Medical Image Analysis 18 (2014) 161–175

Contents lists available at ScienceDirect

Medical Image Analysis

journal homepage: www.elsevier.com/locate/media

Improved segmentation of white matter tracts with adaptive Riemannian metrics

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ARTICLE INFO

Article history:
Received 4 December 2012
Received in revised form 23 September 2013
Accepted 15 October 2013
Available online 25 October 2013

Keywords:
Diffusion tensor imaging
Riemannian manifold
Conformal factor
Geodesic
Front-propagation

ABSTRACT

We present a novel geodesic approach to segmentation of white matter tracts from diffusion tensor imaging (DTI). Compared to deterministic and stochastic tractography, geodesic approaches treat the geometry of the brain white matter as a manifold, often using the inverse tensor field as a Riemannian metric. The white matter pathways are then inferred from the resulting geodesics, which have the desirable property that they tend to follow the main eigenvectors of the tensors, yet still have the flexibility to deviate from these directions when it results in lower costs. While this makes such methods more robust to noise, the choice of Riemannian metric in these methods is ad hoc. A serious drawback of current geodesic methods is that geodesics tend to deviate from the major eigenvectors in high-curvature areas in order to achieve the shortest path. In this paper we propose a method for learning an adaptive Riemannian metric from the DTI data, where the resulting geodesics more closely follow the principal eigenvector of the diffusion tensors even in high-curvature regions. We also develop a way to automatically segment the white matter tracts based on the computed geodesics. We show the robustness of our method on simulated data with different noise levels. We also compare our method with tractography methods and geodesic approaches using other Riemannian metrics and demonstrate that the proposed method results in improved geodesics and segmentations using both synthetic and real DTI data.

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1. Introduction

In order to study normal brain development, as well as neuropsychiatric disorders such as autism, it is crucial to understand how different functional regions of the brain are connected by white matter pathways. One approach to studying white matter in vivo is diffusion tensor imaging (DTI), a magnetic resonance imaging (MRI) modality that measures the diffusion of water in tissue. These diffusion measurements provide a means for inferring the microstructural properties of the white matter and analyzing fiber tracts. Three approaches to DTI analysis are: whole-brain connectivity analysis; localizing white matter regions by registration to an atlas; and segmenting individual white matter tracts from specified regions of interest (ROI). In whole-brain connectivity analysis, the goal is to explore the connectivity among many anatomical regions over the whole brain, typically using tractography and graph statistics (Hagmann et al., 2007). In atlas-based methods, the white matter is analyzed at the voxel level (Barnea-Goraly et al., 2005) or the atlas is used to segment the white matter into several anatomical tracts (Bazin et al., 2011). In this paper, we focus on segmentation of individual white matter tracts connecting two specified ROIs.

Several works have developed segmentation methods for white matter tracts from DTI data. Zhukov et al. (2003) employ level-sets to create geometric models of brain structures. Rousson et al. (2004) extend region-based surface evolution to DTI. Lenglet et al. (2005) model DTI data as multivariate Gaussian distributions and employ a level variational approach to segment the white matter structures. Wang and Vemuri (2005) use the square root of the J-divergence as the distance of tensors in a region-based active contour model for DTI segmentation. Ziyan et al. (2006) propose a modified spectral clustering method to segment thalamic nuclei. Awate et al. (2007) use a non-parametric model to get a fuzzy segmentation of the white matter tracts. Melonakos et al. (2007b) propose a locally constrained Bayesian region growing approach based on a pre-computed anchor path inside the white matter tract. Niethammer et al. (2009) develop a segmentation framework for near-tubular white matter tracts through global statistical modeling and local reorienting of the diffusion orientation. These methods focus on segmenting the white matter tracts of interest from the tensor field and they do not compute parameterized fiber pathways connecting the two end regions of the tracts. Tractography (Mori et al., 1999b; Conturo et al., 1999; Basser et al., 2000; Koch et al., 2002; Behrens et al., 2003; Parker et al., 2003; Lazar and Alexander,

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http://dx.doi.org/10.1016/j.media.2013.10.007

2005; Friman et al., 2006; Jones, 2008) and front-propagation (Parker et al., 2002; O'Donnell et al., 2002; Jackowski et al., 2005; Melonakos et al., 2007a; Pichon et al., 2005; Fletcher et al., 2007; Jbabdi et al., 2008; Hao et al., 2011) approaches, however, provide both a volumetric segmentation of the tract suitable for region-based analysis and a parameterization suitable for along-tract statistics (Corouge et al., 2006). In this paper, we extend the front-propagation approaches and compare our approach to previous methods for front propagation and tractography.

1.1. Properties of tractography

Deterministic tractography (Mori et al., 1999b; Conturo et al., 1999; Basser et al., 2000) computes streamlines (sometimes called fibers) by forward integration of the principal eigenvector of the diffusion tensors from one region. One major problem with tractography is that imaging noise causes errors in the principal eigenvector direction, and these errors accumulate in the integration of the streamlines. Another disadvantage to tractography is that it has difficulty in cases where the goal is to find pathways between two regions. In this scenario, streamlines begin in one of the regions and are accepted only if they eventually pass through the desired ending region. However, several factors conspire to often result in only a small fraction of fibers being accepted. For example, accumulated errors in the streamlines can throw them off the final destination. Also, noise and partial volume effects in the tensor field can cause stopping criteria to be prematurely triggered, either by low anisotropy tensors or sudden direction changes. The Brute-Force (BF) approach proposed by Conturo et al. (1999) can increase the number of accepted fibers by initiating fiber tracking from every voxel in the brain. However, this approach still suffers from the same factors mentioned above and can often segment only the main core of the white matter tracts.

Stochastic tractography (Koch et al., 2002; Behrens et al., 2003; Parker et al., 2003; Lazar and Alexander, 2005; Friman et al., 2006; Jones, 2008) is an approach that deals with the problems arising from image noise. In these methods, large numbers of streamlines are initiated from each seed voxel and are integrated along directions determined stochastically at each point. However, this is a computationally-intensive procedure (typically requiring several hours). Also, stochastic tractography suffers from the same problems with streamlines stopping in noisy or low-anisotropy regions, leading to artificially low (or even zero) probabilities of connection. Although Barbieri et al. (2012) combine tensor clustering technique with stochastic tractography in order to improve the accuracy of the segmentation results, this method introduces more parameters and strongly depends on the quality of the connectivity map.

1.2. Properties of front-propagation

In the DTI literature, front-propagation approaches are one class of methods to analyze the white matter pathways. These methods infer the pathways of white matter by first evolving a level set representing the time-of-arrival of paths emanating from some starting region. Then the pathways are computed by integrating the characteristics vectors of the level set backward from any target point to the starting region (Jackowski et al., 2005). The direction and speed of this evolving front at each point is determined by some cost function derived from the diffusion tensor data. One such method, first proposed by O'Donnell et al. (2002), is to treat the inverse of the diffusion tensor as a Riemannian metric, and the paths in the propagating front as geodesics, i.e., shortest paths, under this metric. This makes intuitive sense: traveling along the large axis of the diffusion tensor results in shorter distances, while traveling in the direction of the small axes results in longer distances. Therefore, the shortest paths will tend to remain tangential to the principal eigenvector of the diffusion tensor.

Front-propagation approaches for analyzing white matter pathways are attractive for at least three reasons. First, the front-propagation algorithms are more robust to noise than both deterministic tractography and stochastic tractography. This is because front-propagation methods compute fibers by optimizing a global criterion over the whole brain, so the wavefront is not constrained to exactly follow the principal eigenvector of the tensors. Although the principal eigenvector of the tensor is the preferred direction for paths to travel, the minimal-cost paths may deviate from these directions if the deviation decreases the overall cost, and hence are less sensitive to noise or partial voluming. Second, front-propagation methods can compute a large number of fibers using a short computational time. Efficient implementations of front-propagation solvers are much faster (typically requiring several seconds) than stochastic tractography. The graphics processing unit (GPU) implementation by Jeong et al. (2007) even runs at near real-time speeds. Finally, as shown by Fletcher et al., 2007, front-propagation methods can be used to segment white matter tracts by solving the geodesic flow from two ROIs and combining the resulting cost functions. This approach has the advantage that the solution will not get stuck in regions of noisy data or low anisotropy, in contrast to tractography methods. However, it also has the disadvantage that it requires the user to predefine two ROIs at the endpoints of the white matter tract of interest. Consequently, this approach is only appropriate when the anatomy of the white matter pathway is well-known, i.e., its endpoint regions can be reasonably identified, because a white matter path will always be found. Although, if a "false positive" connection is found, this can be detected using heuristic connectivity metrics as introduced by Parker et al. (2002) and Jackowski et al. (2005).

1.3. High curvature tract deviation

While front-propagation is a powerful framework for computing white matter pathways and despite the advantages that front-propagation methods have over tractography, there is one severe drawback. These geodesics have the serious deficiency that in high-curvature tracts they tend to deviate from the eigenvector directions and take straighter trajectories than is desired. That is, in high-curvature regions, the incremental cost of following the tensor field is overcome by the cost associated with the longer (more curved) path. The top image of Fig. 1 is a diagram illustrating the problem. In a curved tensor field, one would typically prefer a path that follows, to whatever extent possible, the major eigenvectors of the tensors (shown in blue). The shortest path, using a Euclidean metric (i.e., ignoring the tensors), follows a straight line except at constraints (shown in red). The typical geodesic with a local, anisotropic metric (e.g., using the inverse tensors as metric) will find a compromise between these two (shown in magenta). Although the magenta geodesic is taking infinitesimally higher-cost steps than the blue curve, its overall length under the inverse-tensor metric is shorter.

Fletcher et al. (2007) have addressed this issue previously by "sharpening" the tensor, i.e., increasing the anisotropy by taking the eigenvalues to some power and renormalizing them, which increases the cost of moving in directions other than the principal eigenvector. Actually, the first front-propagation algorithm proposed by Parker et al. (2002) essentially takes this sharpening strategy to its limit, which results in a cost function that is the dot product of the level set velocity with the principal eigenvector, and Jbabdi et al. (2008) show that the geodesics more closely follow the principal eigenvectors as the anisotropy of the noiseless

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