## 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]. For the segmentation of the thalamus itself, we have used a region based level set method on the fractional anisotropy maps. Since the thalamus is hardly differentiable by itself, the level set evolving in the thalamus has been coupled with two other level sets segmenting the surrounding structures using information not only from the anisotropy map but also from a map describing the mean diffusion. This segmentation has then been used as a mask for segmenting the subnuclei.

### **Background**

**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 [2] 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  $\hat{x}$ ,  $d(\hat{x}) = \hat{x}D\hat{x}$ . 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:

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

This gives us a percentage of the common diffusion for the two tensors. The most representative tensor data set is found following the method described in [3]. **Geodesic Active Regions** The Geodesic Active Region model was first introduced by [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 segmentation relies on the fact that the image is composed of homogeneous regions. Hence, the intensity properties of a given region can be determined using a Gaussian distribution. The regions are determined from the histogram by fitting Gaussians according to the Maximum Likelihood Principle. The segmentation is then done by evolving contours that are implemented using level set methods. The theory is well developed for the2D case and the main part of the theories remains valid and works well for segmentation of 3D objects.

Segmentation of the thalamus The segmentation of the thalamus is made directly from the fractional anisotropy images. The histogram of the fractional anisotropy map is approximated by a mixture of Gaussians. The Gaussians form the probability and the region force is then determined according to:

 $-\alpha \log [p_i(I(s))/p_i(I(s))]$ , where  $p_i(I(s))$  is the intensity probability density function for region  $R_i$ .

To improve the segmentation we have coupled the level sets with other level sets aiming to segment adjacent structures. The thalamus itself can sometimes be hard to distinguish on just one set of images. However, it is surrounded by structures such as fiber tracts and the cerebrospinal fluid (CSF) that is highly visible in fractional anisotropy maps and means diffusion maps respectively. Thus, we have evolved three surfaces simultaneously, one surface for segmenting the fibers in the FA-maps, one for segmenting the CSF in the mean diffusion maps and a last one in the thalamus itself. Since all surfaces are not evolving using the same image data the surfaces are only dependent on each other through an artificial coupling force.

Segmentation of the thalamic subnuclei We have developed a method for gray matter segmentation using tensor similarity measure to identify regions. First the most representative tensor [3] is associated to each evolving surface and every voxel is then associated to a region by calculating the similarity between the tensor in that voxel and the average tensor of the different regions. Similar approaches have recently been presented by [4, 5]. In our case the region force will look like:

# $F_i = -\log(S(D, D_{typ,i})/S(D, D_{typ,j\neq i})),$

where S is the similarity described previously.  $D_{typ}$  is the most representative tensor associated with the level set, i. It is continuously recalculated as the surface is evolving and thereby contains a new set of tensors. F<sub>i</sub> will be growing the surface, S<sub>i</sub>, in the direction were the diffusion in the voxels are more similar to the tensor that best describes the tensor set lying inside S<sub>i</sub> than the typical tensors of the other surfaces. If the similarity is smaller and the voxel is thereby more likely to belong to another region the surface will shrink.

#### Validation and results

The thalamus has been segmented on three different patients. The results for one of the patients can be seen in Fig. 1. For the segmentation of the thalamic subnuclei the method was first tested on synthetic data and compared with a k-means algorithm [6]. The method was then tested on three persons. The resulting surfaces are shown in 3D and as 2D contours on fractional anisotropy maps, see Fig. 2. 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 1. Segmentation of the thalamus.



Figure 2. 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.

[1] Paragios et al. Coupled Geodesic Active Regions for Image Segmentation, INRIA 3783, 1999; [2] Basser et al, MR diffusion tensor spectography and imaging, Biophys. J. 66:259-267,1994 [3] Jones et al, Spatial normalization and averaging of diffusion tensor MRI data sets, NeuroImage, 17: 592—617, 2002; [4] Wang et al., Tensor Field Segmentation Using Region Based Active Contour Model, ECCV 2004, Springer LNCS 3024:304-315, 2004; [5] Lenglet et al. Segmentation of 3D probability density fields by surface evolution: Application to diffusion MRI., Proc. MICCAI, 2004; [6] Wiegell et al. Automatic segmentation of thalamic nuclei from diffusion tensor magnetic resonance imaging, NeuroImage 19:391-401, 2003.