

## DOCTORAL THESIS

### Formation of the complex neural networks under multiple constraints

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*Date of Award:*  
2013

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# Formation of the Complex Neural Networks under Multiple Constraints

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A thesis submitted in partial fulfillment of the requirements  
for the degree of  
Doctor of Philosophy

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Hong Kong Baptist University

August 2013

# *Abstract*

Growing evidence shows that the organization of network architecture of neural systems is subjected to a trade-off between physical cost and functional values of the topology. However, two important questions are still not well understood - What these functional values are and to what extent the trade-off between multiple constraints would shape the connectivity of the neural systems? To answer these two questions, we explored the impact of multiple constraints systematically. We reconstructed two known neural networks, Macaque cortical connectivity and *C.elegans* neuronal connections, to optimize the different combination of multiple constraints, and qualitatively compared the reconstructed networks to the real networks. Firstly we investigated the influence of two obvious but apparently contradictory constraints - low wiring cost and high processing efficiency, characterized by short overall wiring length and a small average number of processing steps, respectively. We found that in both neural systems, the reconstructed networks derived from combinatory optimization of the two constraints by a control parameter  $\alpha$  can reveal some important relations between the spatial layout of nodes and the topological connections, and can match several significant mesoscopic properties. In a certain range of  $\alpha$ , the reconstructed networks can reproduce the ubiquitous features of the co-existence of the similar modular and hub structure as the real neural networks. Even the positions of hubs are close to, and partly coincided with the real hubs. Meanwhile, the degrees of nodes in the reconstructed networks under the two constraints are significantly correlated with the density of nodes in their spatial neighborhood and the degrees in the real neural networks. However the correlation values are quite low, which implies the degrees of nodes are still affected by other functional factors. Thus we fixed the degrees of nodes as an additional constraint, and found that much more connections can be recovered in the reconstructed networks from the combination of the three constraints, especially for these long-distance connections. Notably, nearly 70% of connections in the real Macaque cortical network can be recovered under the three constraints. We further discovered that those unrecovered links are concentrated on a few nodes for Macaque cortical network. In both neural systems, we identified the outlier nodes with the recovery rate of their connections even lower than that in the random networks. The organization of the connectivity of these outlier nodes strongly violate the three constraints, especially the wiring cost constraint. Interestingly,

most of these outlier nodes have average degrees, but play important roles in the integration of information processing among different functional regions. This implies that functional integration may be a potentially functional requirement shaping the connectivity of the neural systems. However, for *C.elegans*, there are still a large number of long-distance connections that cannot be recovered by the combination of the three constraints, and two factors, the network capacity from multiple paths and the wiring establishing during development may also affect the connectivity. At the end of this thesis, we characterize the co-existence of modules and hubs in terms of dynamical complexity which can reflect a balance between functional segregation and integration. we found that the reconstructed networks having most similar features to the real neural networks have the maximal complexity. This may further indicate that the real neural network prefer to own these network features to achieve a balance between segregation and integration. The findings in this thesis provide clear quantitative evidence to support the hypothesis of trade-off between physical cost and functional values. The approaches developed here could be applied to human brain connectivity from imaging data, and be further used to study altered connectivity in diseased brain.

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