Graph Signal Processing and applications: Brain neuroimaging

S. Achard, M. Roux[1], P. Borgnat, P. Gonçalvez, G. Frusque[2], and I. Gannaz[3]

[1]Univ. Grenoble Alpes, CNRS, Grenoble INP, GIPSA-lab
[2]ENS Lyon
[3]INSA Lyon, ICJ

1 Introduction

As it was stated in our proposal, we worked on several aspects of graph signal processing with applications to brain data. A close collaboration between Grenoble and Lyon partners has been very active for this part of the project.

— A whole dataset have been made freely available. This dataset consist in brain imaging of 100 subjects scanned twice. The whole description is available online https://graphsip.greyc.fr/node/16.

— During the PhD thesis of Marine Roux, we developed an efficient and accurate strategy for the estimation of graphs when observing time series. These methods are tested on small animals fMRI.

— Graph signal processing techniques developed in WP1 are applied to EEG data.

2 Reproducibility assessment

In order to improve the reliability of methodologies applied on real data such as brain fMRI, we worked previously on the comparison of different methods for test-retest data [1]. For the purpose of this project, the test-retest data were made available in an easy usable format. Indeed, we used the data from the Human Connectome Project, WU-Minn Consortium (Principal Investigators : David Van Essen and Kamil Ugurbil; 1U54MH091657) funded by the 16 NIH Institutes and Centers that support the NIH Blueprint for Neuroscience Research; and by the McDonnell Center for Systems Neuroscience at Washington University. The data were preprocessed in order to extract corresponding time series of brain signals mapped to brain regions. The advantage of these datasets is the possibility to test the reproducibility of the features extracted for each image. Lots of parameters are available to vary such as the size of samples, the number of subjects, the sampling frequency. This would allow to intiate a benchmark so as to test new methods before applying them to the comparison of patients.

3 Multiple testing for graph inference with application on small animals fMRI

During the PhD of Marine Roux, we worked on new methods for graph inference [2]. In this context we developed methods based on multiple testing, see figure 1. In order to test our method, we

acquired data from a dead rat where we know the ground truth. We were able to test our method on these datasets and we showed the efficiency of our approach.

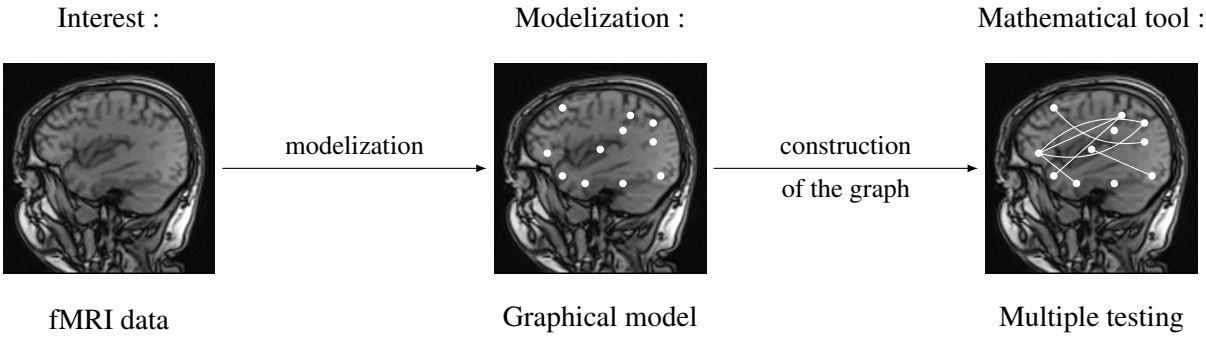

FIGURE 1 – The different scopes dealt with in this thesis.

This thesis is gatering a large part of theoretical work, and we could illustrate our purpose using fMRI data, as illustrated in figure 2.

3.1 Data

Rats are used for acquiring data on the functioning of the brain using fMRI. This provides us a set of time series with spatial localization in the brain of the rats. Four rats are scanned dead (rats 1 to 4), and seven rats are scanned alive under aneasthetic (rats 5 to 11). The duration of the scanning is 30 minutes with a time repetition of 0.5 second so that $3,600$ time points are available at the end of experience. After preprocessing as explained in [3], we extracted 51 time series covering the whole brain of rats.

3.2 Multiple testing approach

Since the whole brain of rats are aggregated into 51 cerebral regions, we have to deal with $50 \times 51/2 = 1275$ tests for each of the 11 rats.

The time series resulting from fMRI experiment are nonstationary with long memory properties, which is not convenient from a mathematical point of view. To avoid such properties, the correlation coefficients are estimated in the wavelet transform domain and then the statistical tests are based on wavelet correlation coefficients [4, 5].

First we are decomposing each time series using a wavelet basis and then for each wavelet scale we are studying all the possible pairs of correlations. From the literature in neuroscience, it is convenient and adequate to focus on low frequencies because we obtain the best signal noise ratio. Here we will focus on wavelet scale 5 corresponding to the frequency interval $[0.03\,;\,0.06]$ Hz.

The wavelet correlation coefficients are typically supposed to have a Gaussian distribution [6]. Thus, the wavelet correlation coefficients satisfy the asymptotic Gaussian assumption (**??**). Note that in practice, we observe that the the wavelet correlation coefficients actually satisfy a Gaussian hypothesis and this assumption is usually made in the neuroscientific literature. Hence, all procedures tested in this PhD are well-suited for the two-sided testing problem and the results of these procedures on the real dataset are discussed.

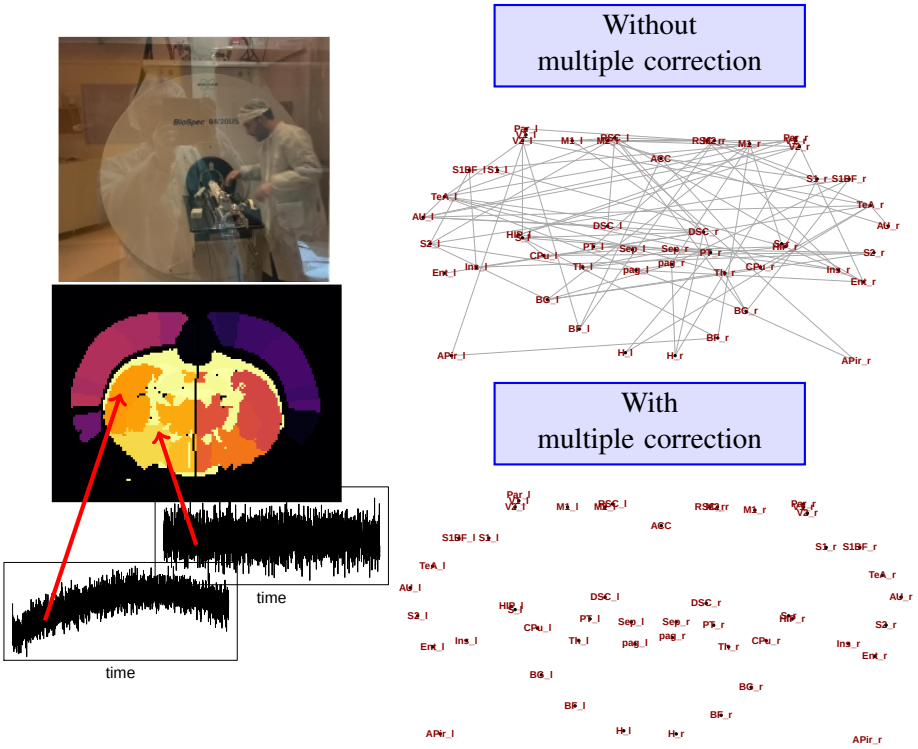

FIGURE 2 – Illustration of the necessity to control for multiple testing on real fMRI data of a dead rat.

3.3 Results

Figure 3 displays the proportion of significant correlations obtained by Bonferroni, Šidák, Romano-Wolf and $\max T_\infty$ procedures. The nominal FWER level is 0.05. As stated previously, only scale 5 of wavelet decomposition is considered, corresponding to the frequency interval [0.03 ; 0.06] Hz.

It is not possible to evaluate the accuracy of procedures on real dataset because of the lack of ground truth. However, since there is actually no cerebral activity in a brain of a dead rat, all null hypotheses to be tested are true nulls and the number of rejected hypotheses must be equal to zero in this case. Indeed, Figure 3 shows that the number of significant correlations is zero or near to zero for dead rats, whatever the method. The highest values are less than 5%, which is in coherence with the fact that we expect to be under the full null hypothesis.

For alive rats, the proportion of rejected null hypotheses is always higher than 5%. Note that there is a high variability with respect to rats, but all methods give the same pattern. The highest number of detections is obtained for the rats 5 and 8 and for the others, the number of detections is between 15% and 25%

4 Graph signal processing and EEG

G. Frusque is doing currently a PhD thesis under the supervision of P. Borgnat and P. Gonçalves. This work has been presented in 2 conferences :

— *Pattern Extraction in multi-trial dynamical graphs of functional connectivities* G. Frusque, P.

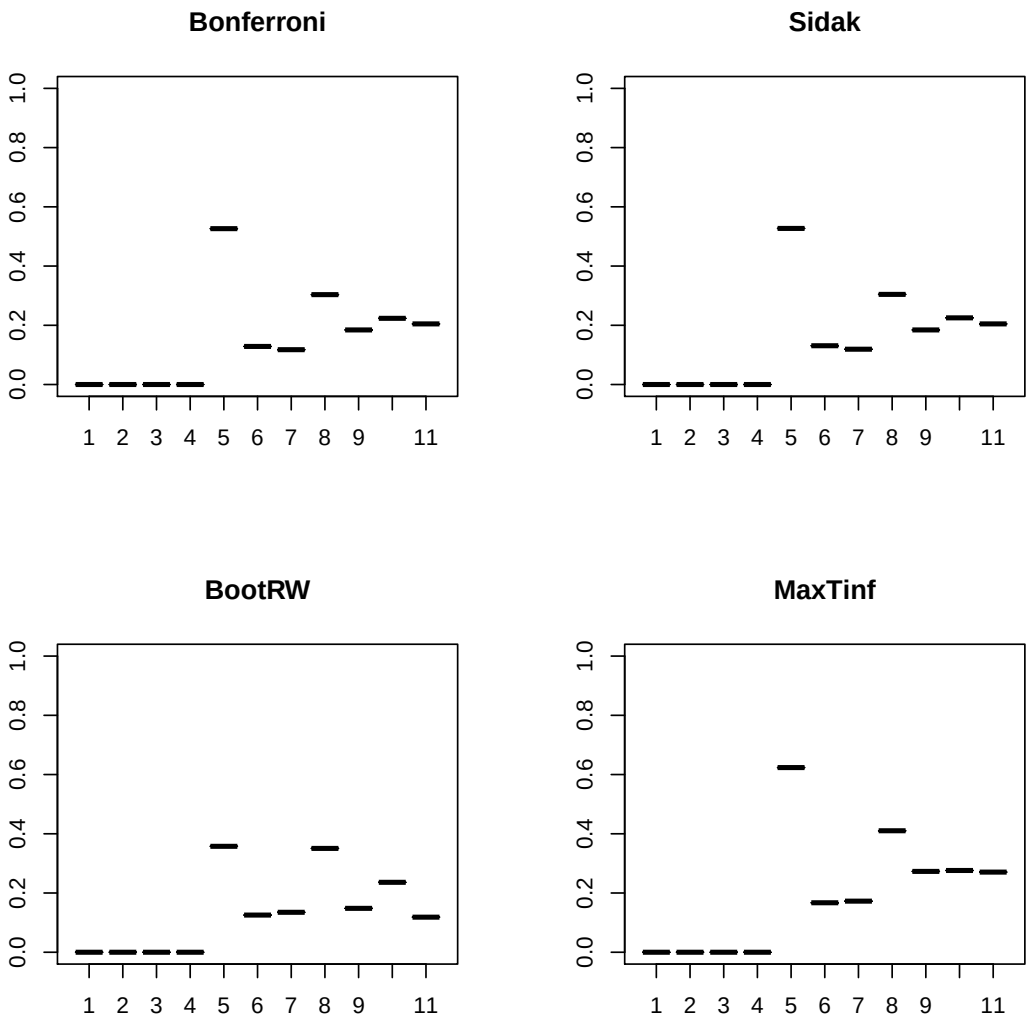

FIGURE 3 – Proportion of rejected null hypotheses obtained by multiple testing procedures defined in the PhD for the rats 1 to 11 (in x-axis). 1275 tests are done for each rat.

Borgnat, P. Gonçalves, Workshop on Graph Signal Processing, EPFL, June 2018

— *Aide à l'analyse visuelle des patterns de connectivité dans le temps et l'espace commun aux différentes crises enregistrées chez un patient via sEEG* G. Frusque, J. Jung, P. Borgnat, P. Gonçalves, Journée Françaises de l'Epilepsie, Lyon, 16-18 Oct 2018

This work will soon be published in a journal paper : *Decomposition of functional Connectivity Dynamical Networks using HOSVD and Clustering* G. Frusque, J. Jung, P. Borgnat, P. Gonçalves.

In parallel, we are developing and testing a new method to extract networks in EEG : "Non-negative Matrix Factorization with PALM", R. Fabregat, N. Pustelnik, P. Gonçalves, P. Borgnat, https ://github.com/raimon-fa/palm-nmf, 2017

Références

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