Characterization of Structural Connectivity in Autism using Graph Networks with DTI

Abstract No:
938

Authors:
Moo Chung[1], Nagesh Adluru[1], Kim Dalton[1], Andrew Alexander[1], Richard Davidson[1]

Institutions:
[1]University of Wisconsin, Madison, WI

Introduction:

Diffusion tensor imaging (DTI) may be used to characterize the structural connectivity of the human brain non-invasively by tracing white matter fiber tracts. Whole brain tractography studies routinely generate up to half million tracts per brain, which serves as edges in an extremely large 3D graph. Currently there is no agreed-upon method for constructing the brain structural network graphs out of large number of white matter tracts. We present the first scalable iterative framework for building a large brain network graph and apply it to testing the over-connectivity hypothesis in autism. We clearly show that autism is characterized by over-connectivity of low degree nodes indicating the connectivity difference in the brain network.

Methods:

Tractography:
Spatial normalization of DTI data was done using the high-dimensional spatial normalization method DTI-TK (Zhang et al., 2007). A population specific tensor template was constructed from all 31 subjects using an iterative diffeomorphic registration strategy. Tractography was performed in the normalized space by solving streamline equations using the TENsor Defelction (TEND) algorithm (Lazar et al., 2003). Fig. 1 shows the FA-map derived from the tensor template and the resulting whole brain tractography result.

ε-neighbor of graph G:
A graph G consists of a vertex set V and an edge set E, i.e. G = {V, E}. A point v is the ε-neighbor of G if the shortest distance between v and some point in V is smaller than given ε in mm unit. Then we identify the point w in V that gives the shortest distance between v and V as the same point.

ε-neighbor algorithm:
Initially a graph G(1) consists of a single tract consisting of two end points and an edge connecting the end points. In constructing the brain network,

only two end points of the tract were considered since all other points along the tract are connected to these two points. Fig.1 shows the extracted end points in subsampled tracts. We now construct the graph in an iterative fashion by adding one tract at a time to an existing graph. At the k-th iteration, we consider how to add the two end points to the existing graph G(k-1) and obtain a new graph G(k). There are four possible scenarios to add the two points to G(k-1) depending if the end points are ε-neighbors of G(k-1). If only one end point is the ε-neighbor, a new vertex and a new edge is added to G(k-1) and obtain G(k). If the two points are the ε-neighbors, we do nothing. If the two points are not the ε-neighbors, we add the two points and the edge to G(k-1) and obtain G(k). Fig.1 shows an example of adding vertices 5 and 6 to existing graph consisting of vertices 1-4.

Results:

The proposed framework was applied to the following data set.

Data:

MR imaging on a 3-Tesla scanner and a quadrature head coil was used to collect 3D T1-weighted (Inversion-prepped fast gradient echo) and diffusion tensor (12 encoding directions, b=1000s/mm2, 2x2x3mm acquired spatial resolution) images. Imaging was performed on 31 subjects: (i) 17 subjects with high functioning autism spectrum disorders (ii) 14 control subjects matched for age, handedness, IQ, and head size.

Adjacency Matrix:

The proposed ε-neighbor method was used in constructing structural connectivity graphs. For this study, a 6mm-neighbor graph was used but the result was similar for other resolutions. The adjacency matrix of a graph is constructed on the fly at each iteration by checking if we are adding a new edge to the existing edge set. The adjacency matrix contains sufficient information to construct the graph. So statistical analysis can be done on the ensemble of adjacency matrices. The resulting 6, 10 and 20mm-neighbor graphs and the corresponding adjacency matrices are given in Fig. 1.

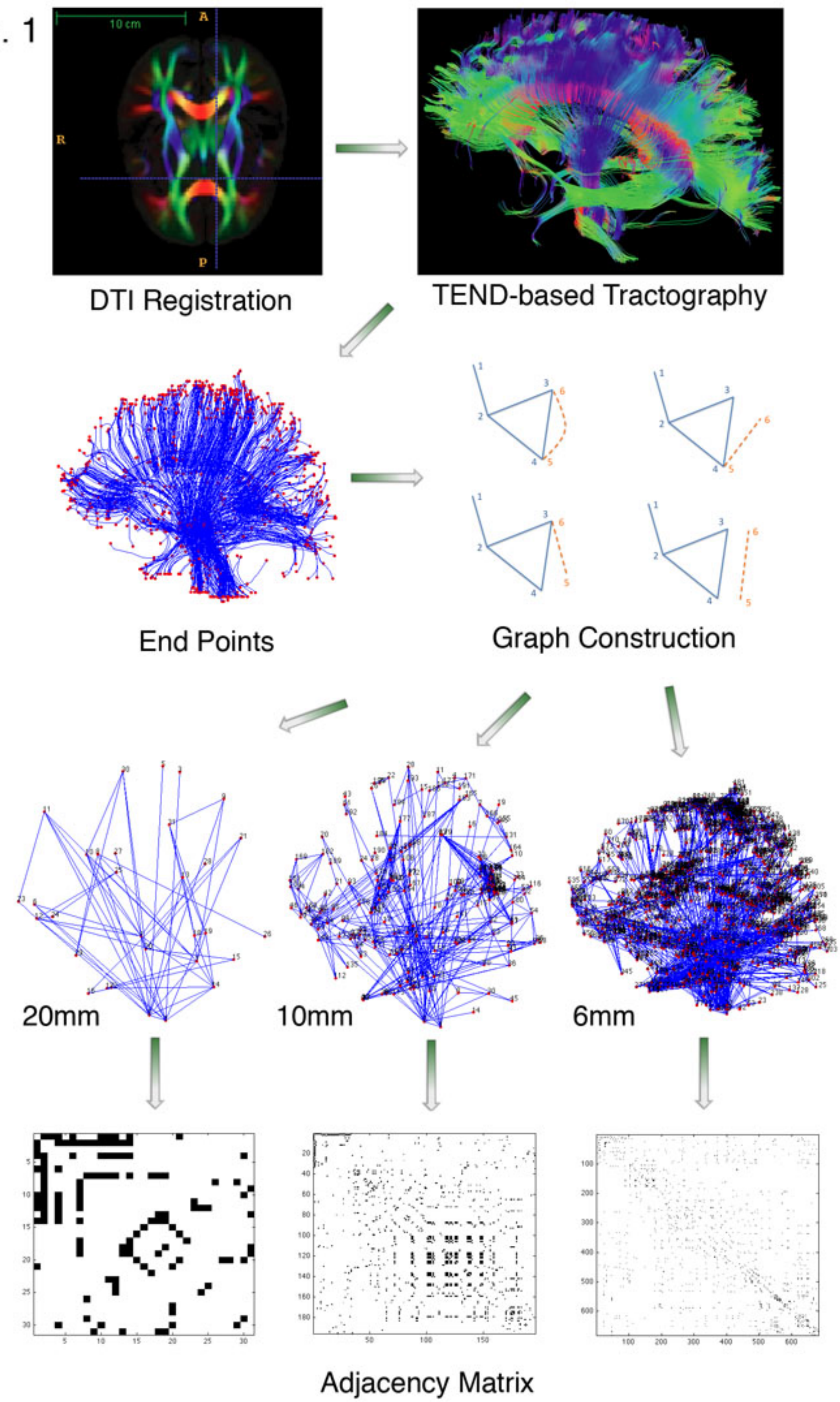
Degree Distribution:

The degree of connectivity of a node is obtained by summing up the corresponding rows in the adjacency matrix. The distribution of nodes is computed from degree 1 up to 25 and renormalized. We did not go beyond degree 25 since there are not many nodes with degree larger than 25 so the tail region is fairly noisy. The autistic subjects (red in Fig. 2) show significant over-connectivity in low degree nodes (degree 1 to 4) compared to the control subjects (blue). In particular, the pvalues for degrees 1, 2, 3 and 23 are 0.024, 0.015, 0.080 and 0.096. Therefore, autism is characterized by the over-connectivity of low degree nodes indicating the connectivity difference of the brain structural network.

Conclusions:

We have presented a novel connectivity graph construction method for DTI.

Fig. 1


10 cm
A
R
P
DTI Registration
TEND-based Tractography
End Points
Graph Construction
20mm
10mm
6mm
Adjacency Matrix

The method is applied in showing over-connectivity in lower degree connectivity nodes. Cortical connectivity is known to exhibit small-worldness (Sporns et al., 2004), which is characterized by high degree of connectivity within local neighborhoods while all nodes of the network are linked by short paths. The degree distributions clearly demonstrate the small-worldness of the brain network such as sparse connectivity and local clustering. On the other hand, the autistic brain network have more nodes with low degree of connectivity, which implies that there are more regions in the brain that are not connected to other regions of brain.

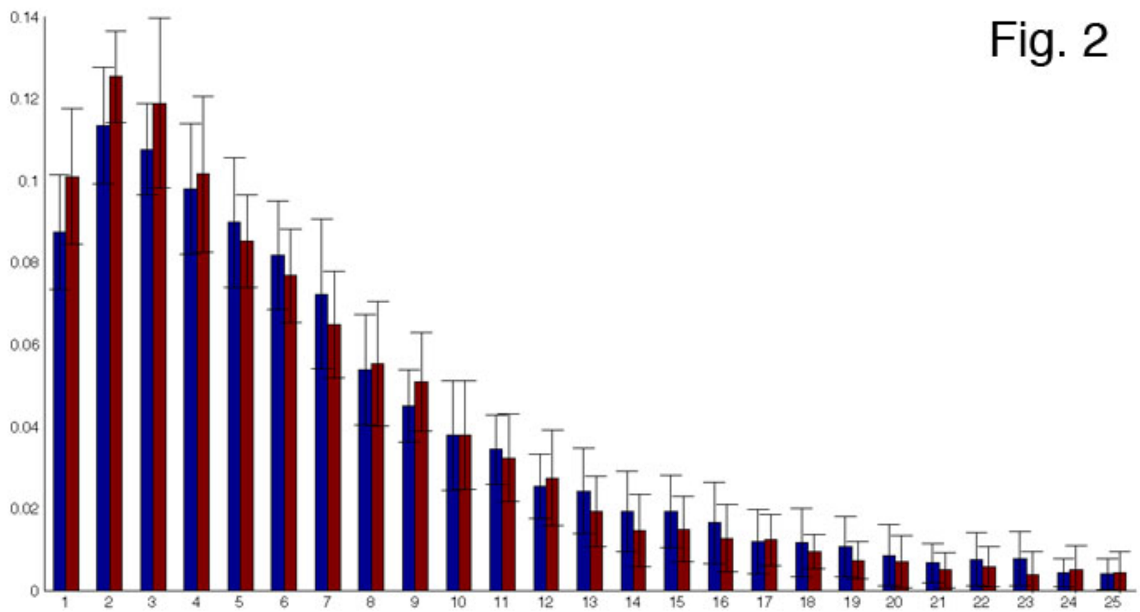


Fig. 2

References:

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

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.

Sporns, O. (2004), 'The Small World of the Cerebral Cortex', *NeuroInformatics*, vol. 2, pp. 145-162.

Categories

DTI Studies, Application (Neuroanatomy)