Graph-based fibre tractography computing shortest paths between regions of interest

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Introduction We present a novel, graph-based method for performing tractography upon diffusion data from human brains. In contrast to local approaches, where tracts are computed from voxel to voxel, graph-based tractography solves the problem globally by considering all possible paths.

Methods We model the diffusion as a weighted, undirected graph where nodes correspond to grey- or white-matter voxels. An edge is created from each node to any white-matter node that is within its [3 x 3 x 3] neighbourhood, where the edge weight reflects the diffusion "strength" along a line connecting the two voxel centres. This represents the pseudo probability of a fibre bundle connecting the two voxels, and is computed from a sampling-based integral over the orientation distribution function (ODF) in each neighbourhood direction. Fibre tractography between two specified regions-of-interest (ROIs) is then performed by finding the shortest path between each pair of voxels within both ROIs by using the log-transformed edge weights as distances. This is equivalent to finding the most probable path using the edge weights. The method is also able to incorporate the *a priori* specification of a waypoint region that all shortest paths are then constrained to pass through. Each of the resulting paths – reflecting a skeleton tract – has a confidence score, i.e. the length-corrected product of all edge weights along the path. Voxels can then be scored by the averaged value of the confidence scores of all the shortest paths which they lie upon. From these scores a heatmap image can be created for visualisation.

Data Tractography was performed on pre-processed diffusion data from five subjects from the Human Connectome Project[1–3]. The Camino toolkit[4] was used to compute a multi-tensor representation for each voxel. Images were transformed and segmented with FSL[5]. Reference tracts for comparison were obtained from the NatBrainLab[6].

Results Performance was tested on the cortico-spinal tract (CST), the inferior longitudinal fasciculus (ILF) and the inferior occipito-frontal fasciculus (IOFF). The resulting shortest paths for all tracts in a single subject can be seen in Figure 1. In addition, average tracts were computed over all subjects for each tract after transforming them into MNI standard space. Those are shown as heatmaps in Figure 2.

Discussion & Conclusion One advantage is that the presented approach is not tailored to certain diffusion representations unlike other graph-based or shortest path methods: Vorburger *et al.*[7] used DTI data together with a bootstrap approach for edge weight computation, Sotiropoulos *et al.*[8] create their graph from a Q-ball representation with multiple edges for crossing fibres, O'Donnel *et al.*[9] and Lenglet *et al.*[10] compute shortest paths in a Riemannian manifold constructed from the DTs. Similar to our method, Iturria-Medina *et al.*[11] can incorporate any ODF. However, all above graph-based methods compute all paths from a single set of seed voxels, leading to path-length dependencies. In contrast, our ROI-based approach does not suffer from those problems because a path will always be found and scores are averaged by the number of voxels on a path. The confidence scores can then be used to assess the reliability of the computed tracts, and this may help the discovery of low probability tracts that are not found by other methods. In future works prior knowledge might be incorporated to boost the confidence of those tracts. Furthermore, the novel method is especially useful for creating brain connectivity graphs[12], whose nodes usually represent ROIs and edges the connection strength between these regions. Besides the discussed advantages, the results show a considerable overlap of the computed tracts with the reference, which highlights the quality of the presented graph-based approach.

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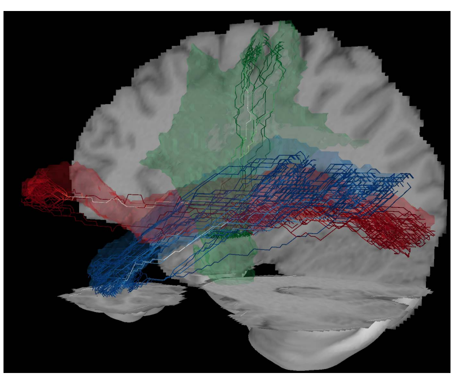

Figure 1: Results (streamlines) for CST (green), ILF (blue) and IOFF (red) for subject 110411 with the reference tract (volume).

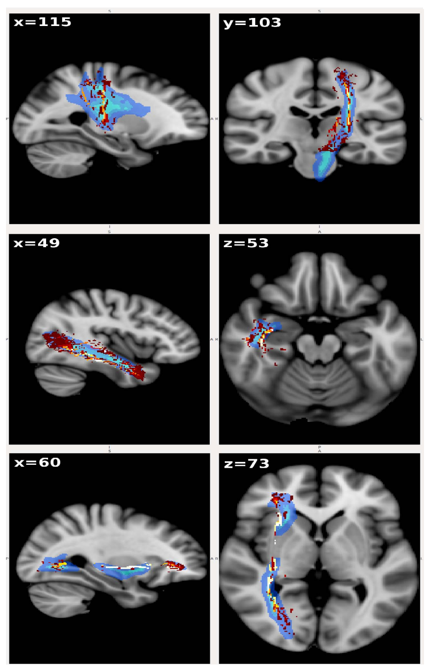

Figure 2: Heatmaps of average tracts (top: CST, middle: ILF, bottom: IOFF) with reference tract (blue) in MNI space. The heatmap colour scheme shows red for low values and white for high values.

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