18th Annual Meeting of the Organization for Human Brain Mapping

Electrical Circuit Model for White Matter Fiber Tracts in Diffusion Tensor Imaging

Abstract No:
7250

Poster No:
405

Authors:

Moo K. Chung[1], Nagesh Adluru[1], Janet E. Lainhart[2], Nicholas Lange[3], Andrew L. Alexander[1]

Institutions:

[1]University of Wisconsin, Madison, WI
[2]University of Utah, Salt Lake City, UT
[3]Harvard University, Boston, MA

Introduction:

Diffusion tensor imaging (DTI) is a non-invasive imaging modality often used in mapping macroscopic brain connectivity through the tractography. The strength of connection from one gray matter region to another is often measured by counting the number of fiber tracts connecting the two regions in predefined parcellations. However, the problems with this approach are the use of arbitrary parcellation and the negligence of the distance between the regions [4].

Motivated by these limitations, we present a parcellation-free data driven network model. We model fiber tracts as wires in an electrical circuit. The strength of connection corresponds to the resistance of the wire. Any complex circuit can be replaced by a simpler circuit with the equivalent resistance. Similarly we can simplify whole brain tractography result into smaller number of tracts. As an application, we apply the proposed technique in constructing the structural network of autistic and normal control (NC) subjects.

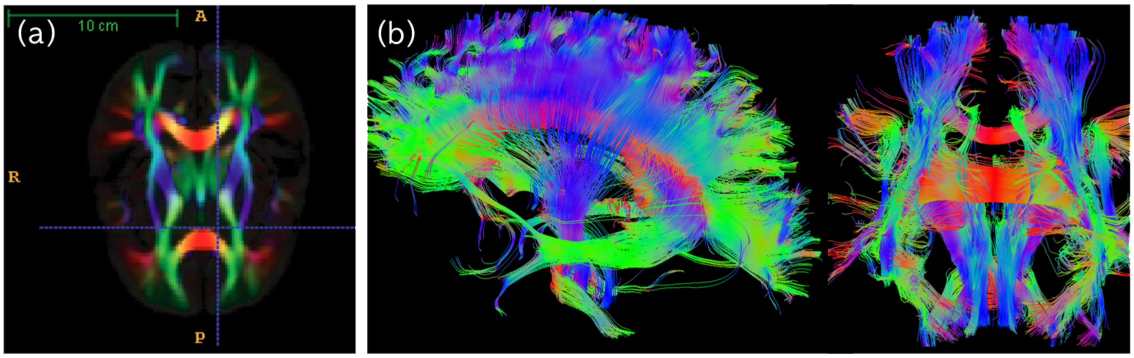


Figure 1. (a) DTI registration was done using an iterative diffeomorphic regisration strategy. FA map of the population specific DTI template is shown. (b) TENsor Defelction (TEND) algorithm was used for tractography in the normalized space.

Methods:

Tractography:
DTI were acquired on a 3-Tesla scanner. The imaging parameters are given in [2]. Spatial normalization of DTI data was done using via a diffeomorphic registration strategy [5]. A population specific tensor template was constructed. Tractography was done in the normalized space using TEND [3] (Fig. 1).

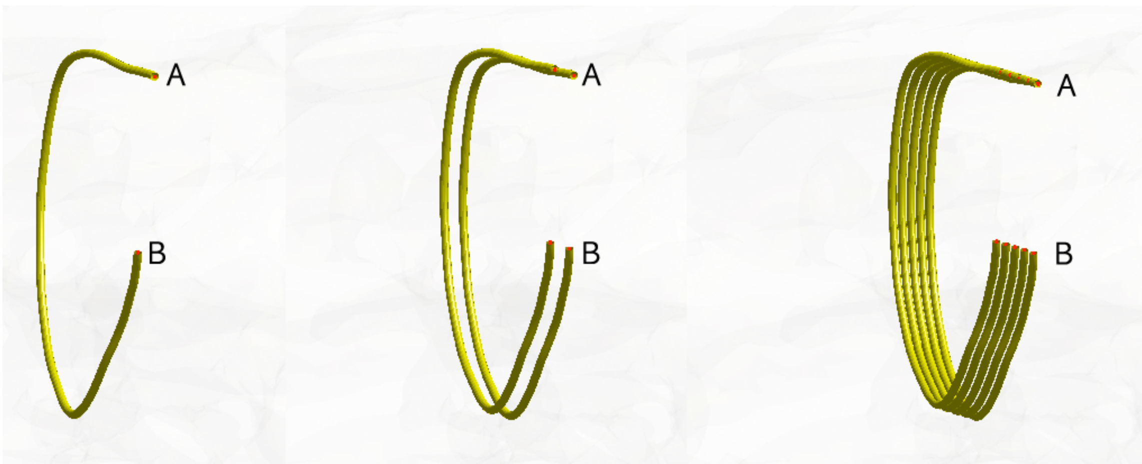
Electronic circuits:
The brain network can be modeled as an electrical system consisting of series and parallel circuits. Each fiber tract is viewed as a wire with resistance R proportional to the length of the wire. If two regions are connected through an intermediate region, it forms a series circuit. In the series circuit, the total resistance is addictive. If multiple fiber tracts connect two regions, it forms a parallel circuit, where the total resistance is

$$1/R = 1/R(1) + \ldots + 1/R(k).$$

R(k) is the resistance of the k-th tract (Fig. 2). Any parallel circuits in an electrical system can be simplified using a single wire with the equivalent resistance. This idea is used in simplifying the whole brain fiber tracts into a small number of tracts (Fig. 3).

Circuit simplification:
The proposed electronic circuit model is used in constructing the brain network without a predefined parcellation. All the tracts are sorted in terms of length and the two end points are identified. Every tract whose end points are within the ball of ε-radius is considered as connected. ε=10mm is used

for the study. The collection of tracts and ε-radius balls form a complex circuit, which is iteratively simplified by replacing a parallel circuit with a single equivalent tract. Initially we start with the longest tract and go on to the second longest tract in the next iteration. This process completely removes all the parallel circuits (Fig. 3). So for any two ε-radius balls, there is only one tract connecting them. Hence, the simplified circuit forms a graph with the resistances as the edge weights. The graph has uniformly distributed nodes and no two nodes will be within ε-distance. So the nodes sufficiently cover all the brain regions.



$R = 10$

$$\frac{1}{R} = \frac{1}{10} + \frac{1}{10}$$

$R = 5$

$$\frac{1}{R} = \frac{1}{10} + \frac{1}{10} + \frac{1}{10} + \frac{1}{10} + \frac{1}{10}$$

$R = 2$

Figure 2. Multiple fiber tracts connectiong the regions A and B are modeled as a parallel circuit. The resistance in a wire is proportional to the length of the wire. So the resistance of a tract is simply defined as the length of the tract. As more tracts connect the regions in parallel, the strength of connection increases and the reistance decreases. If all the tracts are 10 cm in length, the total registances become 10, 5 and 2 as the number of tracts increases to 1, 2 and 5.

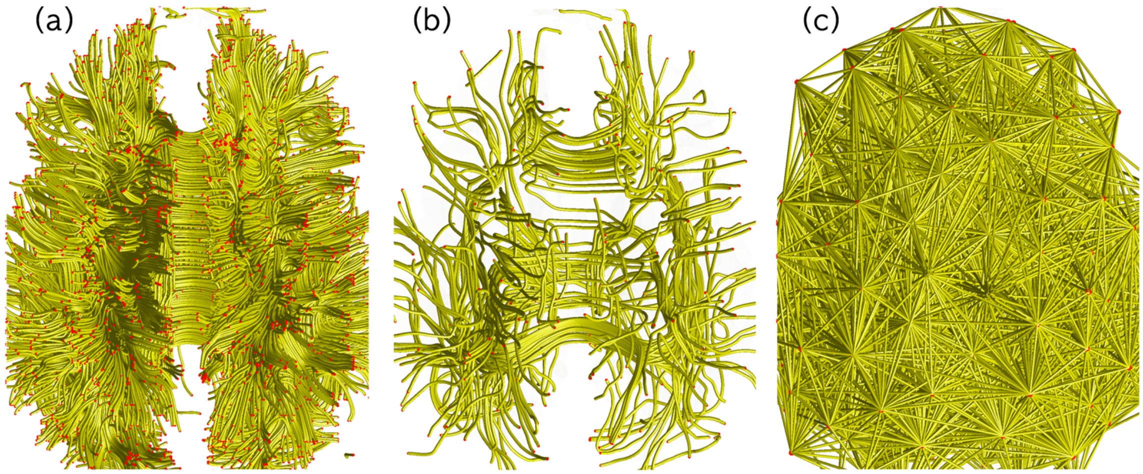


Figure 3. (a) The end points of tracts are identified. Tracts whose end points are within the ball of epsilon radius are considered as connected. The fiber tracts and the balls constitute a complex electronic circuit. (b) All the parallel curcuits present in the system (a) are shown. Each parallel circuit is replaced by a single tract with equivalent resitance. (c) The simplified circuit then forms a graph wihere the edge weights are given by the resistance.

Results:

The proposed method is applied to DTI of 36 NC and 41 autistic subjects. The resistance matrix (RM) is constructed for each subject (Fig. 4). Smaller resistance corresponds to stronger connection. The nodes are indexed in such a way that long tracts have smaller indexing. Long tracts tend to have higher resistance. Entries are sparser at the bottom right.

RM is normalized by the maximum resistance. The total resistance is computed by summing RM. The average resistance is 225 for NC and 212 for autistic subjects. The difference is found to be statistically significant using the rank-sum test ($p=0.07$). Higher resistance implies that NC must have more longer tracts and less redundant parallel circuits.

Conclusions:

We presented a novel data-driven network construction method for DTI. The method is applied constructing the connectivity matrix in terms of resistance of circuits.

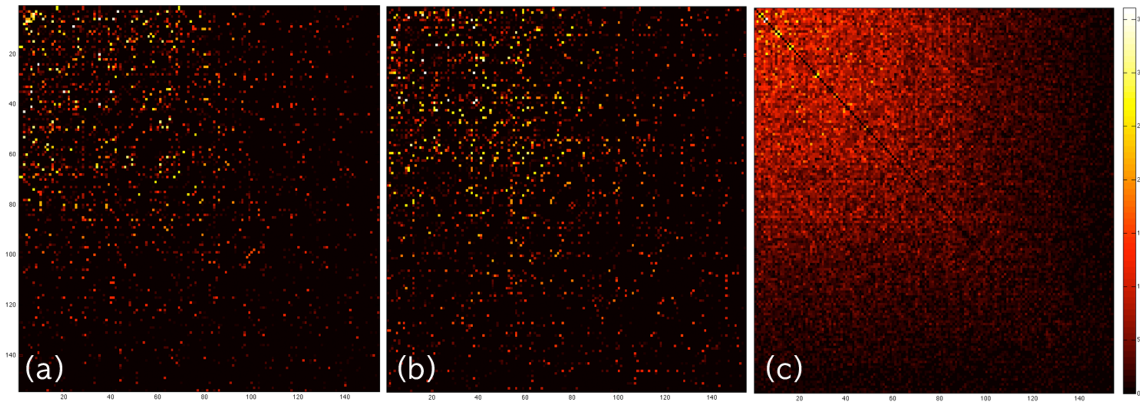


Figure 4. Registance matrix for subject 1 (a) and subject 2 (b). (c) Graoup average for all 36 subject.

References:

[1] Chung, M.K. (2011), 'Scalable brain network construction on white matter fibers', SPIE Medical Imaging.

[2] Chung, M.K. (2010), Cosine Series Representation of 3D curves and its application to white matter fiber bundles in diffusion tensor imaging', Statistics and Its Interface, vol. 3, pp. 69-80.

[3] Lazar, M. (2003), 'White matter tractography using tensor deflection', Human Brain Mapping, vol. 18, pp. 306-321.

[4] Zalesky, A. (2010), 'Whole-brain anatomical networks: Does the choice of nodes matter?', NeuroImage, vol. 50, pp. 970-983.

[5] Zhang, H. (2007), 'High-dimensional spatial normalization of diffusion tensor images improves the detection of white matter differences: An example study using amyotrophic lateral sclerosis', IEEE Transactions on Medical Imaging, vol. 26, pp. 1585-1597.

Modeling and Analysis Methods:

Diffusion MRI Modeling and Analysis