FUZZY ANATOMICAL CONNECTEDNESS USING DIFFUSION MRI: AN APPROACH TO TRACTOGRAPHY OF THE BRAIN

S. N. Sotiropoulos[1], C. R. Tench[1], and L. Bai[2]

[1]Clinical Neurology, University of Nottingham, Nottingham, United Kingdom, [2]Computer Science, University of Nottingham, Nottingham, United Kingdom

Introduction

Commonly used streamline tractography techniques propagate a curve within the vector field of fibre orientations, estimated from the processing of Diffusion-Weighted (DW) images. A hard binary relationship is assumed between voxels during this procedure, i.e. voxels can be either 'connected' or 'not connected'. However, medical images have inherent inaccuracies and are fuzzy [1]. Therefore track delineation should be governed by fuzzy relationships. Expressions such as 'very connected', 'quite connected', 'weakly connected' can form a superset of the binary expressions and describe better the relationship between voxels. Probabilistic tractography techniques address this issue by computing indirectly an index of connectivity. In this study, we introduce a new framework for tractography, based on the fuzzy connectedness algorithm [1] that computes a fuzzy relation between voxels and can infer connectivity. Fuzzy connectedness (FC) has been previously used for object segmentation. We present here a slightly modified version applicable to tract reconstruction. In our analysis, we use Diffusion Tensor Imaging (DTI) data, however any technique that provides local fibre orientation estimates can be potentially utilised.

Methods

Fuzzy Connectedness Theory: The FC algorithm assigns a global strength of connectedness between two voxels *A* and *B* by using a local fuzzy relationship called affinity. The affinity between two voxels incorporates the adjacency of the voxels, as well as the similarity between intensity-related features, and shows how affiliated the voxels are in the local scale. Once affinities are defined, FC considers all possible paths connecting *A* and *B*. Each of these paths is assigned a strength, the minimum affinity between any two grid points along that path. The strength of the strongest path is the connectedness between *A* and *B*. The algorithm was implemented using dynamic programming that allows interactive execution times [2].

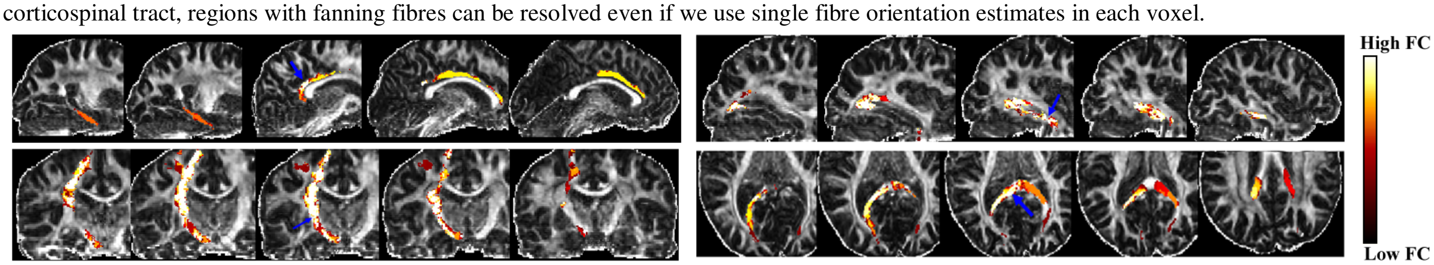
Affinity: In this study, the affinity between two voxels *A* and *B* was defined using the local fibre orientation estimates. To account for curvature in the path connecting *A* and *B*, we fit -in a least squares sense- a quadratic curve, by imposing the following conditions: a) The curve starts from the centre of voxel *A* and terminates at the centre of voxel *B*, b) The tangent to the curve vectors at the start and terminating points are given by the eigenvectors of *A* and *B* respectively. Once the curve is fit, the maximum radius of curvature is calculated along its path. A Gaussian function that checks deviation of this radius from a large value is used as the affinity. Thus, the more curved the path connecting two voxels the lower their affinity. A 3x3x3 neighbourhood is considered for each voxel *A* and affinities are calculated between *A* and its neighbours.

FC Tract Reconstruction: Once a seed voxel is specified, propagation of the FC algorithm is performed once towards the directions that have a positive dot product with the seed voxel's eigenvector and once towards the opposite directions, just like the two-step streamline propagation. Affinities are calculated on-the-fly and the voxel directions are flipped when necessary in order to agree with the current direction of propagation.

Data Acquisition and Processing: Scans were performed on a healthy subject that gave informed consent using a single-shot, spin-echo, echo-planar, DW sequence (acquisition matrix 112x112 with in-plane resolution 2x2 mm, 2 mm slice thickness, TE=60 ms, TR=9500 ms) in a Philips 3T Achieva clinical imaging system. A parallel imaging factor of 2 was used. Three non-DW and 32 DW images were acquired at b=1000 s/mm^2. Images were corrected for eddy current distortion and interpolated at 1x1x1 mm^3 using FSL [3] and diffusion tensors were calculated as described in [4].

Results

We applied the FC-based tract reconstruction in different regions of the brain. The following figures show connectedness values between a seed voxel (indicated with a blue arrow) and all other voxels in the brain. The connectedness maps are superimposed with fractional anisotropy images. To aid visualization, only connectedness values above a certain threshold are presented. The seed voxels are placed respectively (figures from left to right) in the cingulum, the anterior part of the inferior longitudinal fasciculus, the internal capsule and the splenium of the corpus callosum. Major components of these tracts are identified by the fuzzy connectedness algorithm started from a single voxel. The connectedness is high for voxels connected to the seed through a strong path and reduces with the optimum path strength. As observed in the inferior longitudinal fasciculus and the corticospinal tract, regions with fanning fibres can be resolved even if we use single fibre orientation estimates in each voxel.



Discussion

The above results indicate the potential of using the fuzzy connectedness algorithm in tract reconstruction. The framework presented here utilizes estimates of local fibre orientations and is independent of the technique used to get these estimates. Although the DTI model is utilised in this study, any model-based or model-free algorithm that computes fibre orientations can be used. Proper selection of the affinity function is of great importance to the success of the algorithm. The current implementation uses an affinity function that is quite sensitive to direction changes across voxels. The connectedness between voxels is reduced by not taking into account the uncertainty in the orientation estimates and by considering a discrete fibre orientation vector field. We are exploring affinity functions that address these limitations.

References: [1] Udupa JK, Samarasekera S. Fuzzy Connectedness and Object Definition: Theory, Algorithms, and Applications in Image Segmentation. Graphical Models and Image Processing 1996;58:246-261. [2] Nyul LG, Falcao AX, Udupa JK. Fuzzy-connected 3D image segmentation at interactive speeds. Graphical Models 2003; 64:259-281. [3] Smith SM, Jenkinson M, Woolrich MW et al. Advances in functional and structural MR image analysis and implementation as FSL. NeuroImage 2004; 23(S1):208-219. [4] Basser PJ, Mattiello J, LeBihan D. Estimation of the effective self-diffusion tensor from the NMR spin echo. J Magn Reson B 1994;103(3):247-254.

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