Brain Tractography Classification using Curvature Points

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Abstract

Classification of fiber tracts is an important problem in brain tractography.We propose a supervised algorithm which learns features for anatomically meaningful fiber clusters, from labeled DTI white matter data. The classification is performed at two levels: a) Grey vs White matter (macro level) and b) White matter clusters (micro level). Our approach focuses on high curvature points in the fiber tracts, which embodies the unique characteristics of each class. A test fiber is classified into one of these learned classes by comparing proximity using the learned curvature-point model (for micro level) and with a Neural Network classifier (at macro level). The proposed algorithm is validated over brain DTI data for three subjects containing about 2,50,000 fibers per subject, and has been shown to yield high classification accuracy at both macro and micro levels.

1. Introduction

Communication between different sub-divisions of brain is carried out via neuronal connections known as fibers, consisting of dendrites and axons. The brain tissue is divided into 2 primary types - white matter and grey matter. The former mainly contains axons that connect different parts of grey matter, while the latter contains cell bodies, dendrites and axons.

In the white matter space, many fibers form a bundle or cluster called Neural tracts; pathways that connect different parts of the brain, typically divided into 8 major classes: Arcute, Cingulum, Corticospinal, Forceps Major, Fornix, Inferior Occipitofrontal Fasciculus, Superior Longitudinal Fasciculus and Uncinate.

Diffusion Tensor Imaging (DTI) is non-invasive MR technique that enables one to determine the fiber tracts in the brain. The process, know as "Tractography", visualizes the fiber structure in 3D image obtained using DTI. An example is shown in Figure 1.

The segregation of these fibers into different anatomically significant bundles provides a better understanding of the brain structure and more insight into different neural disorders. However, a manual segmentation process is too ambitious a task, owing to enormity of the data (with a few hundred-thousand fiber tracts per subject). Hence, automatic classification of fibers into different bundles (groups) is an important but a challenging problem.

We propose an approach that uses labeled white matter DTI data to automatically learn features for different anatomically meaningful fiber clusters of brain's white matter. The features involve high-curvature points on the trajectory of each fiber, to learn the individual model for each class of the 8 primary classes. Furthermore, at a macro level, a model is trained to classify the data into 2 groups: one containing a group of 8 white matter tracts and one containing fibers not belonging to any of them. Any test fiber is classified into one of the classes by comparing a proximity based on the learned high-curvature-point based model.

[1.1] Related Work: While the problem of identifying the fiber tract clusters is relatively recent, some approaches have been reported. In some unsupervised approaches (Catani et al., 2002) (Maddah et al., 2005) (Wakana et al., 2004), regions of interests (ROI) are chosen manually, and fibers are grouped based

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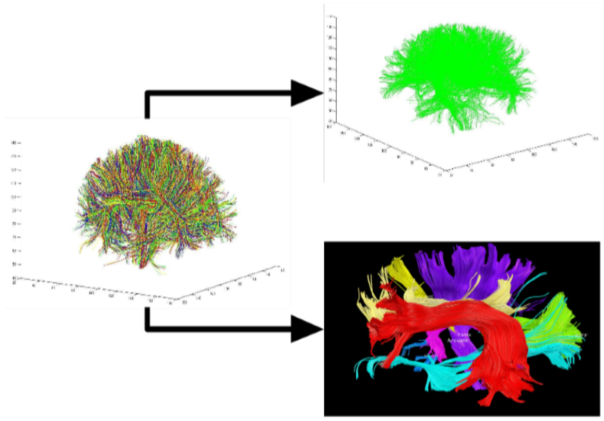

Figure 1. DTI fibers tracts: Unclassified (left), Grey matter (top right), White matter tracts (bottom right).

on these. Unlike these, in our approach the ROI are found out automatically, from labeled data. Donnell and Westin (O'Donnell & Westin, 2007) used spectral clustering to generate a white matter atlas automatically. The similarity is calculated between fibers using Hausdorff distance, and the clustering is employed in embedded space, formed using the Eigen-vectors of the distance matrix. In (Wang et al., 2011) hierarchical Dirichlet process is used to determine the number of clusters. In (Nikulin & McLachlan, 2010), certain points are selected automatically for representing each class. Instead of selecting many points our algorithm chooses only those points that have high curvature.

2. Proposed Solution

In this section, we discuss in detail various components of our approach such as fiber trajectory representation, feature extraction, clustering etc.

[2.1] Curvature Points : A good representation of the underlying data is important for building a model. We propose that high curvature points of the fiber trajectory can serve as unique characteristics to represent the fiber trajectories. Fibers will have high curvature value around regions where they significantly change direction. These regions would be similar for all the fibers in same cluster. Thus, we build our model using the fiber curvature at high curvature points.

The input to our approach is an array of fibers where the size of the array will be equal to number of fibers, and each fiber consists of 3D points. The number of points varies from fiber to fiber. f_{ij} represents a point

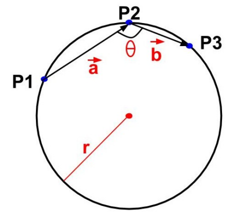

Figure 2. Circumradius fit for triplet of points

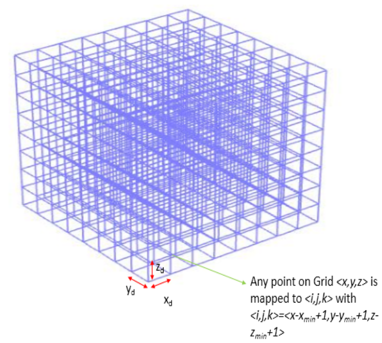

Figure 3. Voxel grid

with co-ordinate $< x, y, z >$ that is j^{th} point of i^{th} fiber.

To get the point having high curvature with good approximation we use the circum-radius viz. a unique circle fitted for every triplet of consecutive points in the fiber. as shown in Fig. 2. The points which would have high circum-radius would have less curvature and hence are less interesting. On the other hand, the points that have small radius would amount to a larger change in path of the curve.

[2.2] Space Discretization: We wish to compare fibers using the points that have high curvature. But as a large number of fibers are considered, the curvature data is often noisy (due to non-uniform distance between the fiber points), which makes it difficult to approximate regions that best characterizes the curve. Hence, to overcome this problem we work on a voxel grid, which is constructed as follows: Let the minimum and maximum values are computed for each 3D point coordinate x,y and z.

$$x^c_{min} = \min_{i,j} \lfloor f^c_{ij}(x) \rfloor \quad x^c_{max} = \max_{i,j} \lceil f^c_{ij}(x) \rceil \qquad (1)$$

Where f^c is set of fibers belonging to class c. Hence, a grid of size $(x^c_{max} - x^c_{min}) \times (y^c_{max} - y^c_{min}) \times (z^c_{max} - z^c_{min})$ is formed and is divided into voxels of size $x_d \times y_d \times z_d$ for each class c. An example of the voxel grid is shown in Figure 3.

Each point belonging to the fiber of class c is then approximated to the nearest grid point. A $3D$ array $bGrid^c(i, j, k)$ is constructed for each grid point, which stores the number of points approximated at $< x, y, z >$ for class c. A similar $3D$ array $bVal^c(i, j, k)$ stores the sum of the circum-radius of all points approximated at $< x, y, z >$. The relation between $< x, y, z >$ and $< i, j, k >$ is

$$< i, j, k >=< x-x_{min}+1, y-y_{min}+1, z-z_{min}+1 > \quad (2)$$

Now, only those grid points that have higher frequency of such 3D points than the predefined threshold are selected. Grid points that have less frequency can be considered noisy and are discarded. The points we get after this step are far less than the original set because multiple points would overlap to a grid-point and only fraction of these grid-points are chosen. This step helps in improving the computational efficiency and noise reduction.

[2.3] Clustering: The array $bVal^c(i, j, k)$ will have the sum of curvature values of all the points approximated at that grid point. Hence, the average value of curvatures in a voxel, is obtained by

$$bAvg^c(i, j, k) = bVal^c(i, j, k)/bGrid^c(i, j, k) \quad (3)$$

Now 30% points are chosen that have least $bAvg^c(i, j, k)$ value, which would correspond to those with highest curvature value of the accumulated fibers. These points would be distributed in different regions. We cluster them to get a single mean for each region. Each class will now have different number of regions and hence different number of clusters. The latter is determined empirically for each class. Fig. 4, depicts an example of the above discussed sequential categorization of fiber points for a class.

[2.4] Feature Extraction and Classification: We compute eight distance features which represent the proximity between classes. We want to capture the information about relative position of the fibers of each class . For example, for fibers of class 4, which has some relative positions to all $1-8$ class centers, we would expect the distance of class 4 fibers and those in other classes to have some pattern.

After the previous step, we have cluster centers for each class. For classification of new fiber, we calculate the circum-radius values and choose top 30% high curvature points. Let this set be S. These points should be closer to the centers of the correct class than other classes. So for each i in S, a distance,

$$Dist(i, j) = \max_{\forall k} \mathcal{N}(P_i; mean\_arr_{ck}, \Sigma) \quad \forall i \in S \quad (4)$$

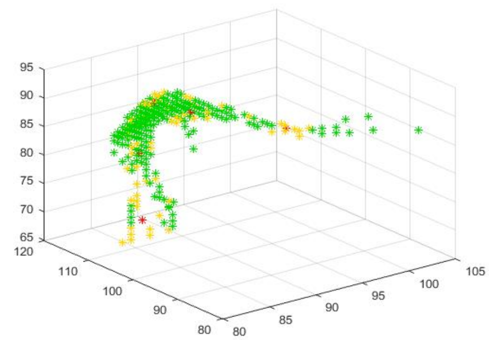

Figure 4. An example of the sequential categorization of fiber points: Green points remain after the elimination based on the frequency of points in each voxel, yellow points are those with high curvature value, and red points are the cluster means after clustering.

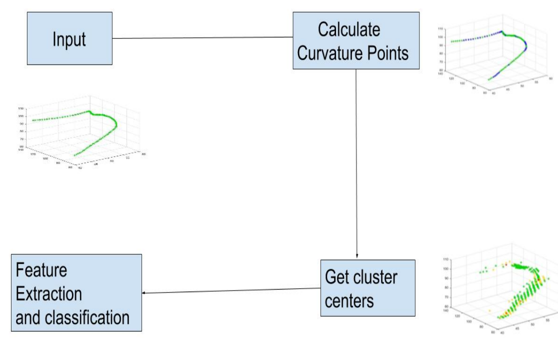

Figure 5. Overview of our approach.

is calculated. Where $mean\_arr_{jk}$ is k^{th} center of j^{th} class. $\mathcal{N}$ is normal distribution with mean $mean\_arr_{ck}$ and co-variance diagonal matrix Σ with diagonal values 20. Essentially for all points of fiber, $Dist(i, j)$ gives nearest center of class c.

For the macro level classification, we compute the above distance for all training fibers, and define

$$f(c) = \sum_{i \in S} Dist(i, c) \quad (5)$$

which is the total sum of the nearest center of each point in fiber to class c. These $f(c)$ values then fed to a neural network for classification.

For the micro-level classification, the distance in equation (5) is directly used for test fibers, and the class label yielding the minimum distance is assigned to the fiber. The various blocks in our overall approach are depicted in Figure 5.

Macro		
Intra	Brain-1	98.02%
	Brain-2	96.14%
	Brain-3	96.69%
Inter (using brain1 as training)	Brain-2	91.32%
	Brain-3	94.03%
Mixed	-	94.87%
Micro		
Intra	Brain-1	97.34%
	Brain-2	93.49%
	Brain-3	95.96%
Inter (using brain1 as training)	Brain-2	88.05%
	Brain-3	93.66%
Mixed	-	93.95%

Table 1. Results of the proposed approach for three experimental strategies, and two levels.

3. Experimental Analysis

We validate our approach on the DTI data for 3 patients. Each patient data consists about 2,50,000 fibers. The average length across different fiber classes varies between 36 to 120, highlighting that our approach is insensitive to the fiber length.

The experiments are carried out at two levels of classification - 1) Macro-level: Done between white-matter (classes $1-8$ considered as one) and grey-matter. At this level, we employ a neural network with 1 hidden layer and 8 hidden nodes for classification. 2) Micro-level: At this level, classification is performed among classes 1 to 8.

[3.1] Testing Strategy: Three strategies have been adopted to compute the accuracy of our algorithm. 1) Intra-Brain: Training and Testing data will be taken from same brain. 2) Inter-Brain: One complete brain data is taken for training and the approach is tested against data from other brains. 3) Mix-Model: 50% data from 3 brains to train, and the other 50% data from 3 brains to test. We compute the classification accuracy as,

$$Accuracy = \frac{Correctly\ classified\ fibers}{Total\ No.\ of\ fibers} \tag{6}$$

[3.2] Experiments: In table 1 we show our results and discuss these below.

i.) Intra-Brain: This model is trained and tested with sets of 50% data from the same brain. As expected, this strategy yields best results among all. Such an experiment highlights the reduction in manual labeling, even if it is for the same brain data.

ii.) Inter-Brain: We used complete brain 1 for training and test the model on brain 2 and brain 3. This strategy leads to somewhat less classification. This is because many white matter fibers are classified as grey matter at the macro level. However, the micro-level accuracy is still quite high.

iii.) Mix-Model: To account for variability among different brains, we use sets of 50% from all 3 brains to train and test. As the data varibility is high, the accuracy is lower than the first case. However, it still maintains a healthy accuracy of above 93%.

4. Conclusion

In this work, we reported an approach for classification of fiber tracts in DTI brain data. Our approach exploits a representation based on high-curvature points on fiber tracts, and their clustering. We perform classification on the macro and micro levels, and show a high classification accuracy across three experimental strategies. This highlights the efficacy of our approach under variability in data.

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