RAPPORT FINAL DE PROJET

Intitulé du projet : Neural Communication

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Durée du projet : 24 mois

Rappel des objectifs du projet :

Le projet « Neural Communication » s'inscrit dans le cadre du laboratoire d'excellence **Cominlabs**. Il est porté par V. Gripont. (Lab-STICC, CNRS, Brest) et F. Wendling (LTSI, Inserm, Rennes). **L'objectif principal du projet** « Neural Communication», qui étend les travaux effectués par les deux équipes dans le cadre du projet « Neural Coding » (Labex Cominlabs 2012-2015), est de développer des méthodes permettant le suivi des **dynamiques spatiotemporelles des réseaux cérébraux**, en lien avec le traitement de l'information dans le cerveau, à l'échelle de la milliseconde.

Summary of research activities

1. Scientific context of the project

Dense Electroencephalography (EEG) is an imaging technique that allows reaching both high time resolution (about 1ms) and high spatial resolution. In this context, it becomes possible to track the dynamic processes of brain activity during resting state or cognitive tasks. Neural Communications aims at taking benefit of this fact to inspire and stress abstract mathematical models of mental information processing. Its central tool is graph theory.

Neural Communication is collaboration between three partners:

- Télécom Bretagne/Lab-STICC
- Université de Rennes 1/LTSI
- Orange-Labs Lannion

The methodology used in Neural Communications consists in the following steps:

- Collect neuroimaging data
- Use the existing expertise to process it
- Develop novel tools to analyze it
- Exploit the results
- Propose models

In the following section, we summarize the results of the research carried out during Neural Communications.

2. Spatio-temporal dynamics of brain activity during resting state

Here, we used dense-EEG data recorded during task-free paradigm to track the fast temporal dynamics of spontaneous brain networks. Results obtained from network-based analysis methods revealed the existence of a functional dynamic core network formed of a set of key brain regions that ensure segregation and integration functions. Brain regions within this functional core share high betweenness centrality, strength and vulnerability (high impact on the network global efficiency) and low clustering coefficient. These regions are mainly located in the cingulate and the medial frontal cortex. In particular, most of the identified hubs were found to belong to the Default Mode Network. Results also revealed that the same central regions may dynamically alternate and play the role of either provincial (local) or connector (global) hubs. A typical example of the results is presented in figure 1.

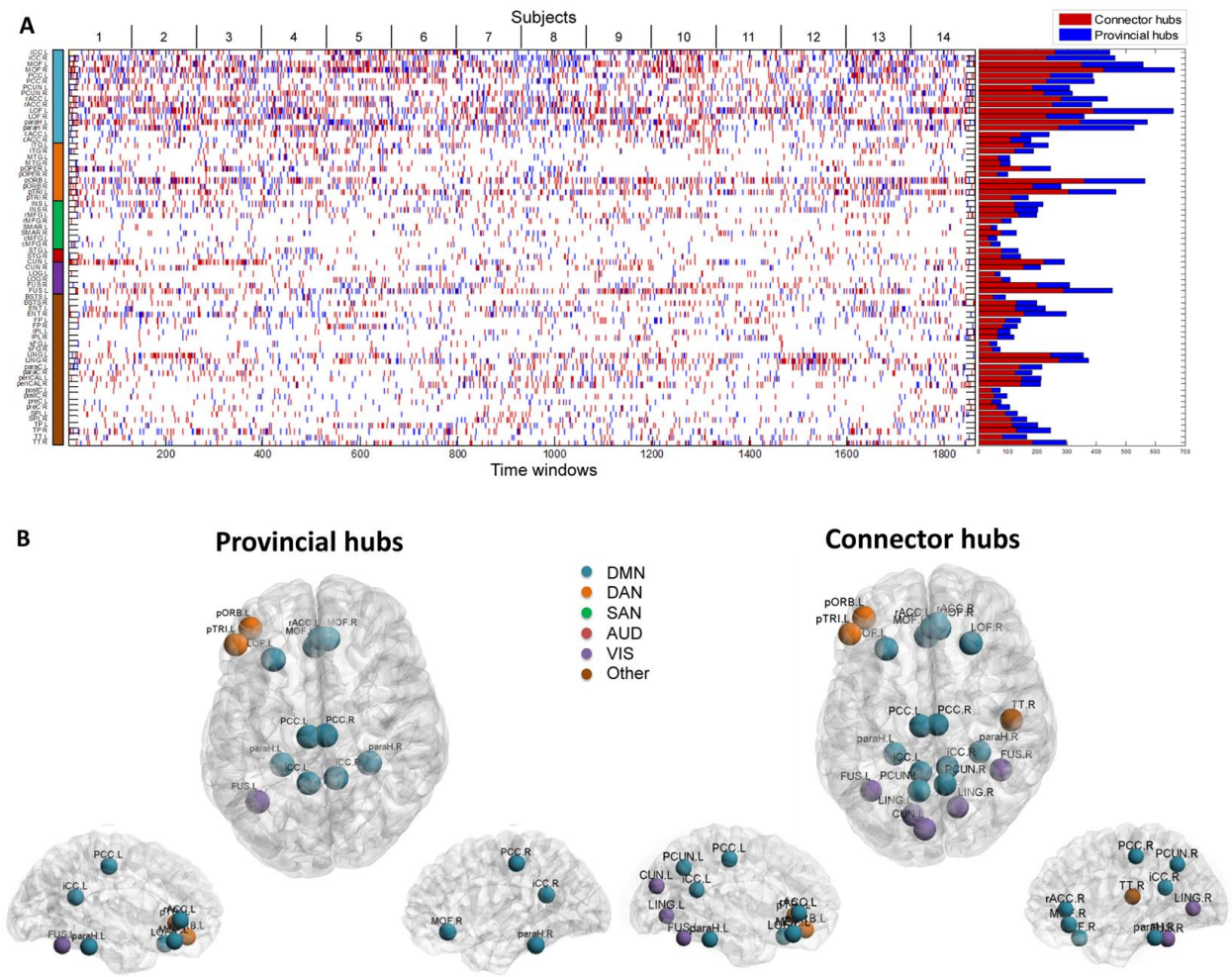


Figure 1: Dynamic analysis: modularity. (**A**) *left*: The variations of the node's type (provincial vs. connector) across time for each of the 68 brain regions, *right*: The bar plots represent the number of times a node is considered as provincial hub (blue color) and as connector hub (red color). (**B**) The spatial distributions of significant provincial hubs, and significant connector hubs.

3. Spatio-temporal dynamics of brain activity during cognitive tasks

3.1 A novel algorithm to identify functional connectivity patterns

We developed a new method for the analysis of dynamics of neural activity at rest and during cognitive tasks. This method is based on multivariate decomposition of functional connectivity (FC) patterns. FC corresponds to the analysis of statistical dependencies between brain signals, usually performed by estimating covariance. Recently, analysis methods have attempted at estimating time-varying aspects FC, using sliding windows, followed by clustering algorithms such as K-means.

In Neural Communications, we extended this approach by introducing two key ideas:

- We consider temporal sequences of FC using consecutive sliding windows instead of isolated ones,
- We use sparse dictionary learning to decompose these temporal sequences

The result consists in obtain spatiotemporal patterns each associated with a time series, corresponding to transitions in connectivity. Here is an example of such patterns. The leftmost panel corresponds to the temporal average of a dynamic FC pattern, while the central panel corresponds to standard deviation. These two matrices respectively show stable and dynamic aspects of connectivity, structured in subnetworks. The rightmost panel depicts the associated activation time-series, showing transitory activations and time-varying aspects of these dynamic patterns.

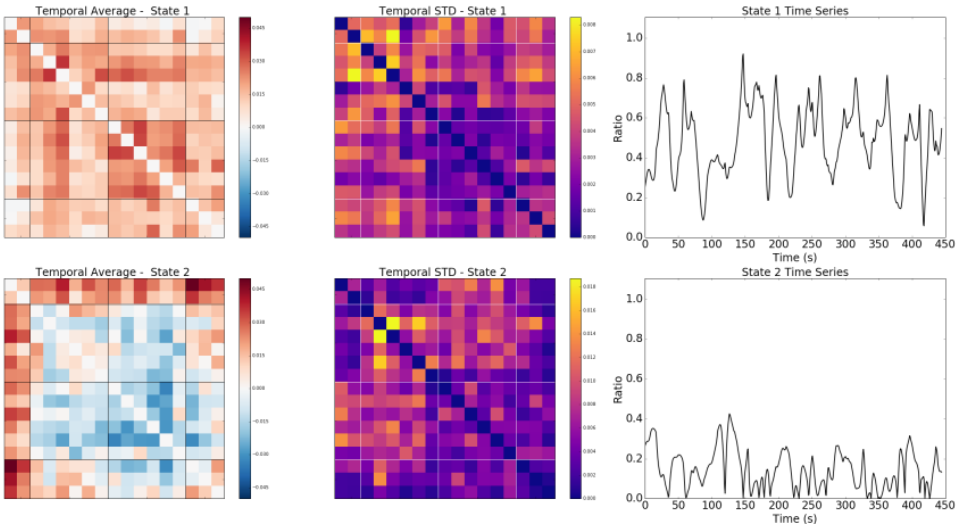
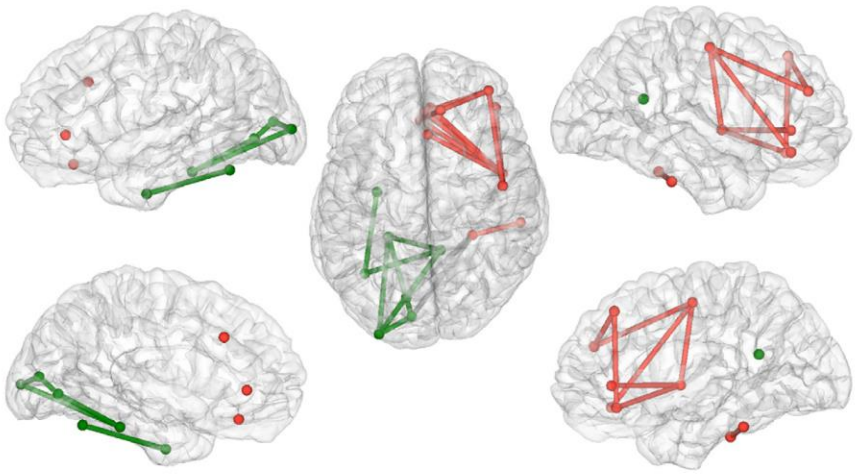


Figure 2: Brain states obtained using the algorithm

3.2 Application: dynamic reshaping of functional brain networks during visual object recognition

Here, we investigate brain network modularity while controlling stimuli meaningfulness and measuring a participant's reaction time. We particularly raised two questions: i) does the dynamic brain network modularity change during the recognition of meaningful and meaningless visual images? And (ii) is there a correlation between network modularity and the reaction time of the participants? To tackle these issues, we collected dense- EEG data from 20 healthy human subjects performing a cognitive task consisting of naming meaningful (tools, animals…) and meaningless (scrambled) images. Functional brain networks in both categories were estimated at the sub-second time scale using the EEG source connectivity method. By using multislice modularity algorithms, we tracked the reconfiguration of functional networks during the recognition of both meaningful and meaningless images. Results showed a difference in the module's characteristics of both conditions in term of integration (interactions between modules) and occurrence (probability on average of any two brain regions to fall in the same module during the task). Integration and occurrence were greater for meaningless than for meaningful images. Our findings revealed also that the occurrence within the right frontal regions and the left occipito-temporal can help to predict the ability of the brain to rapidly recognize and name visual stimuli. We speculate that these observations are applicable not only to other fast cognitive functions but also to detect fast disconnections that can occur in some brain disorders.

A



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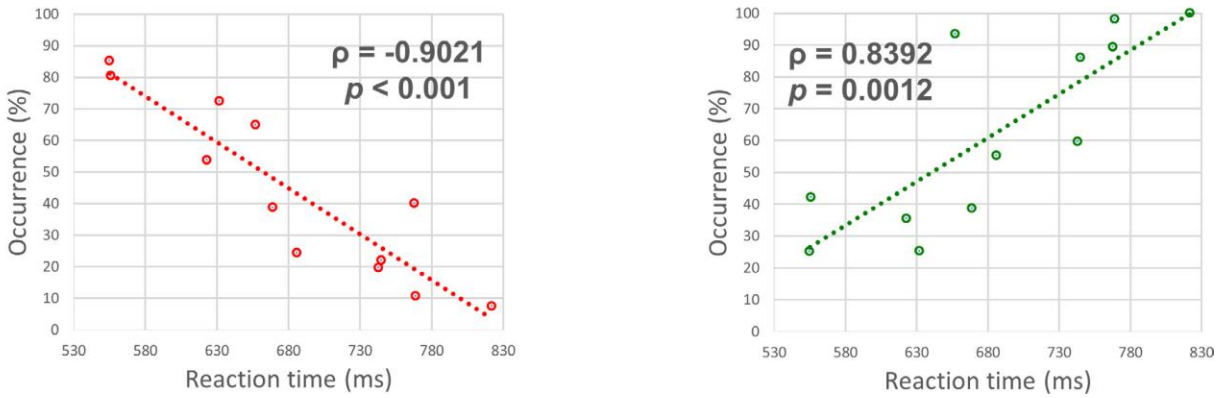

Figure 3: (A) Brain regions of 12 participants that showed significant correlation between their occurrence values and the participant's reaction time. (B) Correlation between the average occurrence over these connections and the minimal reaction time for each participant. (Note that this part was realized only on the meaningful pictures as for meaningless pictures participants were asked to say nothing and for only 12 participants as the reaction time was only available for them.)

4. Graph signal processing and fMRI classification

While early discoveries in neuroscience relied on massively univariate statistics or signal processing techniques such as time-series or time-frequency analysis, there has been a recent paradigm shift towards the application of multivariate analysis and machine learning to "decode" brain functions. Under the natural assumption that neural signal properties are related to the topology of brain graphs, graph signal processing (GSP) offers algorithms that fruitfully leverage this relational structure.

In Neural Communications, we experimented the use of GSP to improve supervised classification by taking into account Functional Connectivity as well as spatial relationships between regions of interest (ROI) in the brain. Specifically, we devised a set of experiments on simulated and real fMRI data in order to test the potential of GSP for classification. First, we built graphs using both information about the geometrical coordinates of ROIs, as well as statistical correlation between the signals in the ROIs. We showed that using

a semilocal graph (composed of a weighting between statistical and geometrical properties) yielded the best results. Next, we compare dimensionality reduction techniques, as well as the use of graph sampling techniques.

The following figure depicts the weights of a Support Vector Machine trained to discriminate fMRI patterns between two visual stimulation conditions. fMRI signals were first averaged from a 2x2x2 mm grid down to 444 ROIs, then a subset of 100 ROIs was selected using Graph Sampling.

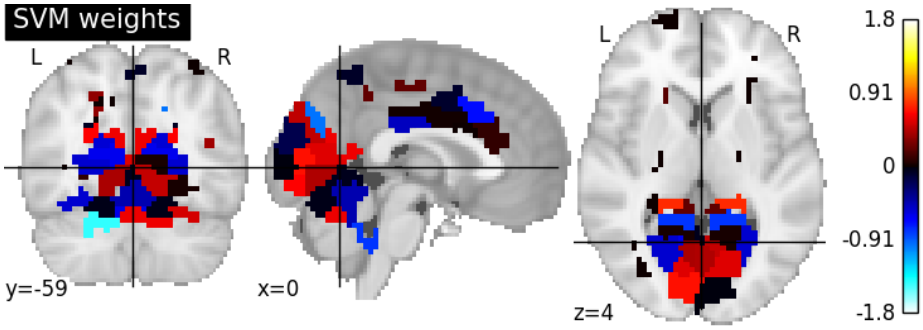

Figure 4: Typical example of obtained results.

The following table shows the result of our comparisons for Easy and Difficult simulated cases, as well as for the real fMRI (Haxby) Dataset (tabled adapted from Menoret et al. 2017, GlobalSIP), using the semilocal graph and a SVM. We show the interest of using Graph Sampling coupled with the use of a semilocal graph.

TABLE II
COMPARISON OF GRAPH SAMPLING (*Semilocal* GRAPH), PCA, ICA AND ANOVA. CLASSIFICATION ACCURACY WITH 50 COMPONENTS FOR THE SIMULATED AND HAXBY DATASETS.

Method	Simulation		Haxby	
	Easy	Difficult	Face-House	Cat-Face
PCA	88.8%	65.5%	82.7%	63.6%
ICA	90.2%	65.3%	84.4%	67.0%
ANOVA	**92.1%**	67.3%	85.5%	65.5%
Graph sampling	90.9%	**72.5%**	**88.2%**	**69.0%**

6. Models of brain communication

We established how point-to-point communications between two regions of the brain is biologically plausible. Noise generated by failing synapses and external interferences has been modeled. For any neural network, external noise can simply be generalized and modeled by insertion and erasure parameters. We showed that Neural clique networks can be used as hubs of local associative memories in the brains, for communications with other regions of the brain.

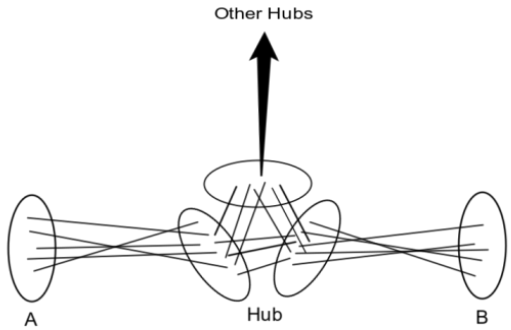

Figure 4: Neural cliques networks

7. Toward a characterization of brain networks during binaural hearing: data collection

In partnership with Orange laboratories in Lannion, this part of the project is devoted to the testing of the methods previously developed on visual tasks. Indeed, if resting state analysis offers the best substrate for brain connectivity analysis, we also developed methodological tools and processing pipelines for task-related signals. Thanks to this new analysis on binaural sounds, we want to assess and extend experimentally the method validity to any kind of sensory input. We also want to pave the way to use connectivity graphs (static and dynamic) as valid, reproducible and sensitive biomarkers of the functioning brain. Binaural sounds will indeed be qualified according to the feelings of people (pleasant vs. unpleasant) and their spatial location. Preliminary results obtained using by identifying the EEG source-space networks for the three conditions: Stereo, Real and Amb and the similarity between them is presented in figure 6 and 7.

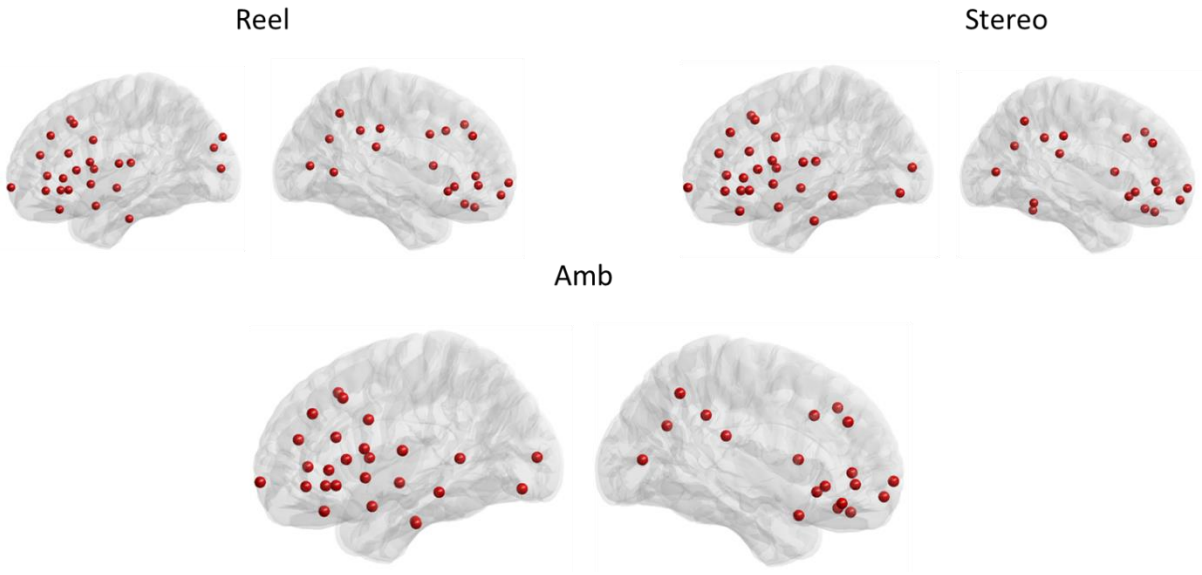

Figure 6: Networks obtained during the task for a given subject.

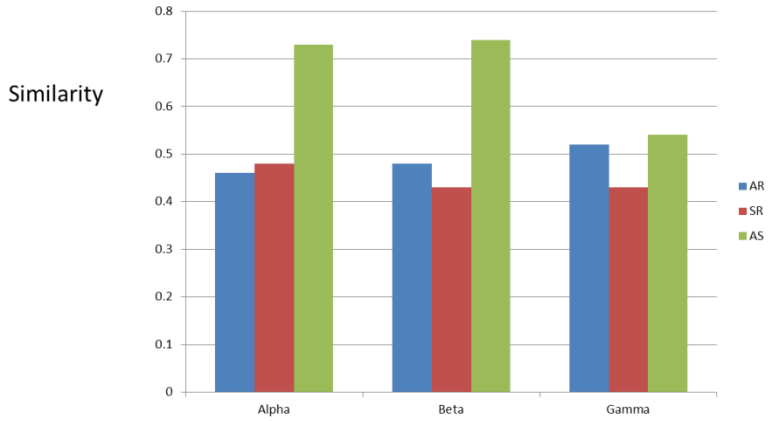

Figure 7: similarity between the EEG-source space networks for the three conditions at different frequency bands.

Role of the staff hired on the project

Nicolas Farrugia was recruited as a postdoc in November 2015 until July 2016. Nicolas performed the research on Dynamics of Cognitive Activity, proposing a new method for the analysis of time-varying FC patterns. Nicolas presented his work as an oral presentation at the annual meeting of the Organisation for Human Brain Mapping in Geneva in June 2016. In July 2016, Nicolas obtained an assistant professor position at IMT Atlantique.

Mathilde Ménoret was hired in September 2016 as a postdoc, and stayed until the end of the project in October 2017. Mathilde contributed to the research effort of Neural Communication by exploring graph signal processing for fMRI classification. She published a conference paper at GlobalSIP'17 in Montreal.

Olivier Dufor was previously a postdoc in the NEUCOD ERC project, and was funded by Neural Communications in September 2017 (one month). Olivier worked on data collection for source localization in binaural setting.

Mahmoud Hassan was recruited as a postdoc in November 2015 until December 2017. He worked on the identification of the brain network through dense-EEG and the tracking of the brain network dynamics at sub-second time scale.

Main project output

- Consolidated Hebbian learning and parsimonious energy consumption, resulting in large capacity associative memories, Eliott Coyac, Vincent Gripon, Charlotte Langlais and Claude Berrou, ICMNS 2015
- Neural clique networks in an unreliable environment, Eliott Coyac, Vincent Gripon, Charlotte Langlais and Claude Berrou, ICMNS 2015
- Impact du bruit synaptique sur les performances des réseaux de cliques neurales, Eliott Coyac, Vincent Gripon, Charlotte Langlais and Claude Berrou, Gretsi 2015

- Distributed Coding and Synaptic Pruning, Eliott Coyac, Vincent Gripon, Charlotte Langlais and Claude Berrou, ISTC 2016
- Performance of Neural Clique Networks subject to synaptic noise, Eliott Coyac, Vincent Gripon, Charlotte Langlais and Claude Berrou, COGNITIVE 2017 (submitted)
- Neighborhood-Preserving Translations on Graphs, Nicolas Grelier, Bastien Pasdeloup, Jean-Charles Vialatte and Vincent Gripon, GlobalSip 2016.
- Identifying Spatiotemporal patterns of functional connectivity using dictionary learning, Nicolas Farrugia, Julia Huntenburg, Daniel Margulies and Vincent Gripon, OHBM 2016.
- An intrinsic difference between vanilla RNNs and GRU models, Tristan Stérin, Nicolas Farrugia and Vincent Gripon, Cognitive 2017.
- Evaluating Graph Signal Processing for Neuroimaging Through Classification and Dimensionality Reduction, Mathilde Ménoret, Bastien Pasdeloup, Nicolas Farrugia and Vincent Gripon, EUSIPCO 2017.
- Gait improvement via rhythmic stimulation in Parkinson's disease is linked to rhythmic skills, Nature Scientific Reports, 2017.
- Electroencephalography Source Connectivity: Aiming for High Resolution of Brain Networks in Time and Space, Hassan M., Wendling F., IEEE Signal Processing Magazine, Vol. 35, issue 3, pages:81-96, 2018.
- SimNet: A Novel Method for Quantifying Brain Network Similarity, Mheich A., Hassan M., Khalil M., Gripon V., Dufor O. and Wendling F., IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 2017.
- The dynamic functional core network of the human brain at rest, Kabbara A., El Falou W., Khalil M., Wendling F., Hassan M., Scientific Reports, 2017.
- Dynamic reshaping of functional brain networks during visual object recognition Rizkallah J., Hassan M., Kabbara A., Dufor O., Benquet P., Wendling F., Journal of Neural engineering, 2018.
- Reduced integration and improved segragation of functional brain networks in Alzheimer's disease Kabbara A., Eid H., El Falou W., Khalil M., Wendling F., Hassan M., Journal of Neural engineering, 2018.