# Robust segmentation of the thalamus using Kohonen algorithm from diffusion tensor images

J. Dauguet[1], V. Frouin[1], Y. Cointepas[1], D. Hervé[1], N. Ayache[2], P. Hantraye[1]

[1]CEA, Service Hospitalier Frédéric Joliot, Orsay, France, [2]INRIA, Epidaure Project, Sophia Antipolis, France

**Synopsis** : Most of the neuroscience applications of diffusion tensor imaging (DTI) concern the tracking of fibers [1], but it may be used for tissue segmentation in structures like the thalami where classical imaging yields no contrast between main nuclear groups [2].

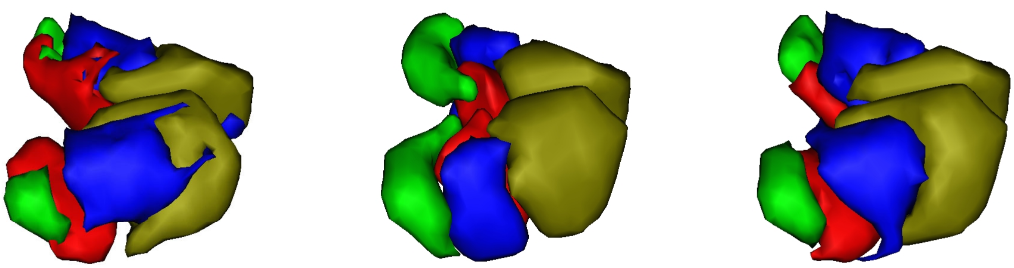
In this work, we describe the robust processes to derive parameters from raw DTI images and identify the different kinds of information that can be used for the segmentation process. This process is performed using Kohonen auto-organized maps combined with a hierarchical ascending classification.

**Material and methods** :

*Robust processes* : Six T1-weighted images and six diffusion-weighted data sets were acquired in humans on a GE 1.5T according to this protocol : 4 with 9 diffusion-sensitizing gradient directions (voxel size: 1.9x1.9x2.8 mm), and 2 with 31 directions (voxel size: 0.9x0.9x2 mm). The DTI images are obtained in a robust manner in two steps. First, a correction of the geometric distortions induced by large diffusion gradients is achieved by registering each slice of the diffusion image on the first *T2* image using affine transformation (unidirectional stretch, translation and shearing). Second, the tensors are estimated from the corrected sequences replacing the standard least squares-based approach by the Geman McLure M-estimator, reducing artifacts [3]. The use of both thalami signal at the same time in the classification process obviously increases its robustness. Therefore, symmetrical *T2* image were built. We estimated the transformation to register the original image with its symmetric with respect to the plane P defined by $x = dimX/2$. The middle transformation superimposes the inter thalamic plane with *P*, so that the image is straightened [4]. The tensors are re-computed in the new referential and the sign of the components related to the *X* direction of one thalamus was changed so that the same regions of both thalami present comparable tensors values.

*Segmentation* : the mask of external contours of each thalamus was obtained on the anatomic *T1* image of the same individual. This *T1* image was then registered rigidly with the corrected *T2* image, allowing the extraction of the thalami on the diffusion tensor image. A classification of all the voxels of the two thalami was then performed using Kohonen auto organized maps. Each voxel was represented by a vector $V = \alpha.[D_{xx}, D_{xy}, D_{xz}, D_{yy}, D_{yz}, D_{zy}, D_{zz}, 0, 0, 0]' + \beta.[0, 0, 0, 0, 0, 0, x, y, z]'$ where D.. are the six components of the diffusion tensor and x, y, z the three spatial positions. Three sets of weights were used for the 6 tensor components and the 3 spatial components respectively : first 1 / 0 (tensor contribution only), second 0 / 1 (spatial contribution only) and third we have looked for an intermediate weightings leading to the most realistic segmentation. The number of classes for the Kohonen step was set to 100, using a 2D 10 by 10 map and with 10000 iterations. After this first classification, classes were gathered in clusters. In order to determinate these clusters, which are difficult to appreciate in a 9 dimension space, a Hierarchical Ascending Classification (HAC) with Ward distance was applied [5]. The study of the curb of fusion costs allowed to define the number of meta classes which could be differentiated, that is to say in our study the number of parts of the thalamus which can be segmented using the diffusion tensor.

**Results** : The whole procedure was applied to the database. For the three sets of weights, the HAC was stopped when 4 meta classes were remaining which was corresponding to the first significant skip in the cost function for most images. Each class contained only one big connected component. The first choice of weights (tensors only) led to a segmentation on which the same 4 parts could easily been guessed in each thalamus but artifacts remained. The second choice (positions only) led to a regular segmentation, quite different from the precedent one, and which did not correspond to anatomical or functional information. The last choice of weights chosen heuristically at 0.75 / 0.25 looked like the first one but was regularized by the spatial components. The results on the 6 images demonstrate both reproducibility and robustness of the methodology proposed. This segmentation was moreover naturally symmetric: this means that the same class appears in the same place in the two thalami, although nothing forced the classification to regroup the voxels in this way. An image of the two thalami with a color for each meta-class can thus be realized for each study (fig. 1).



A B C

**Fig.1:** Results of the segmentations of the thalami. A : tensor only weights, B: position only weights and C: tensor regularized by position.

**Discussion and conclusion** : The classification proposed is based on the diffusion tensor, which depends mainly on the direction of the fibers. The classification thus obtained should discriminate nuclei containing fibers oriented along different directions. A confrontation with an atlas [6] demonstrated a pertinent anatomical classification that could be worth using *in vivo*. According to us, this is a promising way to distinguish internal areas in the thalami *in vivo*. The best results were obtained with the mixed weighting. The tensor terms, which correspond to pertinent information, had the biggest weight (0.75) whereas the spatial information was just used as regularizing factor.

Our results are three folds: we obtained classes with a good anatomical coherence, we contrasted the interest of the different kinds of information and finally we got preliminary indications about the number of thalamus putative sub-nuclei that can be inferred from current DTI. The use of Kohonen/HAC enabled the selection of the number of pertinent classes, contrary to standard classification algorithms like the k-means.

**References** :

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