Effect of SNR of DTI on the structural network

H. Cheng[1], D-J. Kim[1], O. Sporns[1], Y. Wang[2], J. Sheng[2], and A. Saykin[2]
[1]Indiana University, Bloomington, IN, United States, [2]Indiana University, Indianapolis, IN, United States

Introduction: Diffusion Tensor Imaging (DTI) has been widely used to map white matter fiber bundles using the fiber tracking technique named as tractography. Recently this technique was incorporated with graph theory to study the structural network of human brains[1]. A network is defined by a collection of nodes and links between pairs of nodes. The nodes of the structural network are parcellated anatomical regions, while the links of the network are the fibers between those regions[1, 2, 3]. The accuracy of tractography is largely affected by the signal-to-noise ratio (SNR) of the DTI data. Low SNR can lead to large deviation of the track path originating from a voxel[4]. On the other hand, there are many different parcellation schemes, resulting in ROIs with different sizes. As the nodes of the structural network may occupy many voxels, a track connecting two nodes may still connect the same nodes despite path deviation. How the final network is affected by the SNR has not been investigated. In this work, the SNR of tractography is modulated by selecting different number of gradient directions from 48 direction DTI data sets. A deterministic tractography algorithm was used to perform fiber tracking and construct corresponding structural networks. We propose a simple approach to evaluate the influence of SNR on the network variability and accuracy.

Methods: Two back to back DTI scans on a human subject were performed on a Siemens TIM Trio 3 T scanner using a 32-channel head coil. The scan covered the whole brain with 2 mm isotropic resolution. Images of 48 different gradient directions with b value of 1000 were collected along with 8 images with b = 0. To reconstruct DTI data with smaller SNR, a number of subsets with directions of 6, 12, 18, 24, 30, 36, and 42 were selected from the 48 directions. To avoid biases of gradient directions, a special procedure of selection was adopted. First, the 48 directions were put into six groups based on their intersection with the six faces of a cubic centered on the origin. Then equal number of directions were randomly selected from the six groups (e.g., for 6 directions, only one direction is selected in each group; for 12 directions, two directions were selected in each group, …), this procedure was repeated 1000 times and only the one with least overall coulomb force is regarded as the desired set of directions. This approach will guarantee suboptimal gradient directions for diffusion tensor computation and fiber tractography. With all the sets of directions, the corresponding DTI images were picked from both data sets and combined with the 8 b0 images to construct the diffusion tensors for fiber tracking. The Tractography was performed on Diffusion Toolkit (http://trackvis.org/) using FACT algorithm and 10 random seeds. The stop angle threshold was set to 35 degree. Parcellation was done using FreeSurfer (http://surfer.nmr.mgh.harvard.edu/) on the MP-RAGE high resolution anatomical image to obtain 68 ROIs of gray matter. A track is considered to connect two ROIs if and only if its end points fall in the two ROIs. The corresponding weighted networks were then constructed according to $w_{ij} = \frac{2}{n_i + n_j} \sum_m \frac{1}{L_{ij}}$ with n_i the number of voxels in ROI_i and L_{ij}^m denoting the length of the m^{th} track between ROI_i and ROI_j. The network is represented by a matrix *M_w*. A similar matrix was also obtained for the number of fiber tracts denoted as *M_nf*. To estimate the standard deviation of number of tracks and network weights, a similar approach to NEMA standard[5] for noise calculation was used. First, a difference matrix was obtained by subtracting the two matrices *M_nf* or *M_w*, the variation of *M_nf* and *M_w* were characterized by the standard deviation of the difference matrices scaled by the mean values of the nonzero elements in the matrices. The variations are then plotted against the number of gradient directions. To evaluate the accuracy of network matrix, the root of mean square error (RMSE) for all networks against the network derived from 48 direction data were calculated. The RMSE was also scaled by the mean values of the nonzero elements in the matrices.

Results: Fig. 1 shows an example of the FA map from 6 directions and that from 48 direction DTI data. It is clear that the FA map from 6 gradient directions is much noisier. The corresponding network matrices are also shown in Fig 1, which are visually similar to each other. The variation of *M_nf* and *M_w* for different number of gradient directions are shown in Fig. 2a. There is no clear relation between the variation and number of gradient directions. However, the RMSE of *M_nf* and *M_w* from reduced datasets decrease rapidly as the number of gradients increases until it reaches 18 directions, after which the curve becomes flat as shown in Fig. 2b.

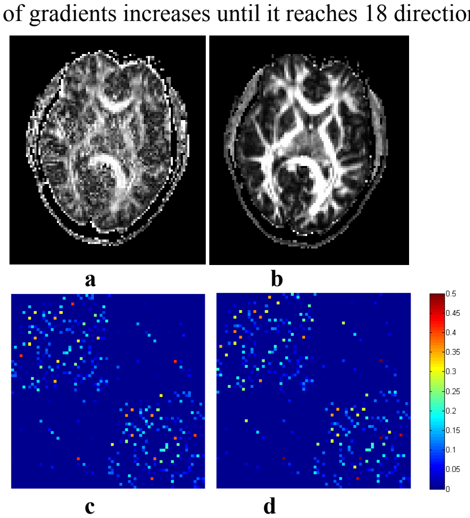
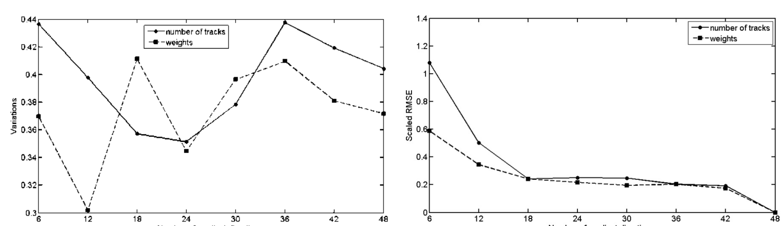


Fig. 1. FA maps from 6 gradient directions a) and 48 directions b); Corresponding structural network matrices are shown in c) and d).



a b

Fig. 2. Variation a) and RMSE b) of number of tracks and weights for different number of gradient directions in DTI.

Discussion: We propose a method to evaluate the effect of SNR of DTI on structural networks. Our results indicate few numbers of gradient directions does not necessarily lead to more variations in the network. However, the RMSE analysis shows that the SNR does have an impact on the accuracy of the network, which could be largely compromised by few gradient directions. At least two factors affect the deterministic fiber tracking. The first is the SNR of the DTI data. The second one is the uncertainty of the fiber tracking from random seeds, which is closely related to the first factor. Since the two data sets were used different random seeds in tractography, a significant portion of the variation is attributed by the random seeds effect (as discussed by another abstract). We should also emphasize that the results depend on the parcellation scheme, especially the size of the network nodes.

References: 1. Gong H. et al., Cerebral Cortex, 2009;19:524-536. 2. Rubinov M. et al., Neuroimage. 2010;52:1059-69. 3.Hagmann P. etl al., PloS ONE. 2007;2:e597. 4. Lazzar M. et al., NeuroImage 2003;20:1140-1153. 5. NEMA Standards Publication MS 1-2008.