PostDoc position offer at CEA/NeuroSpin: Multivariate Scale-free Analysis of Brain Activity Recorded in MEG

Supervision:

- Dr Philippe Ciuciu, Head of Inria-CEA MIND team (philippe.ciuciu@cea.fr, +33 1 6908 7785)
- Dr Patrice Abry CNRS, ENS Lyon, (patrice.abry@ens-lyon.fr)

Duration: 12 months, with possible 12-month extension. Salary commensurate upon background and experience

Location: The candidate will be hired by NeuroSpin at CEA Saclay, in the framework of an ANR grant (DARLING) and will develop research activities in the MIND team. Possible visits at ENS Lyon to collaborate with P. Abry.

Application: Candidates should send a CV, a motivation letter and at least two references to Ph. Ciuciu and P. Abry.

Context. The human brain is a large system which exhibits complex behavior and dynamics, characterized by patterns such as avalanches [1], spontaneous activity, oscillations [2] and long range temporal correlation (LRTC) either in the infra-slow (< 2Hz) or oscillatory regimes. Those patterns can be understood from different perspectives such as analyzing a dynamic system operating near a critical point of a phase transition [3] or directly using advanced signal processing tools that provide a sophisticated quantification and an explantory power of the complexity of brain activity, recorded at rest or during task performance in magneto- and electro-encephalography (MEG/EEG). Both lines of thought have evidenced the importance of scale-free properties in the brain. Indeed, one on hand, dynamic systems operating near a critical point display dynamic scale invariance [4]. On the other hand, the renewed interest in *scale-free* properties of neural activity have been sparked by multiple studies [5, 6, 3, 7] which rely on statisitcal models of increasing complexity, first self-similarity analysis that entirely characterizes time series by a single Hurst exponent [8], which is typically measured from the second-order statistical moments as it linearly scales on the log-log plot of the power spectrum (see see Fig. 1(center)). Second, multifractal analysis [9] permits to describe scale-invariance in a more complete and accurate manner in the stattistical sense as it allows us to compute a collection of scaling exponents [10] that may differ across statistical orders. In this project, we foucs on mulifractal analaysis of brain activity recorded in MEG as we already have demonstrated that multifractal properties of brain activity is modulated during task performance and with brain plasticity associated with visual learning [11, 12]. Howvever functional neuroimaging data such as MEG and EEG are noisy, multivariate and embed a spatial dimension (see Fig. 1(left)) that permits to probe long range interactions between distant brain regions, hence allowing us to uncover the graph structure of functional networks.

The challenge. While functional connectivity assessment is well established both methodologically and practically for oscillatory bands (e.g., α in (8, 12)Hz, β in (13,30)Hz and γ beyond 30Hz) through for instance weighted phase lag index (wPLI) or imaginary coherence (ICOH), it is far less the case for scale-free dynamics. This is mostly due to the fact that theoretical models commonly involved in scale-free dynamics analysis, such as self-similarity and multifractality, remained, up to a recent past, univariate in nature. However, recently, multivariate self-similarity and multifractality analyses were devised theoretically and corresponding multivariate signal processing tools were developed accordingly (see e.g., [13] for a review). As a first step forward, we have recently extended the wPLI and ICOH estimators to the context of self-similar functional connectivity analysis in the low frequency regime of the broadband spectrum (< 2Hz) [14] for MEG/EEG time series.

Work plan. The goal of the proposed work is now to instantiate the recently developed multivariate multifractality analysis tools [15] on real MEG data by designing first multifractal functional connectivity estimators between pairs of MEG/EEG signals to quantify dependencies between time series at higher statistical orders, i.e., beyond crosscorrelation (see a synthetic example in Fig. 1(right)). To this end, MEG data have been collected at NeuroSpin on 20 healthy participants performing a timing task (estimation of various durations). The experimental protocol was conceived by the Cognition & Brain Dynamics team (Dir: V. van Wassenhove) as an extension of recent works [16, 17, 18]. Based on preliminary supporting evidence for univariate multifractal temporal dynamics in such data, the goal will be to uncover the functional network associated with time perception and see whether long range interactions between distant brain regions within this network are restrained to second-order correlation or shaped by exchange of multifractal properties, such as co-occurrence of bursty dynamics in the two distant time series.

The work will imply i) understanding enough of the mathematical concepts underlying multivariate self-similarity and multifractality, ii) developing new or complementing existing codes within a Python package, dedicated as of now to univariate multifractal analysis[1], iii) performing MEG data analysis, and iv) analyzing and interpreting the obtained results from a neuroscientific perspective.

Environment. This postdoc will take place at NeuroSpin, in the MIND team. This is a large team focused on mathematical methods for statistical modeling of brain function using neuroimaging data (fMRI, MEG, EEG) as well as advanced computational imaging methods. Particular topics of interest include machine learning techniques, advanced MEG/EEG source localization approaches and analysis of brain dynamics, applications to cognitive and clinical neuroscience, and scientific software research and development.

Skills. We seek candidates who are strongly motivated by challenging research topics in neuroscience and signal processing. Applicants should have a PhD in one of the following domains: Biomedical engineering, signal processing, neuroimaging or neuroscience. Solid experience and skills in statistical analysis of brain activity recordings. Background knowledge in statistical signal processing and hypothesis testing. Clear taste for interdisciplinary research activities (neuroscience, statistical signal processing) and for combining methodological development with real data analysis. Proficiency in scientific Python is expected (`numpy`, `scipy`, `scikit-learn`, `pandas`). Preliminary knowledge of `mne-python` is a plus but not mandatory.

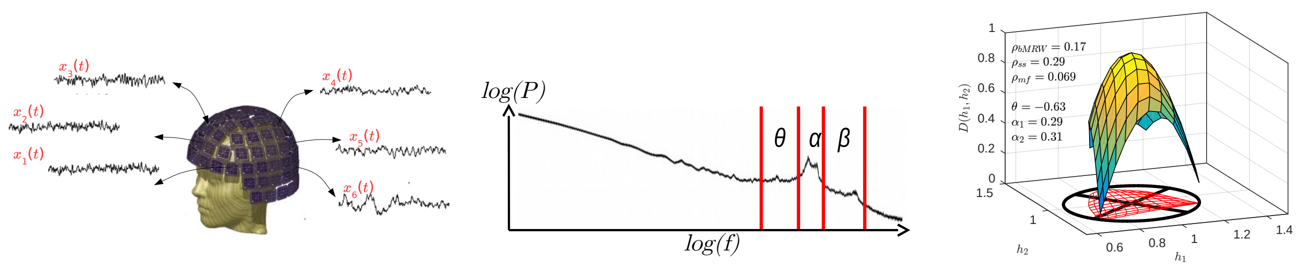

Figure 1: **Multivariate brain dynamics in MEG:** MEG brain recordings (left), Scale-free or arhythymic brain dynamics (center) in the spectral domain (log-log plot of the power spectrum), bivariate multifractal analysis (right).

References

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