Combinatorial Fiber-Tracking of the Human Brain

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Introduction

DTI based tractography is becoming increasingly popular for delineating white matter trajectories of the human brain [1,2]. In recent years dozen of algorithms have been suggested to solve the inverse problem of fiber tracking – i.e. connecting DTI's main eigen-vectors to produce a trajectory from a starting seed voxel [2]. DTI has two main disadvantages – it fails in areas of complicated white matter (white matter edges, crossing fibers areas) and highly sensitive to noise. Those intrinsic limitations of DTI often results in erroneous estimation of the desired fiber tracts. Recently, a probabilistic approach to tractography has been introduced to cope with the problems of noise and partial volume effect in DTI [3,4].

Based on the probabilistic tracking approaches, we have developed a new probabilistic fiber tracking framework (named combinatorial tracking) that is based on graph theory and combinatorial optimization [5]. This framework has two main properties: transforming the tensor field into a network and weighting the connection strength between neighboring voxels. Using this brain network, two parameters can be used for estimation of connectivity and fiber path: the "shortest" path between two regions and the mean first passage time [6]. We will demonstrate the use of these tracking parameters on the reconstruction of thalamus-cortex connections.

Methods and Theory

The basic concept of combinatorial tracking is that the regular grid diffusion tensor data is mapped to a graph (as in Graph Theory), were the center of each voxel (graph node) is connected to its 26 neighbor voxel centers by graph edges (Figure 1A and 1B). Each edge is assigned with a transition probability, which is calculated by numeric integration of the Gaussian probability density function [7]. The model enables for fibers in 13 different directions to cross a voxel. Each two voxels can be connected by a path, but some paths have higher probability than others. .Figure 1C shows the most probable connections of the human brain depicting, as expected most of the white matter (the colors of the pixel connection indicates the probability - blue colors means strong connection while red colors weaker connection). Since the transition probability between each voxel to its neighboring voxels is summed to 1, the graph corresponds to a Markov chain transition probability matrix, where each voxel correspond to a state [6].

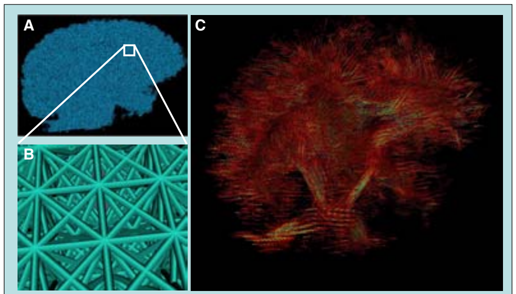

Figure 1: Combinatorial Tracking

On the calculated probability graph one can choose either of the following ways to perform tracking: 1) "Shortest path" – calculating the most effective path, probability wise, that connects a source and target voxels by finding a path which maximizes the transition probabilities product (using the Dijkstra's shortest path algorithm [5]). 2) Mean first passage - the average number of steps for a random walker starting at the source node to reach the target region for the first time. Once the target voxel (the one with the lowest mean first passage time) is selected the path can be reconstructed using the maximization of the probabilities product.

For validation and visualization of these tracking approaches, we used the M1 cortical strip and thalamus as source and target regions, respectively. Thalamus, cortex and thalamic sub-nuclei segmentation was done based on the Talairach coordinate space atlas. Combinatorial tracking was evaluated under Matlab © (Mathworks, USA) and visualized using VTK (Kitware Inc.)

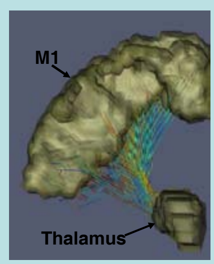

Figure 2: Combinatorial Tracking of cortex-thalamus connections

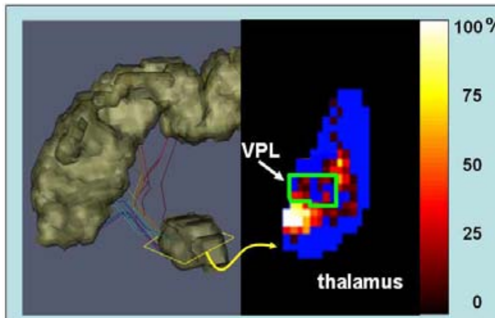

Figure 3: Combinatorial Tracking of M1 segments

Results and discussion

To demonstrate the strength of the combinatorial tracking we used the thalamus and the M1 strip of the cortex and source and target regions. The result of such tracking using the "shortest" path approach is shown in Figure 2 where the branching of the fibers into the cortex is nicely demonstrated and resembles the real appearance of this fiber system. It is known that the thalamus is connected to the M1 cortical strip through the ventral-posterior lateral nucleus, VPL. We have arbitrarily divided the cortex to 16 segments and from each calculated the mean first passage time index to the whole thalamus. The extracted paths for each segment are shown in Figure 3. In addition we have used the mean first passage time index of each thalamus voxel to produce a probabilistic map of thalamus showing which pixels are most likely to be connected with the thalamus (Figure 3B). This map shows that the most probable area in the thalamus connected to the cortex is within 3-pixel proximity to the Talairach definition of the VPL. The difference between the atlas and the combinatorial tracking results might be due to various sources of noise: noise in the DTI tensor field and noise in the normalization process to Talairach space. One of the strength of the proposed tracking approach is that each brain pixel can be connected to any other brain pixel. Although the most probable path between the cortex and thalamus was found to lie near the VPL we can force a VPL-cortex connection. It is known that cortical fibers connects to the VPL is a laminar manner, i.e. each segment of the VPL connects to a specific segment of the cortex (see Figure 4A). By using the shortest path index from each cortical segment to VPL segment this laminar fiber arrangement can be reconstructed (Figure 4B).

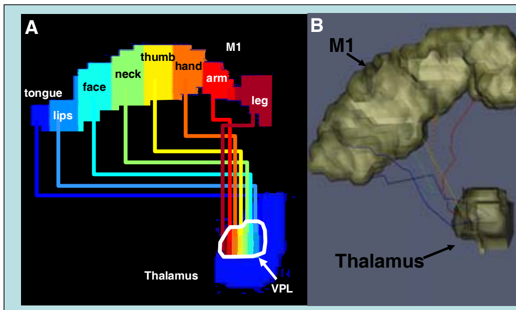

Figure 4: Laminar organization of the VPL and M1 and corresponding combinatorial tracking

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