Robust extraction of fiber skeleton based on whole fiber tensor information and active contour method

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Introduction
In the analysis of DTI data, fiber-based quantitative analyses are becoming more widely used for cross subject comparison [1,2]. With tract based analysis, tractography is usually used first to detect the fiber trajectory or fiber of interest, and a group analysis is subsequently conducted on/along the fiber. Various tractography methods, including streamline tractography (SLT) [3] and probabilistic diffusion tractography [4], have been used for the definition of fiber. Because they track fibers according to local diffusion orientation, which are highly sensitive to noise, tracking errors can be accumulated along fiber track [5], making it possible to miss some known fibers [6] or to result in wrong pathways [7]. On the other hand, in tract-based spatial statistics (TBSS) [8], fiber skeletons were derived based on FA data alone. In this work, we introduce an approach to extract fiber skeleton using an active contour model, which allows us to optimize the fiber trajectory in a global sense based on contour regularity and measured tensor data in terms of both FA and eigenvector orientation. This approach, dubbed active contour based fiber skeleton extraction (ACFSE), is demonstrated to provide robust extraction of fiber skeleton.

Material and Method

Data Collection: Six healthy subjects were imaged with a 3.0T Siemens MRI scanner using diffusion weighted echo planar imaging. Each subject was scanned 6 times (TR/TE: 6500/90 msec, matrix: 256x256, FOV: 220x220mm, slice thickness: 2.5 mm, b value: 1000s/mm², 12 gradient directions). Using FSL version 4.0 [9], DT-MRI data were corrected for eddy current effects and analyzed to generate diffusion tensor and FA values.

Active contour based fiber skeleton extraction (ACFSE) method: Energy based active contour method [10] was adopted for obtaining fiber trajectory. A fiber is represented by an evolving curve $C(s,\tau) \equiv \{C_n(s),\tau\}$. Here $n$ represents the discrete points of $s$ on contour $C$. $\tau$ represents evolution time. An energy function $E(C,\tau)$ is defined on the contour as $E(C,\tau) = E_{int} + E_{ext}$, where $E_{int}$ and $E_{ext}$, respectively, denote the internal energy and external energy. $E_{int}$ determines the regularity, and the minimization of $E_{int}$ controls the smoothness of the contour. $E_{ext}$ determines the consistency of the contour with FA values and eigenvectors. $E_{ext}(s) = \int_0^1 \left( E_{img}(C(s,\tau)) \right) ds \equiv \sum_{n=1}^N \left( E_{img}(C_n(s,\tau)) \right) ds = \sum_{n=1}^N \left( E_{img}(C_n(s,\tau)) \right)$.

$E_{ext}(s)$ is defined as the combination of a function of FA, a function of variation of eigenvector directions in a local neighborhood $R$ and a function of the difference of the current location’s eigenvector direction with the curve’s tangent direction. Constants $w_a$, $w_c$, and $w_e$ are the weights to control the relative contributions of these factors. In the present implementation, only the direction of the principal eigenvector is considered (i.e. $\gamma_2 = \gamma_3 = 0$) and $w_a = w_c = 1$, $w_e = 0.5$. The minimization of $E_{ext}$ drives the contour to voxels with higher FA and consistent eigenvectors. This algorithm starts from an initial contour which was obtained by mapping a reference fiber path to the individuals according to user defined start, end, and/or middle regions.

Evaluation: We evaluated the performance of our method and compared them to those obtained by SLT. Seed regions and two end regions were manually defined by an experienced SLT user (step size = 1 voxel, curvatures < 60°, FA in seed region >0.2). No tracking FA restriction was used in SLT; in order to obtain as many connections between two regions as possible. With ACFSE, the defined regions served as the constraints of tracked fiber skeleton, and the step size of curve evolution was set to 1 voxel. For every subject, we combined 5 acquisitions, 3 acquisitions, and 1 acquisition randomly from the 6 acquired to generate data sets with 3 different noise levels; at each noise level, there were 6 datasets.

Results

Fig.1 illustrates the results from ACFSE and SLT of two subjects with data averaged from 6 acquisitions. It is clear that ACFSE was able to identify the cingulum in both subjects and its results are consistent with the results of SLT. Fig.2 presents the results of tracking of the cingulum bundle in the data from the same subject with different data sets from the average of 3 acquisitions. It is evident that ACFSE results in very consistent results while this is not the case for SLT.

Discussion and Conclusion

Our results show that ACFSE is robust and produces smooth and reproducible fiber trajectory. This robust performance can be attributed to the use of the active contour model, which reduces sensitivity to noise and artifacts in the data. In addition, the active contour model provides a more flexible framework to incorporate regularization while maintaining consistency with the measured data. Compared to skeleton identification used in TBSS, the approach described here offers the added value of specific fiber skeleton refinement. ACFSE can provide the orientation and shape of individual’s specific fiber pathway robustly and reliably, an important feature for fiber-based clinical / basic analysis.

Reference

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