

Automatic Segmentation of White Matter Structures from DTI Using Tensor Invariants and Tensor Orientation

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INTRODUCTION

DTI analysis of brain structures has shown to be relevant in a number of neurological clinical pathologies, such as brain ischemia, multiple sclerosis or epilepsy, among others. In schizophrenia, group studies have demonstrated alterations in the diffusion of several fiber bundles within the white matter [1]. The automatic segmentation of these structures from DTI has spurred significant research effort recently, due to its importance for these studies. However, automatic segmentation from DTI is a very challenging issue, and approaches in the literature require the manual identification of a region of interest or starting seeds for the segmentation to be performed. This abstract presents a fully automatic segmentation approach for different anatomical structures in the white matter, based on: (a) the use of tensor invariants, together with the orientation of the tensor, as features to drive the segmentation, (b) a level set formulation based on the statistical modeling of the data through vector-valued Geodesic Active Regions (GAR), and (c) the use of a MRI atlas of human white matter [2], which is nonlinearly registered to the volume under study, to automatically obtain initial contours for the segmentation process. Segmentation on several DTI volumes showed good results, demonstrating that a fully automatic segmentation is possible and also presenting good properties when compared to recent DTI segmentation approaches in the literature.

METHODS

The proposed method is based on a vector-valued version of the GAR level set segmentation method [3]. Let $\mathbf{v}(\mathbf{x})$ be the feature vector at voxel \mathbf{x} . Then, we seek to minimize the following energy functional:

$$E(\mathcal{C}, \Theta_i) = - \sum_{i=1}^2 \int_{\Omega_1} \log p(I(\mathbf{x})|\Theta_i) dx$$

where the PDF of image I at voxel \mathbf{x} on region i is parameterized by Θ_i . For tensor-valued images, Gaussian distributions directly on the tensor data have been proposed using intrinsic tensor dissimilarity measures such as the Kullback-Leibler distance or the information geodesic distance [4]. Instead, we propose to employ a feature vector composed of the three tensor invariants introduced in [5] that describe the tensor shape (these invariants are $K_1=\text{tr}(\mathbf{D})$; $K_2=|\text{dev}(\mathbf{D})|$; $K_3=3\sqrt{6\det(\text{dev}(\mathbf{D})/\text{dev}(\mathbf{D}))}$), where \mathbf{D} is the diffusion tensor and $\text{dev}(\mathbf{D})$ is its deviatoric part), together with the tensor orientation. In order to represent unambiguously the orientation of the main eigenvector \mathbf{e}_1 of the diffusion tensor \mathbf{D} , we compute the outer product $\mathbf{T}=\mathbf{e}_1\mathbf{e}_1^T$, and take its six independent components t_i ($1 \leq i \leq 6$). This way, we represent the tensor information by means of the feature vector $\mathbf{v}(\mathbf{x})=[K_1 K_2 K_3 t_1 t_2 t_3 t_4 t_5 t_6]$. Note that the three tensor invariants are statistically independent whereas, by construction, the components of the outer product \mathbf{T} are not. Therefore, the PDF of the feature vector can be expressed as

$$p(\mathbf{v}|\Theta_i) = \left[\prod_{j=1}^3 p(K_j|\Theta_{K_j,i}) \right] \cdot p(\mathbf{t}|\Theta_{\mathbf{t},i})$$

where we denote $\mathbf{t}=[t_1 t_2 t_3 t_4 t_5 t_6]$. Under a Gaussian assumption for the values of K_j ($1 \leq j \leq 3$) and a multivariate Gaussian assumption for \mathbf{t} , the level set evolution equation that minimizes the energy functional can be shown to be:

$$\frac{\partial \phi}{\partial t} = \delta(\phi) \left[\nu \text{div} \left(\frac{\nabla \phi}{|\nabla \phi|} \right) + \sum_{j=1}^3 \log \left(\frac{p(K_j|\Theta_{K_j,1})}{p(K_j|\Theta_{K_j,2})} \right) + \log \left(\frac{p(\mathbf{t}|\Theta_{\mathbf{t},1})}{p(\mathbf{t}|\Theta_{\mathbf{t},2})} \right) \right]$$

where ϕ is the level set function, $\delta(\phi)$ is an approximation of the Dirac delta and the first term in the brackets is a regularizing term. This equation allows for the introduction of different weights for the terms corresponding to the tensor invariants and the tensor orientation term, thus controlling the relative importance of each tensor property in the segmentation process.

Initial surfaces are obtained by nonlinearly registering an atlas of human white matter [2] onto the volume to be segmented. This way, no manual initialization is needed.

RESULTS AND DISCUSSION

The proposed method has been validated through the segmentation of different anatomical structures in two different DTI volumes corresponding to the same subject. Results in Fig. 1 show that the algorithm is able to successfully segment very different structures in the white matter. Comparison between the segmented structures in the two DTI volumes shows almost identical results, which validates the consistency of the method.

Orientation information is most relevant for segmentation in DTI. Thus, the relative weight of the tensor

orientation term needs to be higher than those of the tensor invariants. The capability to control this balance is one of the advantages of the proposed approach. Recent approaches that rely on the use of intrinsic tensor distances, where the relative importance of the different tensor properties in the segmentation cannot be controlled, find problems in the segmentation when structures with similar tensor properties are adjacent. This is demonstrated in Fig. 2, where we compare our segmentation of the corpus callosum to the one obtained using tensor distances (Kullback-Leibler). It can be seen that this segmentation has trouble distinguishing between the corpus and the cingulum, as they have similar tensor properties except from the tensor orientation.

CONCLUSIONS

This abstract presents a novel method for the fully automatic segmentation of anatomical structures in the white matter from DTI. The proposed method has several important properties: (a) it is fully automatic as a white matter atlas is used for initialization through a nonlinear registration process, (b) it allows a different weighting for the different properties of the diffusion tensor, which yields a better accuracy. The method was validated through the segmentation of different structures in two DTI volumes.

REFERENCES

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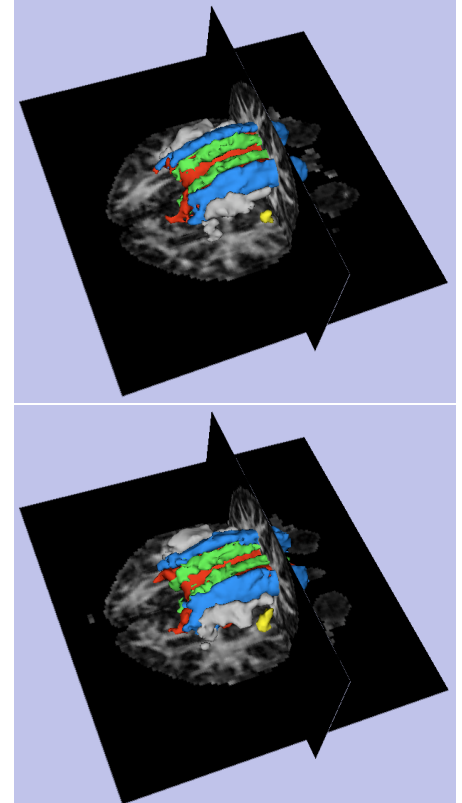


Fig. 2. Segmentation of the different structures in DTI volumes 1 (top) and 2 (bottom). Segmentation results are almost identical. Segmented structures are corpus callosum (red), cingulum (green), corona radiata (blue), longitudinal fasciculi (gray) and uncinate fasciculus (yellow).

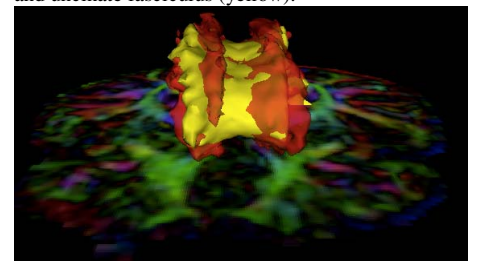


Fig. 2. Comparison of segmentation of the corpus callosum with proposed method (yellow) and the usage of tensor distances (red).