

BootGraph: Probabilistic Fiber Tracking Using Bootstrap Algorithm and Graph Theory

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Introduction

Bootstrap methods were recently introduced in diffusion tensor imaging (DTI) to investigate the measurement precision of tensor derived parameters such as the apparent diffusion coefficient or the fractional anisotropy (FA) value [1-5]. Furthermore, the cone of uncertainty (CU) [2] provides an estimation of the variation in the direction of the tensor's principal eigenvector. This variation is used in probabilistic fiber tracking algorithms and in the computation of connectivity maps [6,7]. Likewise, graph theory was recently applied to DTI data to assess connectivity maps [8,9]. In this work, bootstrap estimates are combined with graph theory for improved probabilistic tractography and, eventually, connectivity maps.

Methods

Data acquisition: Data were acquired on the Philips Achieva 3T system (Philips Healthcare, Best, the Netherlands) using a diffusion-weighted single-shot spin-echo EPI sequence with the following scan parameters: FOV = 210 x 210 mm², matrix = 104 x 102, reconstructed to = 112 x 112, 50 contiguous slices, slice thickness = 2 mm, SENSE factor = 2.1, TE = 43 ms. Diffusion-weighted scans were performed along 30 directions distributed uniformly on a sphere with a maximum b-factor of 1000 s/mm², complemented by one scan with b = 0 s/mm². Cardiac gating was applied in all scans. Eddy current-induced image warping was corrected using a correlation-based affine registration algorithm.

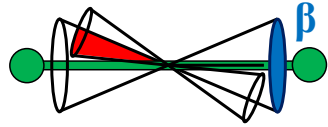


Figure 1: Edge probability defined as volume fraction (red) of the edge-related CU. The nodes and the edge are shown in green.

Bootstrap: A set of 1000 bootstrap samples was generated using the residual bootstrap [4]. The CU with a 95% confidence angle (α) was derived for each voxel.

Graph theory: The DTI data were transformed into a simple, undirected, and weighted graph. A distinct node was assigned for each voxel with a FA ≥ 0.2 and edges were defined to those of its 26 neighbors which lay over the FA threshold. For each edge, the two CUs of the corresponding nodes were linearly interpolated to create an edge-related CU. An additional cone around the direction of the edge (CE) with a solid angle $\beta = 4\pi/26$ was defined in which the nervous fibers passing in this direction should be contained [8]. The edge probability (p_e) was then defined as the volume fraction of the edge-related CU intersected by the CE (see Fig.1). To enable the use of Dijkstra's shortest path algorithm [10] for finding the most probable connection between two nodes the edge weight was set to $w_e = 1 - p_e$. The final probability of a connection between two nodes, and hence two voxels, was computed by multiplying all edge probabilities p_e along the shortest path. Only paths with local curvatures smaller than 60° were accepted.

Results

Figure 2 shows the connectivity maps for a seed region of interest (ROI) in the body of the corpus callosum and two seed ROIs in the internal capsules. The colormap represents the probability of connection from red (high) to blue (low). The shortest paths to all voxels with a connectivity probability of more than 25% are visualized in Fig.3. The used color-coding scheme shows connections from left to right in red, connections from top to bottom in blue and through plane connections in green.

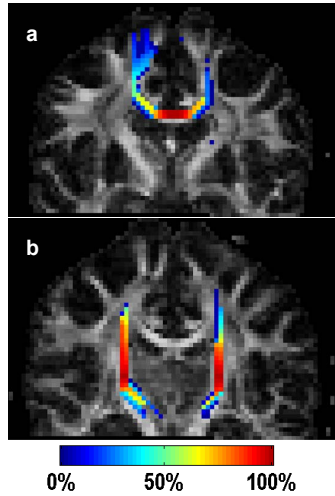


Figure 2: Probability maps with a seed ROI in the body of the corpus callosum (a) and a seed ROI in the left and right internal capsules (b) overlaid onto FA images.

Discussion and Conclusion Graph based probabilistic tractography was extended by including bootstrap derived data uncertainties to compute connectivity maps in the white matter of the human brain. In contrast to previous bootstrap based algorithms [6,7], all tracking relevant parameters, such as the FA threshold or the curvature threshold, can be set after the time consuming calculation of the bootstrap samples before the fast and well established graph algorithms are executed. While former graph based algorithms [8,9] only considered the directional information of the DTI data to derive the edge weights, the presented algorithm takes also the measurement uncertainty of data into account. In conclusion, a new probabilistic tracking method was presented which combines two sophisticated DTI tractography methods: bootstrap statistics and graph theory.

References

- [1] Pajevic, S. et al., [2003], JMR, 161: 1-14.
- [2] Jones, D.K. et al., [2003], MRM, 49: 7-12.
- [3] O'Gorman, R. L. et al., [2006], MRM, 56: 884-890.
- [4] Chung, S. W. et al., [2006], NeuroImage, 33: 531-541.
- [5] Whitcher, B. et al., [2008] HBM, 29: 346-362.
- [6] Lazar, M. et al., [2005], NeuroImage, 24: 524-532.
- [7] Jones, D.K. et al., [2005], MRM, 53: 1143-1149.
- [8] Iturria-Medina, Y. et al., [2007], NeuroImage, 36: 645-660.
- [9] Sotiropoulos, S.N. et al. [2009], NeuroImage, (in press).
- [10] Dijkstra, E., [1959], Numerische Mathematik, 1: 269-271.

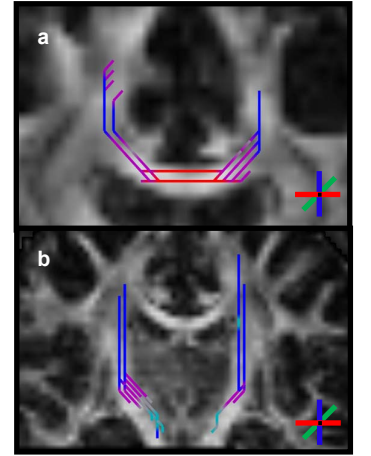


Figure 3: Shortest paths to voxels with a connection probability of more than 25% emanated from a seed ROI in the corpus callosum (a) and a seed ROI in the left and right internal capsules (b) projected onto FA images.