Novel Statistical Models and Segmentation Methods for Fiber Bundles in DTI

S. P. Awate[1], H. Zhang[1], and J. C. Gee[1]
[1]Radiology, University of Pennsylvania, Philadelphia, Pennsylvania, United States

Purpose: We present novel methods for (i) statistically modeling and (ii) segmenting fiber bundles in diffusion-tensor (DT) images. Typical segmentation schemes, e.g. those based on fuzzy C means (FCM), incorporate Gaussian class models that are inherently biased towards ellipsoidal clusters characterized by a mean element and a covariance matrix. *Tensors in fiber bundles*, however, *inherently lie on specific manifolds in Riemannian spaces* (see Figure 1 for a simple example). Unlike FCM-based schemes, the proposed method represents these manifolds using *nonparametric* data-driven statistical models. We employ a consistent technique for nonparametric statistical modeling in Riemannian DT spaces. The proposed method produces a fuzzy segmentation by maximizing a novel information-theoretic energy in a Markov-random-field framework. By enhancing the nonparametric model to capture the *spatial continuity and structure* of the fiber bundle, we exploit the framework to extract the *cingulum* fiber bundle. Typical tractography methods for tract delineation, incorporating thresholds on fractional anisotropy and fiber curvature to terminate tracking, can face serious problems arising from partial voluming and noise. For these reasons, tractography often fails to extract thin tracts with sharp changes in orientation, such as the cingulum [2,3]. The results demonstrate that the proposed method extracts the cingulum significantly more accurately than standard Tractography [4].

Methods: *(1) Modeling Tensor Distributions in Fiber Bundles:* Figure 1 shows the distribution of diffusion tensors in a Riemannian space [1]. We use the kernel-based PDF estimation approach known as Parzen-window probability density function (PDF) estimation that superposes kernel functions placed at each datum. In the case of tensor data, the kernels are smooth functions of the Riemannian geodesic distance on the tensor manifold. The mathematical expression for the Parzen-window tensor-PDF estimate [1] is consistent with the expression for the usual kernel-PDF estimate in Euclidean spaces.

(2) Optimal Fuzzy Segmentation using Information-Theoretic Measures: We employ a piecewise-homogenous Markov random field model **Z** for the tensor image **z**. Our goal is to segment the image into S different fuzzy sets / segments (namely, $s=1,2,\ldots,S$) which are distinguished by their respective PDFs $P(\mathbf{Z}|s)$. Information-theoretic approaches to crisp segmentation employ Shannon's entropy to quantify the homogeneity in a segment. To achieve fuzzy segmentation, we propose to replace the Shannon's entropy for the class c by the following measure that conforms better to the notion of fuzzy segments:

$$h_s(Z) = -\int_{manifold} F_s(z) P_s(z) \log P_s(z) dz$$

In this way, each observation (neighborhood) contributes an amount to the "entropy" of class s---that is proportional to its membership in class s. This modification of the Shannon-entropy function is a novel and intuitive way to enable contributions from each point, to the entropy measure of a class, based on its membership value in that class---the integral/summation is now over all points in the feature space and the contribution from each point is weighted by the membership function. In this way, the proposed entropy function quantifies the homogeneity of tensors in the fuzzy class. We define the fuzzy segmentation as the solution to a constrained optimization problem:

$$\sum_{s=1}^{S}\left(\int_{manifold} F_s(z) P_s(z) \log P_s(z) dz - \alpha \int_{manifold} F_s(z) \log F_s(z) dz \right)$$

where the membership values are constrained to be nonnegative and must sum up to one at each voxel. Here, α is a user-controlled parameter ($0 \le \alpha < \infty$) that controls the *degree of fuzziness* imposed on the segmentation.

Results and Validation: We obtain DT images (voxel size 1.7x1.7x3 mm^3; 128x128x40 voxels) using a single-shot spin-echo diffusion-weighted EPI sequence. For each subject, we produced 12 images measured with 12 isotropically-distributed diffusion-encoding directions (b=1000s/mm^2). Figure 2 (top) and Figure 3 (left) show the results of a standard tractography technique [4] for the tract extraction using two regions-of-interest in the superior part of the cingulum. It is clear that standard tractography fails to extract the cingulum. On the other hand, Figure 2 (bottom) and Figure 3 (right) show that the proposed fuzzy segmentation approach---which exploits the statistical coherence of tensors in the entire structure---performs significantly better. For validation and quantitative comparison, we obtained two manual (crisp) segmentations by using interactive software tool to delineate color-coded scalar FA images---the color at each voxel is derived from the orientation of the tensor at that voxel. The Dice overlap metrics (averaged over the two manual segmentations) for the two DT images were: (i) 0.63 and 0.60 for the proposed method (after thresholding the fuzzy membership values with a value of 0.5) and (ii) 0.32 and 0.33 for tractography.

References: *(1)* Awate, Zhang, Gee. IEEE Trans. Med. Imaging 2007, 26(11):1525-1536 *(2)* Concha, Gross, Beulieu. Amer. J. Neuroradiology 2005, 26:2267-2274 *(3)* Gong et al. Human Brain Mapping 2005, 24:92-98. (4) Mori et al. Ann Neurol 1999

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Figure 1

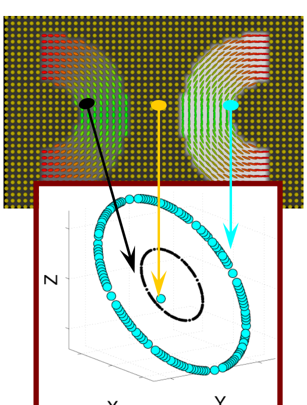

Figure 2
tractography (top); segmentation (bottom)

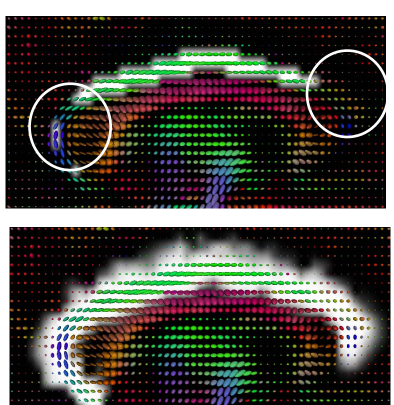

Figure 3
tractography (left); segmentation (right)