DTI Smoothing by Hierarchical, Adaptive and Robust Strategy

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Introduction

Diffusion tensor imaging (DTI) has been widely used to construct the orientation and structure of fibers in biological tissues, particularly in the white matter of the brain [1]. The raw diffusion-weighted images (DWI) from which diffusion tensors are estimated, however, inherently contain large amounts of noise, leading to uncertainty in the estimation of the tensors and their derived quantities, including principal directions. Because many algorithms for fiber tracking reconstruct the directions of fiber pathways based on the principal directions of these estimated tensors, reducing the effects of noise on these estimated tensors is crucial for accurate tracking of fibers.

Method

The noise in DTIs can be typically reduced by performing smoothing on the raw DWI data [2]. The currently available smoothing methods can be roughly grouped into three categories: 1) smoothing raw DWIs before the calculation of the diffusion tensors; 2) smoothing principal directions or tensors after estimation of diffusion tensors; and 3) simultaneously estimating and smoothing diffusion tensors (DT) using DWIs [3]. In this abstract, we propose a new method for adaptively estimating and smoothing DTs based on DWIs. The proposed method has three distinct novelties. First, it used robust anisotropic diffusion [4] in log-Euclidean space [5] for DT smoothing, which combines the techniques of robust statistics and anisotropic diffusion. The robust statistics can effectively detect boundary between the piecewise constant regions in the tensor field that has been smoothed with anisotropic diffusion. Second, it employed a hierarchical strategy to adaptively smooth DTs, starting with smoothing of DTs with large fractional anisotropy (FA) values, and followed by those DTs with low FA values. This hierarchical strategy can improve the SNR while preserving sharp edge information. Finally, to achieve adaptive tensor estimation, an iterative estimation of weighting coefficients was employed to characterize the similarity between neighboring tensors. Specifically, to smooth DT field, the following energy function for each tensor D_i in voxel i was minimized:

$$\min E(D_i) = \sum_{j\in\eta_i} w_{i,j} \sum_k \left\| S_k^j - S_0^j e^{-b\hat{g}_k^T D_i \hat{g}_k} \right\| + \alpha \sum_{j\in\eta_i} \rho(D_i - D_j, FA(D_i), \sigma),$$

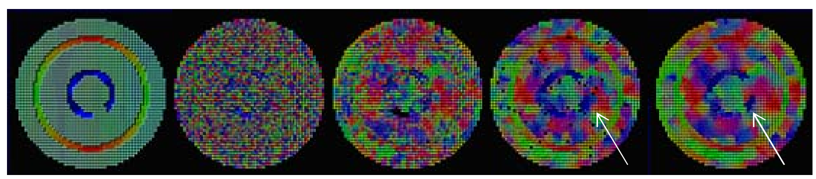
where η_i represents a spatial neighborhood of the voxel i, j is a voxel in this neighborhood, $w_{i,j}$ is a weight characterizing the similarity between the tenors D_i and D_j, and k represents a specific gradient direction. S_k^j is the raw DWI data at voxel j acquired at the k-th gradient direction and S_0^j is the data acquired in the absence of any diffusion-weighted gradient. $\rho(.)$ in the second term is a robust objective function, where σ is a scale parameter, FA is the FA value, D_i is the tensor at current voxel i and D_j is the tensor in the neighboring voxel j. α is used as a regularization parameter. The first term in the equation imposes the Gaussian diffusion tensor model at each voxel and weights these models across the current and neighboring voxels, in which the weights $w_{i,j}$ were calculated adaptively during the smoothing process. The second term is a robust anisotropic diffusion. Turkey robust estimator was used to reduce the influence of outliers. The local scale parameters were computed according to the similarity of DTs within each local region. Smoothing was performed hierarchically according to the values of FA.

Simulated data and real DTI data were used to evaluate the performance of the proposed method and compared it with other two methods implemented in R software and MedINRIA [6][7]. The simulated DWIs were obtained from the DTI package in R software. In vivo DTI was obtained from a healthy subject using 30 diffusion gradient directions. All results are displayed by ExploreDTI [8].

Results

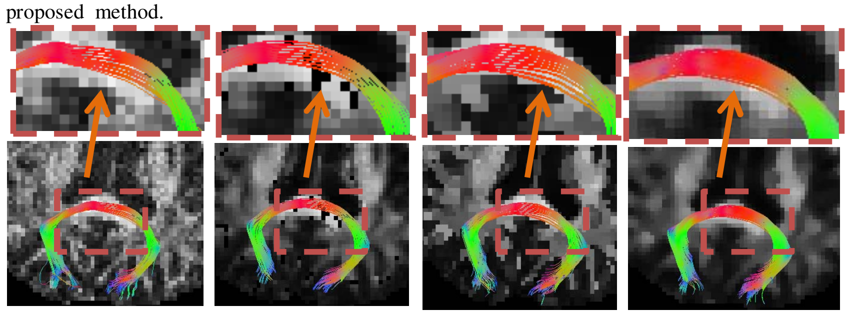
Fig. 1 shows the tensor ellipsoid maps of the simulated data. The original map includes a ring and a C-shape as shown in Fig. 1(a). Fig. 1(b) shows the map of estimated DT field after adding random noise to the original DWIs. The SNR is about 8 db. Fig. 1(c) is the DT field smoothed by MedIRNIA software, in which the anisotropic diffusion was used to directly smooth DTs. It is apparent that the ring and C-shape can not be discerned, indicating the failure of the anisotropic diffusion method. In contrast, both the DTI package in R software (Fig.1(d)) and the proposed approach (Fig.1(e)) effectively recover the ring. However, only our approach yields a much clearer C-shape than that of the DTI package (arrow), indicating the effectiveness of the proposed approach.

For the human data, fiber tracts were generated using the ExploreDTI with a FA threshold of 0.2 and a maximum angle of deviation 30-degree. Although all methods yield similar results, the fiber tracts based on the proposed method is much more uniform (Fig. 2).



(a) (b) (c) (d) (e)

Fig.1. Tensor ellipsoid maps from (a) true DT field, (b) noised DT field, (c) smoothed DT field using MedIRNIA, (d) smoothed DT field using R software, and (e) smoothed DT field by the proposed method.



(a) (b) (c) (d)

Fig.2. Tractography of (a) original DT data, (b) DT data smoothed by MedIRNIA, (c) DT data smoothed by R software, and (d) DT data smoothed by the proposed method.

Conclusion

We have developed a DTI smoothing method, utilizing robust anisotropic diffusion filtering along with hierarchical and adaptive strategy in Log-Euclidean space to adaptively smooth the DT field. Both the simulated and human data suggest that the proposed approach outperforms the currently existing approach. Evaluation of the performance of the proposed method on large dataset is currently ongoing.

References

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