Tractography by segmentation of high angular resolution diffusion MR images

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Introduction

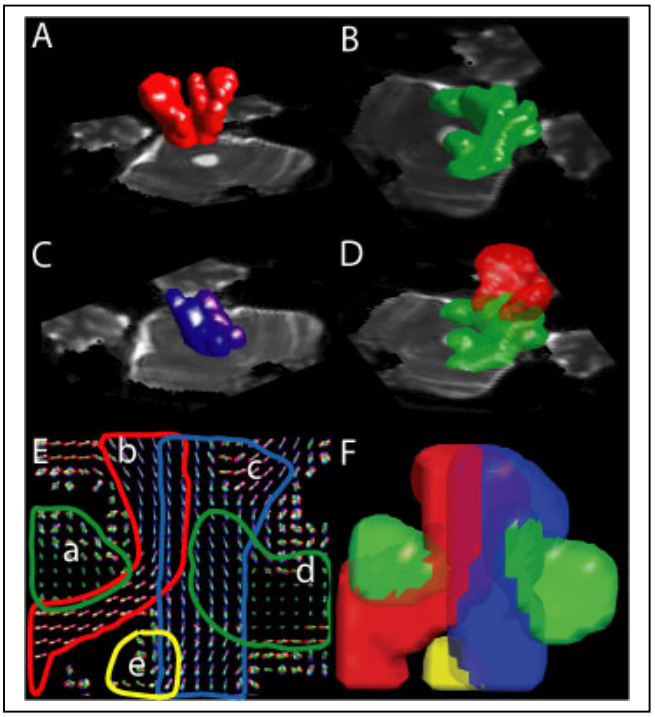
The advent of high angular resolution diffusion imaging enables tractography to be addressed by classical image segmentation approaches, where fibertracts are defined as disjoint clusters in a 5D space. Although fibertract identification is usually solved by generating integral paths in a field of principal diffusion vectors [1,2], some attempts have been made to address the question by segmentation [3]. However, performing the segmentation in 3D space, as it is usually done, raises topological difficulties when fibertracts cross in a single voxel. This is why we propose to reformulate the segmentation problem in a 5D position-orientation space and we show how it disentangles crossing fiber tracts. We then perform tractography by using standard classification or segmentation tools.

Theory

What is Position-Orientation Space (POS)? In HARDI, as for example Diffusion Spectrum Imaging (DSI) [4], diffusion in every voxel is represented with an Orientation Diffusion Function (ODF). An ODF is a function that measures an intensity of diffusion for any direction in space. Accordingly, the image we consider is a function not only of the 3 Cartesian dimension (*x*,*y*,*z*) but also of diffusion direction, (i.e. any polar coordinates *theta, phi*). It is therefore natural to call this 5D space of variables *x, y, z, theta* and *phi* the POS.

Some intuition on the separation power of POS. Consider 2 crossing fibertract, one going up-down (*theta=0*), the other left-right (*theta=90°, phi=90°*). In 3D space they occupy the same voxel (*x, y, z*) whereas in POS they are disjoint as the pixel (*x, y, z, theta=0, phi*=any) is very far from pixel (*x, y, z, theta= 90°, phi = 90°*).

Segmentation of POS in two classes: The aim of the first step is to classify POS in 2 classes which are 5D-pixels lying within a fiber-tract (class label *1*) and 5D-pixels lying outside a fibertract (class label *0*). To perform this task, we adapt, to the particular topology of POS, a Markov Random Field Maximum A Posteriori (MRF-MAP) classification algorithm developed by [5]. We consider *S* a subset of $\mathbf{Z}^5$ where each element *s* of *S*, called a site, belongs to POS. On *S* we define a neighborhood system $N=\{N_s\}_s$ where N_s is the set of sites neighboring *s*. N needs to be chosen carefully as it defines the topology of POS. The neighbors of a 5D-pixel are the elements that are located in within a small radius of Euclidian and angular distance. We define a set of random variables $\mathbf{X}=\{x(s)\}_s$ taking its values in the configuration space {fiber = 1, no-fiber = 0} and a set of random variables $\mathbf{Y}=\{y(s)\}_s$ in *S* taking its values in a countable configuration space, say {*1, …, D*} which are the possible values of the diffusion on the ODF. We say that **X** is a Hidden MRF on *S* with respect to the neighborhood system N, whereas **Y** is the observable random field. In other words we say that the ODFs of our image (**y**) are a realization of **Y**. A realization (**x**) of **X** is a configuration of fibers. We look for the configuration **x** that maximizes the conditional probability p(**x**|**y**). According to the MAP criterion we have to formulate the following optimization problem: $\mathbf{x} = \text{argmax}_{\mathbf{x}} \{p(y|x)p(x)\}$. The MRF can be equivalently characterized by a Gibbs distribution; hence we have an equivalent optimization formulation in terms of energy functions: $\mathbf{x} = \text{argmin}_{\mathbf{x}} \{U(\mathbf{y}|\mathbf{x}) + U(\mathbf{x})\}$. Where U(**y**|**x**) is the likelihood energy and U(**x**) the posterior energy. Although mathematically simple this type of MAP problem can be computationally difficult. We use Iterative Conditional Modes (ICM) [6] that iteratively performs a local minimization and converges after only a few iterations.



Fibertract labeling. By definition 2 separate fibertracts are 2 clusters in **x** that are disjoint with respect to the neighborhood system. We use an iterative algorithm to label the different clusters and consequently identify the different fibertracts.

Material

The diffusion weighted images are acquired with a single shot EPI sequence for 515 different diffusion encoding directions, sampling a sphere of radius r=5 grid units in a 3D grid . The acquisition was made on a 3T Philipps scanner with the following timing parameters: TR/TE/Δ/δ = 3000/154/47.6 /35 ms and b-max = 12000 mm^2/s. We imaged 2 healthy volunteers. On the first we did a brainstem study where we acquired of a block of 128x128x24 voxels at a spatial resolution of 2.4x2.4x2.4 mm^3. On the second volunteer we acquired 5 coronal brain slices of 128x128 voxel with a resolution of 2x2x3 mm^3. In every voxel the data was reconstructed with a classical DSI scheme by taking in every voxel the Fourier transform of the modulus of the q-space signal and represented the data with ODFs: radial projection of the diffusion pdf [4].

Results

Figures A-D display results based on the brainstem acquisition. On Fig. A we can see the segmented corticospinal tract (CST) in red. Fig. B shows the mid-cerebellar peduncle (MCP) and Fig. C both superior cerebellar peduncles (SCP). In Fig. D we see how the CST and MCP cross in the pons and how they share partly the same volume in 3D space. Figures E-F correspond to the coronal acquisition centered on the centrum semiovale. Fig. E is a plot of the odfs in this area on which manually we have drawn lines around objects of interest. (a) is the cingulum (green), (b) are the callosal fibers (red), (c) is the CST (blue), (d) the arcuate fasciculus (green) and (e) part of the thalamus (yellow). Fig. F is the segmentation result of the centrum semiovale and we can appreciate how the different structures have been identified. We see again how different structures share partly the same 3D volume as their surrounding surfaces overlap. For example it is clear that the arcuate fasciculus crosses the CST (i.e. blue and green surface). The same observation is valid for the cingulum and the callosal fibers (red and green surface) as well as CST and callosal fibers.

Conclusion

We have seen that fibertract identification can be formulated as a classical image segmentation problem; however because of the topological structure of the objects of interest it is necessary to perform the segmentation in a space that provides sufficient freedom in order to separate them. At first sight, the naturally occurring POS seems optimal for this task and the results show how nicely on can identify crossing fibertracts. However, the method readily raises an other difficulty which does not seem to be readily solved by POS; kissing fibers overlap in this space as well.

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Acknowledgments: This work was financially supported by NIH 1R01-MH64044 grant, the SNSF grant number 3235B0-102868 and Mr Yves Paternot.