From Tractography to Graph Tracking

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Background - Tractography methods for Diffusion Tensor Imaging (DTI) create 3D graphical objects from vector fields of main diffusivities. Most tractography methods are variants of the FACT algorithm [1], resulting with streamlines connecting two voxels and going through several others. Each streamline is supposed to represent a neuronal fiber that connects the end points of the streamline and passes in white matter voxels through the coordinates of the streamline. Since the data is DTI based, inaccuracies are expected for tracts going through partially volumed voxels, and there is strong sensitivity to noise [2]. Using brute force tracking [3], i.e., creating streamlines from all image voxels and selecting those that pass through the wanted ROI, might reduce false negative streamlines. However, the resulting graphical objects are usually very redundant and have much false positive streamlines. Graph tracking is proposed here as a post-processing analysis for brute force tracking. The collection of streamlines is converted to a single data-structure of a mathematical graph. For large collection of streamlines, graph representation is much more compact. In addition, the graph provides means for quantization and thresholds for fiber tracts. Connectivity is interpreted as connection between nodes on the graph.

Methodology – 1) The first step for graph tracking is producing conventional streamline tractography representation: Diffusion weighted images are acquired and fitted to the Diffusion Tensor Imaging (DTI) model to result with a tensor field, representing diffusivities for each voxel [2]. Brute force streamline tractography is then preformed [2] choosing all image voxels as initialization seeds. The tracing is preformed in both directions and is dependent on the Fractional anisotropy (FA) and curvature for termination. The resulted streamlines are a list of consecutive coordinates, those coordinates are real numbers confined by the image dimensions. For a given ROI a sub-list is created, including all streamlines that pass through any ROI voxel. **2)** The tractography resulted streamlines are converted to a graph: The undirected weighted graph $\boldsymbol{G}$ is defined as a pair $\boldsymbol{(V,E)}$ with weights $\boldsymbol{W}$, where $\boldsymbol{V}$ is as set of vertices and $\boldsymbol{E}$ is a set of edges connecting the vertices. Each image voxel is assigned with a vertex and each vertex can have edges connecting it with vertices representing adjacent voxels (up to 26). The weight, $\mathbf{W}_{\mathbf{ik}}$, of an edge, $\boldsymbol{E_{jk}}$ between vertices $\boldsymbol{V_j}$ and $\boldsymbol{V_k}$ counts the number of different streamlines that pass between the voxel represented by $\boldsymbol{V_j}$ and the voxel represented by $\boldsymbol{V_k}$. The conversion from streamline coordinates to a graph is done by iterating over all streamlines in a given list. For each voxel change an edge is added. Each streamline is constrained to contribute only once for a single edge. The chance of a streamline to pass diagonally to a voxel is very low; therefore we use a “look a-head” check to see if the line passes through more than one neighboring voxels before moving to a 2 steps away voxel. In such cases only the edge between the original voxel and the last neighboring voxel in the coordinate list is updated. **3)** Various analyses are possible on the resulted graph such as: Orientation threshold - edges with weights lower than a threshold can be deleted from the graph; The most probable path – a path between two nodes that minimizes the number of steps and maximizes the weights; The most confident path – The shortest path using edges with weights over a threshold. The graph G can further be transform to a weighted directed graph $\boldsymbol{GM}$ with outgoing weights summing to 1 for each voxel. This is done by doubling any edge $\boldsymbol{E_{jk}}$ in $\boldsymbol{G}$ to edges $\boldsymbol{E_{jk}}$ and $\boldsymbol{E_{kj}}$ in $\boldsymbol{GM}$ with equal weights. For each node in $\boldsymbol{GM}$ the outgoing weights are normalized to sum to 1. This defines $\boldsymbol{GM}$ as a Markov chain transition probability matrix, where each voxel corresponds to a state [4].

Demonstration – The analysis is demonstrated on a DTI vector field. The data set contains 50 axial slices with 128X128 pixels in each slice. Each voxel contains the principal eigenvector of the tensor. Tractography of the pyramidal tracts was obtained by constraining the complete dataset of streamlines to path in both lower and higher slices. The higher slice was restricted to a single hemisphere. As a result a set of 268 streamlines were acquired, with a total of 21112 coordinates (Figure 1A). The graph was generated from this set of streamlines and had only 3444 non zeroed edges over 2055 nodes (Figure 1B). Visually comparing the images shows high similarities, even though the graph image uses 16% less lines than the tractography image. A color coded mapping with darker and opaque colors for low weighted edges, and solid brighter colors for high weighted edges acts as visual thresholding of the graph (Figure 1C) to highlight more important edges. The neglecting edges are assumed to have higher probability to be false-positive (such as the set of edges that cross to the other hemisphere). The visualization can also present the white matter skeleton of the whole brain (Figure 1D). This is done with the same visual thresholding acting on a graph composed from the entire set of streamlines acquired by the brute force tractography. This type of image cannot be achieved by plotting all of the streamlines, since the redundancies are seen as a blob over the whole brain.

Summary – The graph format compacts the streamlines representation by eliminating redundancies. The mathematical structure and the possibility to transform into Markov chain transition matrix introduces quantitative probabilistic measures similar to such obtained in probabilistic tracking [5]. The benefit of Graph tracking is in its simplicity and in its use of results of the familiar streamline tractography. Any algorithm or quantitative measure that is used in Graph theory can be applied on the graph tracking graph. Biologic relevance of those is to be explored.

References - [1] Mori *et al*., NMR BIomed 15,2002. [2] Basser *et al*., MRM 44,2000. [3] Mori *et al*., "MRI atlas of human white matter", Elsevier, 2005. [4] Papoulis and Pillai, "Probability, random variables and stochastic processes, McGraw Hill, 2002. [5] Behrens *et al*., MRM 50, 2003.

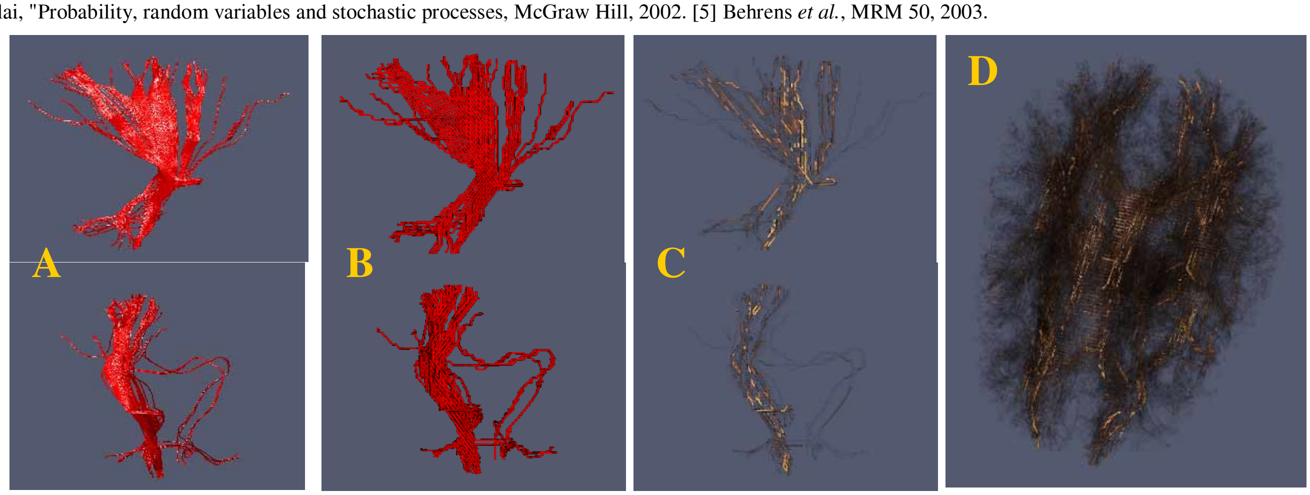

Figure 1: (A) Streamline tractography. (B) Graph tracking (C) Graph tracking thresholded. (D) Graph tracking – whole brain.