A Fast and Robust Graph-based Approach for Boundary Estimation of Fiber Bundles Relying on Fractional Anisotropy Maps

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Abstract— In this paper, a fast and robust graph-based approach for boundary estimation of fiber bundles derived from Diffusion Tensor Imaging (DTI) is presented. DTI is a non-invasive imaging technique that allows the estimation of the location of white matter tracts based on measurements of water diffusion properties. Depending on DTI data, the fiber bundle boundary can be determined to gain information about eloquent structures, which is of major interest for neurosurgery. DTI in combination with tracking algorithms allows the estimation of position and course of fiber tracts in the human brain. The presented method uses these tracking results as the starting point for a graph-based approach. The overall method starts by computing the fiber bundle centerline between two user-defined regions of interests (ROIs). This centerline determines the planes that are used for creating a directed graph. Then, the mincut of the graph is calculated, creating an optimal boundary of the fiber bundle.

Keywords - DTI; fiber tracking; segmentation

I. INTRODUCTION

Diffusion Tensor Imaging (DTI) is a non-invasive imaging modality that provides information about the location of white matter tracts in-vivo based on water diffusion properties. In combination with tracking algorithms, it is possible to estimate the position and course of fiber tracts in the human brain (Figure 1). Based on measurements of water diffusion, tensors can be calculated by using diffusion-weighted pulse sequences that are sensitive to the random motion of water molecules. To calculate the tensor for each voxel, it is necessary to acquire at least six diffusion-weighted images with different gradient directions besides one unweighted image to determine the coefficients of the symmetric diffusion tensor matrix D. By diagonalizing the diffusion tensor matrix, three eigenvectors and three corresponding eigenvalues \( \lambda_1, \lambda_2, \lambda_3 \) can be calculated to describe the main directions of diffusion and their magnitude [3, 9, 12].

The Fractional Anisotropy FA \( \in [0,1] \) represents the fraction of the magnitude of the tensor matrix D that is ascribed to the anisotropic diffusion [13]:

\[
FA = \sqrt{(\lambda_1 - \lambda_2)^2 + (\lambda_2 - \lambda_3)^2 + (\lambda_3 - \lambda_1)^2} / 2(\lambda_1^2 + \lambda_2^2 + \lambda_3^2)
\]

In order to make use of the results of fiber bundle determination, a closed surface of the fiber bundle is necessary for integration into neurosurgical interventions. There are several ways of determining the fiber bundle and the boundary. The most intuitive one is a line propagation algorithm. In the discrete case, starting at a seed voxel with its main diffusion direction as initial tract direction, the next voxel in this direction is tested. If the stopping criteria (e.g. FA value) are satisfied, the tracking stops, otherwise the inner voxel direction is used as the new tract direction [10, 14]. But the results of those algorithms are given as set of lines that do not satisfy the condition for intraoperative integration. To overcome this, hulls can be generated, for
example like presented in [5], but the surface is fully dependent on the tracking results and strongly influenced by errors [10]. Another segmentation method is provided by [9]. Thereby, a closed volume representing white matter tracts is constructed by using a volume growing approach.

In this paper, a graph-based approach for boundary estimation of tracked fiber bundles is presented. This method uses fiber tracking results and the centerline of the tracked bundle between two user-defined regions of interest (ROIs). Rays are sent out radially from the sampled centerline to set up a directed graph. Then, the mincut of the graph is computed to create the boundary of the fiber bundle. Experimental results using several artificially generated DTI data sets demonstrate the feasibility of the proposed approach.

The paper is organized as follows. Section 2 presents the details of the proposed method. Section 3 discusses experimental results. Section 4 concludes the paper and outlines areas for future research.

II. METHODS

A. Preprocessing

The overall method starts by computing the centerline of the fiber bundle based on two user-defined ROIs. Then, the calculated centerline is sampled at n points. For each point, a plane upright to the centerline’s direction is set up. All n planes along the centerline are used to create the directed graph.

B. Graph Construction

After the centerline and the planes have been computed, a graph is set up. The construction of the graph is based on the methods introduced in other works [6, 7, 8], where the planes are “unfolded” by sampling along rays that are sent out radially from different fiber bundle center points (Figure 2). For evaluation, 10-30 rays are used for unfolding in clockwise direction starting with the ray at 12 o’clock within each plane. After all planes have been unfolded, the segmentation starts using these planes to set up a 3D graph $G=(V,E)$, with $V$ including all points derived from “unfolding” plus source and sink nodes $s$ and $t$.

Figure 2. Left: Rays are sent out radially from the fiber bundle center on a single plane. Right: Creation of an unfolded image.

The arcs $(v_{(x,y,z)},v_{(x',y',z')}) \in E$ of the graph $G$ connect two nodes $v_{(x,y,z)},v_{(x',y',z')} \in V$. There are three types of $\infty$-weighted arcs: $x$-arcs ($A_x$), $y$-arcs ($A_y$), and $z$-arcs ($A_z$) where $X$ is the number of rays sent out radially ($x=0,\ldots,X-1$), $Y$ the number of planes ($y=0,\ldots,Y-1$) and $Z$ the number of sampled voxels along one ray ($z=0,\ldots,Z-1$) (Figure 3):

$$A_x = \{ (v_{(x,y,z)},v_{(x,y,z-1)}) | z \in [1..Z-1] \}$$
$$A_x = \{ (v_{(x,y,z)},v_{(x+1,y,max(0,z-\Delta_y))}) | x \in [0..X-2] \}$$
$$A_y = \{ (v_{(x,y,z)},v_{(x-1,y,max(0,z-\Delta_y))}) | x \in [1..X-1] \}$$
$$A_y = \{ (v_{(x,y,z)},v_{(x,y,\max(0,z-\Delta_y))}) | y \in [1..Y-1] \}$$

Additionally, there are arcs connecting each node $v_{(x,y,z)} \in V$ to $s$ or $t$, depending on the sign of calculated corresponding weight. The weights depend on cost-values $c_{(x,y,z)}$ describing the absolute value of the difference of the average fiber bundle FA value and the FA value at $v_{(x,y,z)}$ and are calculated as follows:

$$w((v_{(x,y,z-1)},t)) = c_{(x,y,z-1)}$$
$$w((v_{(x,y,z)},t)) = c_{(x,y,z)} - c_{(x,y,z-1)} \quad \text{if} \quad c' \geq 0$$
$$w((v_{(x,y,0)},s)) = c_{(x,y,0)}$$
$$w((v_{(x,y,z)},s)) = c_{(x,y,z)} - c_{(x,y,z-1)} \quad \text{if} \quad c' < 0$$

Figure 3. Left: $A_x$ arcs. Middle: $A_{xz}$ arcs. Right: $A_{yz}$ arcs.

The intracolumn arcs $A_c$ ensure that all nodes below the surface in the graph are included to form a closed set (correspondingly, the interior of the fiber bundle is separated from the exterior). The intercolumn arcs $A_{xz}$ and $A_{yz}$ constrain the set of possible segmentations and enforce smoothness via two parameters $\Delta_x$ and $\Delta_y$. The larger these parameters are, the greater the number of possible segmentations (Figure 4).
C. Mincut Segmentation

After graph construction, the minimal cost closed set on the graph is computed via a polynomial time s-t cut [4], creating an optimal segmentation of the fiber bundle boundary. In addition, the delta value that controls the stiffness between the planes \(\Delta_y\) is set to a very low value (< 5) to bind the planes very tightly to each other. This is possible because the boundaries between two adjacent planes are similar in their sizes, if the distance between them is small (< 3mm).

D. 3D Model Creation

To visualize and evaluate the calculated fiber bundle boundary, a 3D model is generated. For this purpose, the result of the mincut segmentation given as one point per ray, separating fiber bundle and surrounding tissue, is triangulated. Then, a voxelization of the triangulated surface is performed (Figure 5: generated with 20 directions, 60 points per ray, \(\Delta_x=7\) and \(\Delta_y=2\)). The mask from the voxelization and the mask of a manual segmentation (ground truth) are afterwards used to calculate the Dice Similarity Coefficient (DSC) [15] for evaluation (see Section 3).

III. RESULTS

The methods were implemented in C++ within the MeVisLab platform [1]. Using one hundred planes along the centerline – between the two user defined ROIs – the overall segmentation (unfolding, graph construction and mincut computation) in our implementation took about 5 seconds on an Intel Core 2 Quad CPU, 3 GHz, 6 GB RAM, Windows XP Professional 2003, SP 2.

To evaluate the approach, different number of directions, distances between evaluation points, \(\Delta_x\) and \(\Delta_y\) were used (Table 1) on a software phantom modeling a portion of a torus (voxel size 1x1x1 mm³, bundle diameter 10 mm with complex Gaussian noise (\(\sigma=2\)). For 10 directions, the DSC was between 0.415 and 0.725. In this case, the best results (DSC > 0.7) could be achieved for a distance between the sampled points of 0.5 (30 points per ray), \(\Delta_x\) (5-8) and \(\Delta_y\) (1-3). For 20 directions, the DSC was between 0.374 and 0.75. Here, the best results (DSC > 0.7) could be achieved for a distance between the sampled points of 0.5 (30 points per ray), \(\Delta_x\) (5-7) and \(\Delta_y\) (1-3). For 30 directions, the DSC was between 0.359 and 0.766. The best results (DSC > 0.76) could be achieved for a distance between the sampled points of 0.5 (30 points per ray), \(\Delta_x=6\) and \(\Delta_y\) (1-3) (Table 2). Additional editing is always required after an automatic segmentation, but these edits can be achieved quite quickly because an automatic segmentation with a DSC over 0.7 provides already a border that fits well to the desired contour. As a comparison, a pure manual segmentation by a trained observer takes about 15 minutes. The graph-based approach was also applied to a more anatomical software phantom modeling the right corticospinal tract [2] (Figure 6).

![Figure 4](image.png) Principle of an intercolumn cut for \(\Delta=1\). Left and middle: Same cost for a cut (2\(\times\infty\)). Right: Higher cost for a cut (4\(\times\infty\)).

![Figure 5](image.png) Left: Mincut result of the fiber bundle boundary (blue) between two ROIs (magenta) with complex Gaussian noise (\(\sigma=2\)). Right: Fiber bundle boundary as triangulated 3D mesh (upper) and closed surface (lower).

![Figure 6](image.png) Left: Sagittal view of right corticospinal tract with calculated boundary (red) Right: Axial 2D slice with calculated boundary (red).
IV. CONCLUSION

In this paper, a graph-based approach for boundary estimation of tracked fiber bundles was presented. The introduced method uses fiber tracking results and the centerline of the tracked bundle between two user-defined regions of interest (ROI) to compute the fiber bundle boundary. Rays are sent out radially from the sampled centerline to set up a directed graph. Then, the mincut of the graph is calculated, creating an optimal boundary of the fiber bundle. To evaluate the method, it was applied to artificially generated DTI datasets, varying multiple parameters (number of rays per plane, sampled points along the rays, $\Delta x$ and $\Delta y$).

There are several areas of future work. For example, some parameter specifications of the proposed algorithm can be automated. Furthermore, the method can be enhanced for bifurcated fiber bundles. It will also be evaluated using more complex data (real patient data with intraoperative stimulation) and compared to other approaches.

REFERENCES