Investigating the Coherence between Brain Structural and Functional Networks at Multiple Scales

Hengtai Jan[1], Shih-Yen Lin[1,2], Kuan-Hung Cho[3], Yi-Ping Chao[4], and Li-Wei Kuo[1]

[1]Division of Medical Engineering Research, National Health Research Institutes, Zhunan, Miaoli County, Taiwan, [2]Department of Computer Science, National Chiao Tung University, Hsinchu, Taiwan, [3]Institute of Brain Science, National Yang-Ming University, Taipei, Taipei, Taiwan, [4]Department of Computer Science and Information Engineering, Chang Gung University, Kwei-Shan, Taoyuan County, Taiwan

Introduction

Previous brain network studies have widely reported both structural and functional brain networks show small-world characteristics under certain conditions [1, 2]. However, the strengths of small-worldness may vary due to several factors, such as cortical parcellation number (scale) representing the nodes in a graph, connectivity measure representing the edges in a graph, and selection of sparsity for constructing a binarized adjacency matrix [3]. Although network analysis with graph theory has gradually become an important tool for investigating the brain's wiring and activities, the relationship between the small-worldness and these factors is still unclear. Therefore, in this study, our first aim was to investigate the dependence of small-worldness on the sparsity in either structural or functional networks at multiple scales. The second aim was to investigate the correlation of small-worldness between structural and functional networks. With this systematic analysis, we could facilitate the use of network analysis with adequate parameters and gain more insights into the coherence between structural and functional networks.

Materials and Methods

MR experiments were performed on a 3T MRI system with a 32-channel head coil (Trio, Siemens AG, Germany). A total of ten healthy volunteers (5 males and 5 females, 18-22 yrs, right-handed) were studied under Institutional IRB approval. For structural connectivity, q-ball imaging (QBI) data was acquired on a q-space shell with a total encoding number of 162 and a maximum b-value of 3000 s/mm^2. The sequence parameters of QBI were 2x2x2 mm^3 spatial resolution, 60 slices, TR of 11.7 sec, and the total scan time of approximately 30 mins. The reconstruction of QBI was based on the method proposed by Tuch [4]. To calculate the structural connectivity, a streamline-based fiber tracking algorithm (DSI Studio, http://dsi-studio.labsolver.org/) was employed to obtain the fiber tracks across any of pairs among cortical parcellations. For functional connectivity, resting-state fMRI data was acquired with the following EPI sequence parameters; TR of 2 sec, 3x3x3 mm^3 spatial resolution and 180 repetitions. The pre-processing of resting-state fMRI data includes slice-timing correction, motion correction, grand mean drift scaling and low-pass filtering (0.02-0.08 Hz) by a combinational use of SPM8 (http://www.fil.ion.ucl.ac.uk/spm/software/spm8/) and DPARSF (http://www.restfmri.net/forum/DPARSF). The functional connectivity was derived by correlating the resting-state fMRI time series between any of pairs in cortical parcellations. To analyze the brain network at multiple scales, we employed a weighted k-means algorithm to parcellate the cortical regions in Automatic Anatomical Labeling (AAL) atlas into five levels of scale. The scales used for following network analysis were 90, 180, 360, 720 and 1028. The sparsities used to binarize these adjacency matrices were ranged from 2% to 20%. Three network measures were derived from the binarized matrices, including mean clustering coefficient, path length and small-worldness [5].

Results

With different parcellation scales (figure 1a), the adjacency matrices of functional and structural networks of a single subject are shown in figures 1b and 1c. In functional network, the overall patterns of adjacency matrices are consistent across different scales. However, in structural network, the matrices with higher scales show more low-connectivity points due to insufficient fiber tracks. Figure 2 shows different network measures at multiple scales against the change of sparsities. The tendencies of the clustering coefficient and mean path length against sparsity in both functional (a and b) and structural (d and e) networks at multiple scales are generally similar, whereas the tendency of small-worldness (c and f) between functional and structural networks is slightly deviated. The correlation results of small-worldness between functional and structural networks at the lowest scale (90 parcels) are shown in figure 3a, showing that the correlation values vary across different sparsities. Figure 3b shows a scatter plot of small-worldness in functional and structural networks among a total of ten subjects, showing that the characteristics of functional and structural networks is highly correlated at some sparsities.

Discussion

With sparsities higher than approximately 0.1, our preliminary results have shown that the tendencies of network measures are consistent at all scales. However, inconsistency happens with the sparsities lower than 0.1, which may cause bias in comparison between functional and structural networks. This inconsistency may need to be further addressed by replacing connectivity measures and methods to generate sparse matrix. Our preliminary results (fig. 3) in correlating the small-worldness of functional and structural networks at lowest scale show interesting patterns. At some sparsity pairs, high correlations between functional and structural networks can be found, suggesting that the coherence between them may exist under certain conditions. Our current works will focus to map the correlation of small-worldness between functional and structural networks at higher scales, and investigate how the patterns and the correlated sparsities change with different scales.

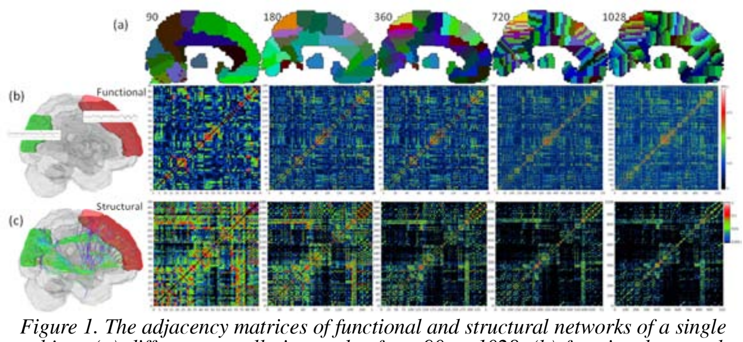

Figure 1. The adjacency matrices of functional and structural networks of a single subject. (a) different parcellation scales from 90 to 1028, (b) functional network matrices and (c) structural network matrices.

Reference [1] M.P. van den Heuvel et al. (2008) NeuroImage 43, p528. [2] M.J. Vaessen et al. (2010) NeuroImage 51, p1106. [3] A. Zalesky, (2010) NeuroImage 50, p970. [4] D.S Tuch, (2004) Magn. Reson. Med., 52, p1358. [5] M. Rubinov et al. (2010) NeuroImage 52, p1059.

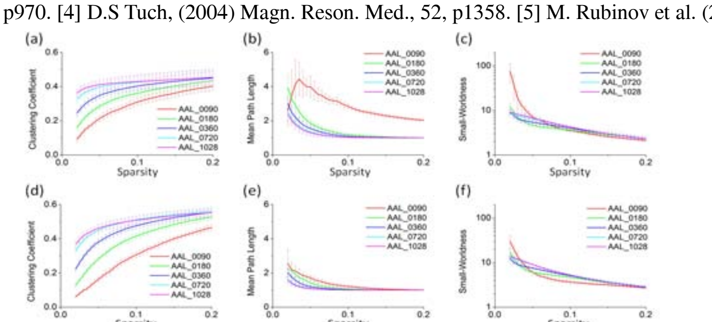

Figure 2. Different network measures at multiple scales against the change of sparsities from 0.02 to 0.2. The upper row shows the plots of functional network measures and the bottom row shows those of structural network measures, including clustering coefficient (a and d), mean path length (b and e) and small-worldness (c and f).

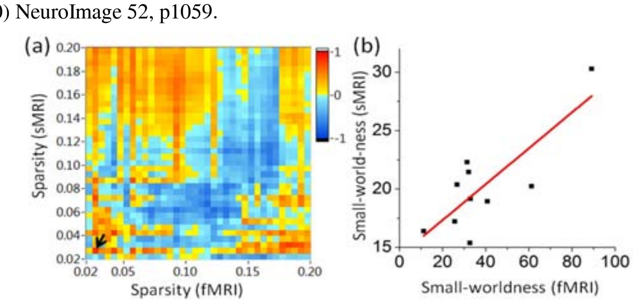

Figure 3. The correlation of small-worldness between functional and structural networks at the lowest scale of 90 parcels. Subfigure (a) shows the correlation patterns with the change of sparisities and the black arrow indicates the highest correlation. Subfigure shows a scatter plot of functional and structural small-worldness among ten subjects.