Adaptive Distance Learning Scheme for Diffusion Tensor Imaging using Kernel Target Alignment

Paulo Rodrigues[1], Anna Vilanova[1], Thorsten Twellmann[2], Bart ter Haar Romenij[1]
[1] Biomedical Image Analysis, Department of Biomedical Engineering, Eindhoven University of Technology
[2] MeVis Medical Solutions AG, Bremen, Germany

Introduction

In segmentation techniques for Diffusion Tensor Imaging (DTI) data, the similarity of diffusion tensors must be assessed for partitioning data into regions which are homogeneous. Various distance measures have been proposed in literature for analysing the similarity of diffusion tensors (DTs) [1], but selecting a measure suitable for the task at hand is difficult and often done by *trial-and-error*. We propose a novel approach to semiautomatically select the similarity measure or combination of measures that better suits the data.

Methods

The distance learning algorithm (see Fig. 1 and Fig. 2) infers the elementary distance or combination of distances that best discriminates two labelled sets of DTs: **P** a selected Region of Interest (ROI); **N** the entire image volume represented by a random sample of DTs.

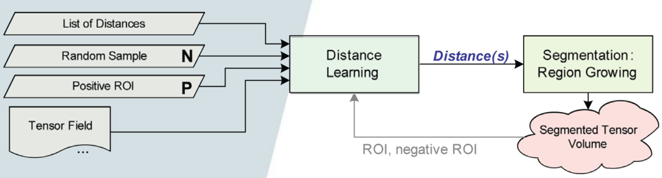

Figure 1: Global gist of the distance/parameter learning algorithm and segmentation.

For each elementary distance, we compute the pairwise distance between these DTs. Kernel matrices (Gram matrices) are calculated by defining a mapping as the inner product. Then, with a linear combination of the different normalized kernels we define a new kernel K with a set of unknown parameters (the weights):

$$K(w) = \sum_{m=1}^{l} w_m K^m, \text{ and } \sum_{m=1}^{l} w_m = 1$$

with K^m being the normalized Gram matrix based on the elementary/basic distance measure *m*.
Using a grid search based method, the weights in the linear combination are estimated in order to maximize the Kernel Target Alignment measure.
This maximum gives the combination of distances that best discriminates the considered data. The parameters are then used to drive a segmentation algorithm. In this paper, we use Region Growing.

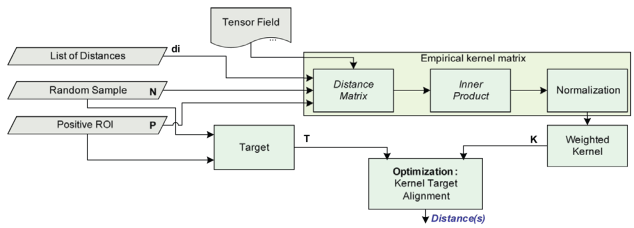

Figure 2: Detailed scheme of the distance learning algorithm

Results

Fig. 3 depicts the *left cingulum* discriminated from its coherently aligned linear shaped DTs.
In Fig. 4, the *corpus callosum* is not entirely captured, the comissural fibers are missing, since no sample of these DTs were given.

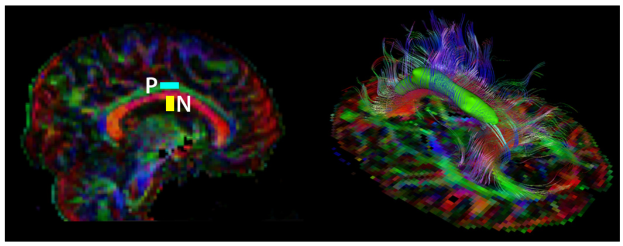

Figure 3: *Left cingulum* segmented with estimated w_{FA} = 0.8 and w_{ang1} = 0.2. Left: **P** – positive region; **N** – negative region.

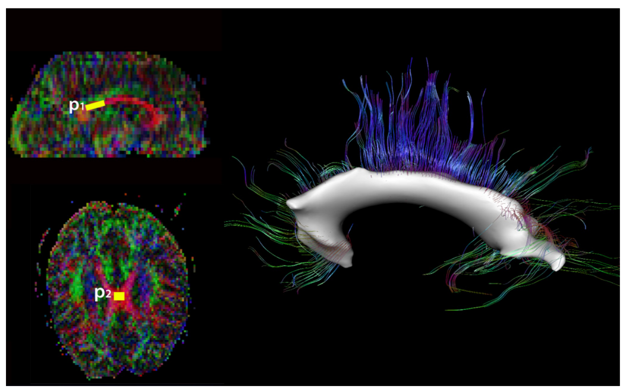

Figure 4: The *corpus callosum*, in a 128 × 128 × 30 DT volume, and the commissural fibers. The estimated combination of distances is w_{FA} = 0.5 and w_{ang1} = 0.5. Left: P1 and P2 were used as positive ROIs.

References

[1]: Peeters and Rodrigues et al: Visualization and Processing of Tensor Fields: Advances and Perspectives (2008);
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