]. The atlas contains eleven diffusion tensors in each voxel, each with a principal eigenvector $\mathbf{e_1}$. The mean orientation and anisotropy is shown on the left in Fig 1. The dyadic tensor in each voxel is $D = (1/11) \sum_i \mathbf{e}_{1i} \mathbf{e}_{1i}^T$, which has eigenvalues $t_1 \geq t_2 \geq t_3$, where $t_1 + t_2 + t_3 = 1$. When the tensors are perfectly aligned, $t_1 = 1$ and when they are uniformly distributed, $t_1 \approx t_2 \approx t_3 \approx 1/3$. The right image in Fig. 1 shows t_1.

Bayesian PDF estimation: The tractography algorithm is based on the Bayesian framework presented by Friman et al [4]. The posterior distribution on the fiber orientation $\mathbf{x}$, given the DW data Δ and the "nuisance" parameters θ is $P(\mathbf{x}, \theta \mid \Delta) = P(\Delta \mid \mathbf{x}, \theta)\ P(\theta)\ P(\mathbf{x}) / P(\Delta)$. We use the "constrained model" of the diffusion data, that is, the minor diffusion tensor eigenvalues are equal, yielding a five-parameter model of a diffusion-weighted measurement $S = S_0 \exp(-\alpha b) \exp(-\beta b[\mathbf{g} \bullet \mathbf{x}]^2)$, where S_0 is the estimated signal at b=0, $\mathbf{g}$ is the gradient direction, and α and β are positive scalars. The nuisance parameters are $[S_0, \alpha, \beta]$. These parameters have Dirac priors as suggested in [4], allowing the posterior to be evaluated by densely sampling the likelihood over the sphere. The key difference between [4] and the present work is that Friman et al use a prior on $\mathbf{x}$ that depends on the previous direction, so $P(\mathbf{x})$ for step i is proportional to the curvature between the current orientation and the previous one. This prior is applied equally to all paths in the brain. We use an atlas prior $P(\mathbf{x}) \propto \exp(\kappa [\mathbf{m} \bullet \mathbf{x}]^2)$, where $\mathbf{m}$ is the principal eigenvector of the dyadic tensor, i.e. the mean of the 11 fiber orientation estimates for the voxel in the atlas, and κ is a scalar parameter that describes the concentration of the distribution, which is high when there is good alignment of the orientations in the atlas. We calculate $\mathbf{m}$ and κ from the dyadic tensors in the atlas, after warping the dyads into the subject space using the algorithm in [6]. The procedure for fitting κ comes from Mardia and Jupp [7]. When $\kappa = 0$, the distribution is uniform, as κ increases the probability density function (PDF) $P(\mathbf{x})$ becomes more concentrated about $\mathbf{m}$.

Probabilistic tractography: Given the posterior PDF on $\mathbf{x}$ in each voxel, tracking proceeds from a seed point in steps of 0.5 mm, using the interpolation scheme described in [8]. We track 1000 from each seed point, with the fiber orientations in each voxel randomly sampled from the posterior distribution. The tracking stops if the streamline reaches the surface of the brain, if it intersects itself, or if it curves by more than 80 degrees over the largest voxel dimension (2.2 mm). The tractography method, including the Bayesian PDF estimation is implemented in the open-source Camino toolkit [9].

Results: We demonstrate the method in one of the atlas subjects. Seed regions of interest (ROI) were defined manually in the image space of the subject. The connectivity of each seed ROI to another voxel in the brain is defined as the number of probabilistic streamlines that intersect the voxel. The results are thresholded for display; connectivity greater than 1% of the total number of probabilistic streamlines in the ROI is shown. The results are rendered within the T1-weighted image of the subject using MRICro [10]. The results in Fig. 2 show seed regions placed (from top) in the middle cerebellar peduncle, the right cingulum, and the fornix. These paths are difficult to track because of their high curvature and proximity to other whiter matter tracts. In all cases, the atlas prior increases connectivity along the pathway and allows the tracking to include more of the structure.

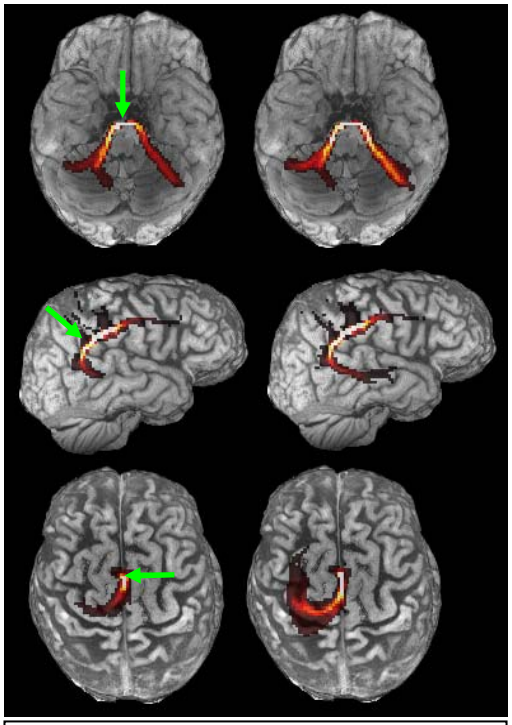

Fig. 2: tracking with no prior (left) and the atlas prior (right). The arrows point to the seed ROIs.

Conclusions: The atlas provides an anatomically-based prior that appears to improve tractography along known pathways. The prior is derived directly from the study population after normalization. Additionally, the atlas prior is specific to the local white-matter structure in the population, whereas heuristic curvature priors are typically specified once for the entire tract, regardless of local anatomy. Limitations in the present work include the small sample size, which we shall increase in future work. The prior is implicitly weighted to account for disagreement between the atlas mean and the subject's diffusion-weighted data, because the subject is part of the atlas and hence disagreement between the subject and the rest of the population always decreases the concentration of the prior. Future work will include testing on subjects not used in the atlas construction. Another innovation, which may be possible with a larger data set, would be to use a more complex prior distribution, such as the Bingham distribution, that can model a prior PDF with elliptical contours.

References: **1**. Mori et al, Ann Neurol 1999, 45:265-269. **2**. Basser et al, J Magn Reson B 1994 103:247-54. **3**. Coulon et al, Med Imag Anal 2004 8: 47-67. **4**. Friman et al, IEEE-TMI 2006 25:965:978. **5**. Zhang et al, Proc MICCAI 2007. **6**. Zhang et al, Med Imag Anal 2006 10:764-785. **7**. Mardia and Jupp, *Directional Statistics* Wiley, 2000. **8**. Behrens et al, Magn Reson Med 2003 50:1077-1088. **9**. Cook et al, Proc ISMRM 2006, p 2759. **10**. Rorden, Brett, Behav Neurol 2000 12:191-200.

Acknowledgement: We thank the National Institutes of Health for funding this work through grants NS045839, HD046159, HD042974 and MH068066.