Improving Diffusion Tensor Imaging Segmentation Through an Adaptive Distance Learning Scheme

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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 in terms of tensor characteristics. Various distance measures have been proposed in literature for analyzing 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 define the similarity measure or combination of measures that better suit the data. We use a linear combination of known distance measures, jointly capturing multiple aspects of tensor characteristics, for comparing DTs with the purpose of image segmentation. The parameters of our adaptive distance measure are tuned for each individual segmentation task on the basis of user-selected ROIs using the concept of Kernel Target Alignment [2]. The results of the presented method can then be used in any segmentation algorithm as, for example, region growing.

METHODS: The distance learning algorithm (see Fig. 1 and Fig. 2) infers the elementary distance or combination of distances that best discriminates two labeled sets of DTs: **P**, a set of representative DTs from a user defined ROI (positive ROI); and **N**, a set of representative DTs for the whole volume (negative ROI). Distance matrices are constructed by calculating the distance between all pairs of tensors in the set **S** = **P** ∪ **N**. Each row is considered as a feature vector with the distance from a tensor to all others in the training set. From these feature vectors, symmetric matrices, referred to as kernel matrices (i.e., Gram Matrices), are calculated by computing all possible inner products between each vector. For a uniform behavior of the algorithm, without minding the scale, a normalization of the individual kernel matrices is performed.

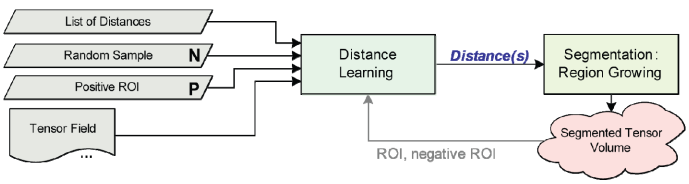

Figure 1. Global gist of the distance/parameter learning algorithm and segmentation.

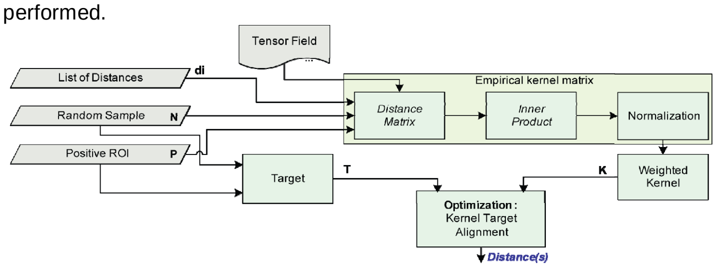

Figure 2. Detailed scheme of the distance learning algorithm.

Then, with a linear combination of the different normalized kernels we define a new kernel K with a set of unknown parameters (the weights):

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

with K^m being the normalized Gram matrix based on the elementary/basic distance measure *m*.
The weights in the linear combination are estimated, using a grid search based method, 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.

RESULTS: The synthetic image in Fig. 3 was designed to test and illustrate the behaviour of the method. The regions have different DTs but some properties are common. E.g. with a ROI in R1 and R2, w_{FA}=0.3 and w_{ang1}=0.7, since anisotropy and coherent orientation discriminates these two regions from the rest. Fig. 4 depicts the *left cingulum* discriminated from its coherently aligned linear shaped DTs.

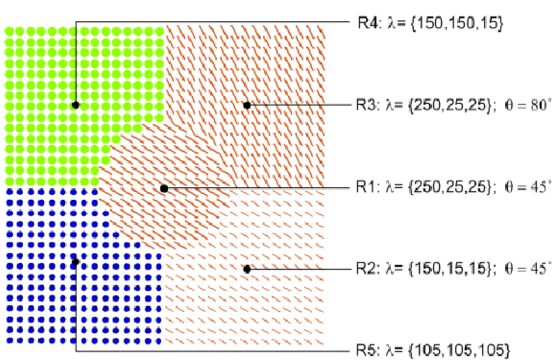

Figure 3. Superquadric glyphs showing the five distinct regions in a 30x30 tensor synthetic image. DTs have λ as eigenvalues and θ as rotation.

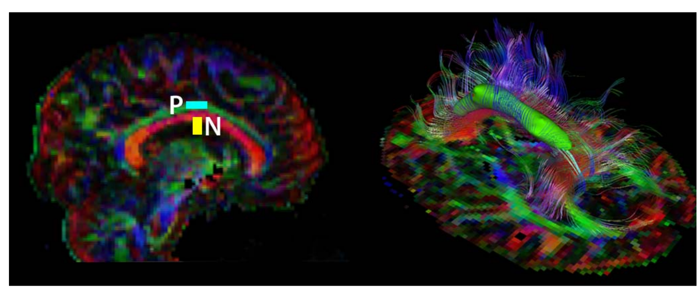

Figure 4. Left *cingulum* segmented with estimated w_{FA}=0.8 and w_{ang1}=0.2, for a 128x128x66 DT volume. Left: P – positive region; N – negative region.

CONCLUSION: In this abstract, we present a new method to estimate homogeneity distance measures that better fit the data. As a proof of concept we apply it to synthetic and real data, demonstrating its potential. The used measures are of different nature and capture different aspects of the tensor data. We present an initially flexible learning scheme that infers the combination of measures that give good results, although, the resulting similarity measure will not be necessarily intuitive. Kindlmann et al [3] decompose tensor variations into changes in shape and orientation. The path integrals of tangents of geodesic-loxodromes will be used to achieve an intuitive and biologically significant combination of measures. However, doing a good evaluation is a challenging problem, which starts with the definition of a good ground truth. The present algorithm can be extended to HARDI (High Angular Resolution Diffusion Imaging) approaches to diffusion, since it is still unknown which are the useful distances between two spherical functions such as DOT and Q-ball for applications like segmentation [4].

REFERENCES: [1] Rodrigues et al IMS'08; [2] Cristianini et al NIPS'01; [3] Kindlmann et al, MICCAI 2007; [4] Descoteaux et al, MICCAI 2007;