Coupled region-based level sets for segmentation of the thalamus and its subnuclei in DT-MRI.

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Abstract

We present a method for segmenting the thalamus and its subnuclei from Diffusion Tensor Magnetic Resonance Images(DT-MRI) using coupled, region based, level sets in 3D. Each surface, formed from the zero'th level set of the level set function, is associated with the most representative tensor contained within the surface. All neighboring voxels are then assigned to a region by finding the surface which representative tensor is most similar to the actual tensor. From these similarity measures a region based force is defined and the surfaces are dependent on each other through a coupling force [1].

1 Introduction

Diffusion Tensor Magnetic Resonance Imaging(DT-MRI) is a new modality that permits non-invasive quantification of the water diffusion in living tissues. The Diffusion Tensor(DT) provides information about the intensity of the water diffusion in any direction at a certain point. The water diffusion in the brain is highly affected by its cellular organization. In particular axonal cell membrane and myelin sheath are the main components restricting water mobility [2]. Hence the measured DT becomes highly anisotropic and oriented in areas of compact nerve fiber organization, providing an indirect way of fiber tract identification. Today, DT-MRI is mostly used for determining brain connectivity using fiber tractography algorithms [3, 4, 5, 6].

Only recently, DT-MRI have been used for segmentation purposes. The first approaches began by performing a fiber tractography and then used the result for segmentations. The most recent approaches have used Partial Differential Equations(PDE), variational methods and level sets [7, 8, 9]. In Jonasson et al. [7] we presented a geometric flow implemented with level set methods for fiber tract segmentation by measuring the diffusive similarity between voxels. Since then several papers containing very nice theoretical work using PDE's and level set methods for segmentation of DT-MRI have been published. Wang et al. [8] was the first to define regions from the DT and used region based forces for the front propagation. The region-based force is defined from a distance metric between tensors not too different from the concept of similarity measures we presented in Jonasson et al. [7, 10].

First we will briefly present the concept of diffusion tensors and basic theories on region based front propagation with level set implementation. We will then show how to use similarity measures for diffusion tensors to propagate a surface and how this can be used for white and gray matter segmentation.

2 Background

2.1 Diffusion tensors

DT-MRI permits in vivo measures of the self-diffusion of water in living tissues. The tissue structure will affect the Brownian motion of the water molecules which will lead to an anisotropic diffusion that is measured by diffusion weighted MRI along at least six independent axes. A normalizing image without diffusion weighting is also required. As a second order approximation, the measured anisotropic motion can be modeled by an anisotropic Gaussian that can be parameterized by the diffusion tensor in each voxel to create a 3D field of diffusion tensors.

The diffusion in a certain direction, $d(\hat{x})$ is given by the double contraction of the DT with the vector , $\hat{x}$, $d(\hat{x}) = \hat{x}\mathbf{D}\hat{x}$. A way of directly comparing the diffusion between two tensors is to use a similarity measure, S, that compares the diffusion in the direction of all unit vectors on a sphere, $\hat{x}$, using the double contraction:

$$\mathrm{S}(D_1, D_2) = \int \min\left(\frac{d_1(\hat{x})}{d_2(\hat{x})}, \frac{d_2(\hat{x})}{d_1(\hat{x})}\right) d\hat{x}, \qquad (1)$$

This gives us a percentage of the common diffusion for the two tensors.

To find the most representative tensor data set, Jones et al. [11] uses a distance metric between two tensors, (A, B):

$$d(A, B) := \sqrt{(A - B) : (A - B)}. \qquad (2)$$

A similar distance metric between a pair of images, i and j is then defined as:

$$d_{ij} = \sqrt{\sum_{\text{all voxels}} d(D_i, D_j)^2}. \qquad (3)$$

The root means square distance between a tensor in a voxel in the i'th image and the corresponding voxel in the other data set becomes:

$$c_i = \frac{\sqrt{\sum_{i=1, j\neq i}^{n} d_{ij}^2}}{n - 1}. \qquad (4)$$

The most representative data set is then the data set with the lowest value of c_i.

We will use this approach later to define the most representative tensor of the set of tensors contained within our level set.

2.2 Geodesic Active Regions

The Geodesic Active Region model was first introduced by Paragios et al. [1]. The approach is based on the theory of geometrical flows and curvature- or curve shortening flows. The model consists on segmenting an image into different regions by calculating the probability of every intensity value in the image of being in each region. The key hypothesis that is made to perform the segmentation is that the image is composed of homogeneous regions. Hence, the intensity properties of a given region can be determined using a Gaussian distribution. The segmentation is then done by evolving contours that are implemented using level set methods. The theory is well developed for the 2D case and the main part of the theories remains valid and works well for segmentation of 3D objects.

A general flow for a 3D closed surface can be described as:

$$\frac{\partial S}{\partial t} = (F + \kappa)\overrightarrow{N}, \qquad (5)$$

where F is an image based speed function, κ is an intrinsic speed dependent on the curvature of the surface, S is the surface, $\overrightarrow{N}$ is the surface and t is the time.

To solve this time dependent PDE we use the level set method, introduced by Osher et al. [12], where the evolving surface is considered as a constant level set of a function of a higher dimension. By doing this we obtain a numerically stable algorithm that easily handles topology changes of the evolving surface. In our case the function of higher dimension is the signed distance function, $\phi(t)$, of the evolving surface. It has been shown by Osher et al. [12] that the evolution of the zero level set coincide with the evolution of $S(t)$. Thus, the evolution of the signed distance function is described by:

$$\frac{\partial \phi}{\partial t} = (F + \kappa) \mid \nabla\phi \mid . \qquad (6)$$

3 Method description

We have developed a method for segmentation of DT-MRI that works for white matter as well as gray matter structures. We have based our work on the concept of geodesic active regions and level sets, as presented in the previous section. The regions are set by using tensor similarity measures that can be seen as a probability of a voxel belonging to a certain region. First the tensor that best represents the tensors contained within each level set is computed according to the method presented by Jones et al. [11]. These representative tensors are then associated to each evolving surface and every voxel in the vicinity of the evolving surfaces are then associated to a region. This is done by calculating the similarity between the tensor in that voxel and the representative tensors of the different regions. The similarity measure that we use for comparing the tensors is the integrated similarity presented in (1).

The similarity measure will give us a percentage of the common diffusion each tensor has with the different regions. Even though it is not exactly a probability measure it can be considered as one, the closer the value is to one the higher the probability that the tensor belong to that region. With that definition a region based force can be defined according the theories of Paragios et al. [1]:

$$F_i = -\log\left(\frac{\mathrm{IS}(\mathbf{D}, \mathbf{D_{typ,i}})}{max(\mathrm{IS}(\mathbf{D}, \mathbf{D_{typ,j\neq i}}))}\right), \quad (7)$$

where IS is the integral similarity described in (1). $\mathbf{D_{typ}}$ is the most representative tensor associated with the level set, ϕ_i and is computed according to (4). It is continuously recalculated as the surface evolves and therefore contains a new set of tensors. F_i will be growing the surface, S_i, in the direction where the diffusion in the voxels are the most similar to the representative tensor, $\mathbf{D_{typ,i}}$ of the tensor set lying inside S_i than the typical tensors of the other surfaces, $S_{j\neq i}$. If the similarity with $\mathbf{D_{typ,i}}$ is smaller than $\mathbf{D_{typ,j\neq i}}$, the voxel is more likely to belong to another region the surface will shrink.

Each one of our surfaces, i, are now evolving according to:

$$\frac{\partial S_i}{\partial t} = (F_i + \kappa_i + H_i)\overrightarrow{N} \quad (8)$$

where F_i is the regions based force (7), κ_i is the mean curvature and H_i is the coupling force as described in Paragios et al. [1].

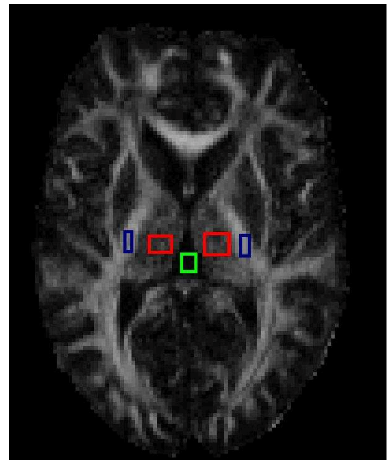

Figure 1: Placing the initial surfaces for the segmentation of the thalamus. Image above shows the color map of a horizontal section of a tensor field. The image shows how the surfaces have been initially placed, one in the surrounding fibers, one in the CSF and the third one in the thalamus itself.

4 Result

The thalamus and its nuclei has been segmented on three different patients. The initial surfaces for the thalamus segmentation has been chosen by looking at colormaps, as in Fig. 1. Each surface represent a significant structure surrounding the thalamus. The results for one of the patients can be seen in Fig. 2. The segmentation if the thalamus was then used as a mask for the segmentation of the thalamic nuclei. The resulting surfaces are shown in 3D and as 2D contours on fractional anisotropy maps, see Fig. 3. The colors of the surfaces are determined from the direction of principal diffusion of the most representative tensor inside the surface. The nuclei in the 2D cut have been identified into four different parts, the Anterior group, the Lateral group, the Posterior group and the Medial group. The nuclei are marked with the corresponding letters, A, L, P, M.

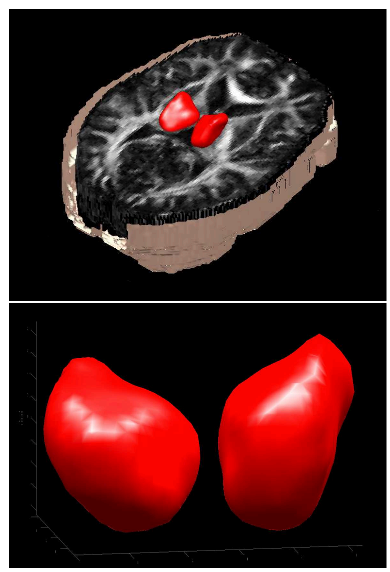

Figure 2: The segmentation of the thalamus displayed to the left on the whole brain and to the right a zoom of the thalamus is made.

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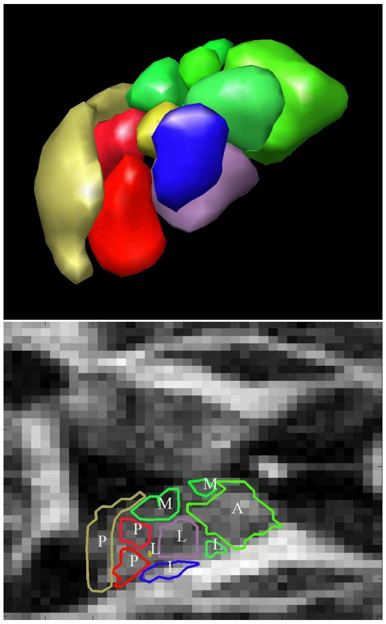

Figure 3: Segmentation of the thalamic subnuclei. The colors of the surfaces are determined from the direction of principal diffusion of the most representative tensor inside the surface. Right image shows 2D cut of segmentation, the nuclei have been identified, see text.

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