Proposition of PhD position:

MODELING BRAIN STRUCTURAL AND FUNCTIONAL CONNECTIVITY

Deadline for application: May, 2019

Research teams
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Context

Mapping the connectivity of brain circuits is crucial for investigating the neuronal underpinnings of the healthy as well as pathological brain. Over the last decade, some research projects such as the Human Connectome Project (HCP) have proposed to map the connections between neural pathways that underlie brain function and behavior, in order to improve our understanding of the brain functioning. Mathematical modeling from graph theory provides an extremely powerful approach in the study of brain networks. Indeed, the connectivity map can be represented by a graph in which the nodes represent the different cortical zones and the edges symbolize the connections between these nodes.

Electroencephalography (EEG), functional magnetic resonance imaging (fMRI) or near infrared spectroscopy (NIRS) are procedures used to obtain direct and indirect measurements of brain neural activity, at different spatial and temporal scales: EEG has a high temporal and low spatial resolutions, while fMRI has high spatial and low temporal resolutions, NIRS being intermediate. Integrating simultaneously these modalities, to establish an enhanced high-resolution spatiotemporal imaging technique could yield a powerful tool, to expand the knowledge of our brain and to exhibit robust biomarkers, more sensitive to pathophysiological changes. However, the integration challenge of these three modalities, as well as the resulting graph estimation remains a real challenge that needs to overcome various spatial and temporal resolutions as well as temporal properties of the data. This methodological challenge increases if at the same time we want to integrate information describing how axons connect structurally these different regions. This is what can provide diffusion MRI through the microstructural modeling of the diffusion of water molecule along the axons in the brain.

Scientific project

This thesis will address this challenge of modeling at the group or the individual level how brain territories connect together. We propose to tackle this challenge by exploring how graph theory can handle the joint modelling of the brain structural and functional connectivity. As such, two major challenges will be addressed: 1) How to combine neuroimaging data as a multidimensional graph? 2) Methodological developments will combine machine learning techniques (including deep learning) with from signal processing one.

The first challenge of this PhD is to estimate a robust multimodal graph-based connectome, considering the temporal and statistic properties of the data. Solutions from the emerging field of graph signal processing (GSP) and graph theory are tailored for this purpose, such as graph Fourier transform, graph signal filtering or Wavelet, or even Convolutional Graphs implementing machine learning solutions. Moreover, novel integration strategy will be proposed to enrich our estimation of the connectome.

The second aim is to develop a predictive model to identify patterns that can act as biomarkers for different diseases. Machine learning techniques have become increasingly popular in the field of network-based classification. However, the application of convolutional networks has been proposed only very recently and has remained largely unexplored, especially in the context of multimodal graphs. In this PhD, we intend to develop new method considering the multimodality nature of our graphs, i.e. through Graph Convolutional Network (GCN).

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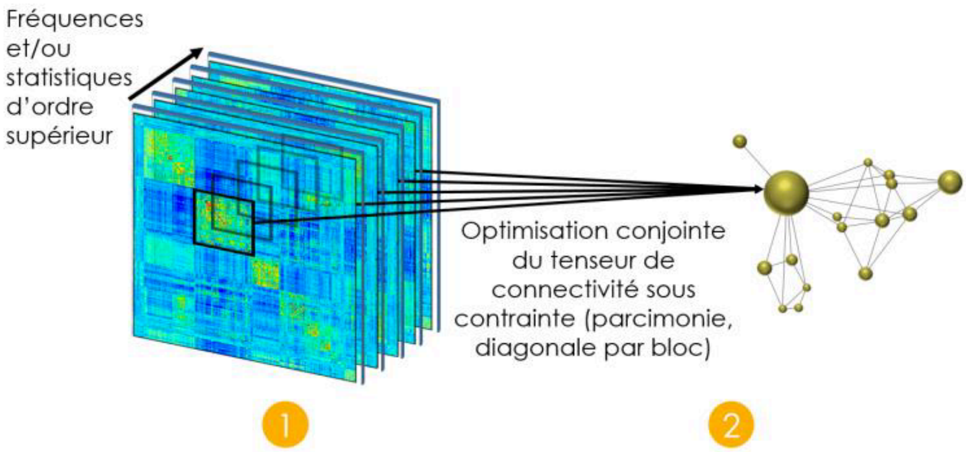

Figure 1 : Representation of brain data from each subject (1) and joint optimization of this connectivity by using graph theory