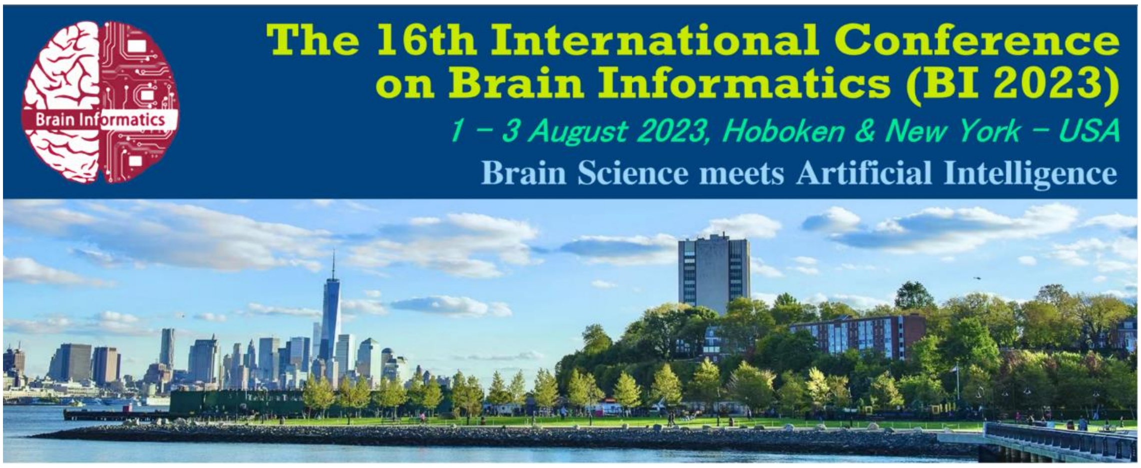

Time Domain Analysis of Neural Oscillations

Abstract:

Cortical oscillations are one of the essential part of brain functionality. In human electrophysiological recordings such as scalp electroencephalogram (EEG), magneto-encephalogram (MEG) these oscillations manifest visible rhythmic patterns or equivalently as a local concentration or narrowband peaks in power spectral density. Some of the commonly used tools to characterize these oscillations are band-pass filters and frequency domain analysis of the signal. Unfortunately, results of these ad-hoc methods are difficult to interpret since they do not adhere to any generative models to formally represent oscillations. For example, bandpass filters can produce spurious oscillations when applied on a broad-band signal.

In general, these methods suffer from confounding from cooccuring oscillations and broadband activities, loss of spetro-temporal resolution due to windowing, leading to noisy, inefficient measures of derived metrics, such as amplitude, phase etc.

In this context, this session focuses on time domain or state space modeling of neural oscillations to decompose time series in multiple oscillations and trend components. We start with a new conceptual construct that makes clear, from a dynamical systems perspective, when oscillations are present or not. Using that construct, a novel method is developed to identify and characterize neural oscillations distinct from broad-band noise. We then demonstrate how these extracted component oscillations improve statistical efficiency in parametric, time-varying cross frequency phase amplitude coupling analysis.

Next, we show the utility of state space models of rhythms in estimation of phase, i.e., the local time index of the waves of a rhythm, that is tolerant of model misspecification. Using this model, we can improve on how current state-of-the-art real-time methods of phase estimation deal with common confounds such as broadband rhythms, phase resets and co-occurring rhythms. Moreover, for offline phase analysis, we found

that while phase can be multiply-defined, different methods converge during times of low uncertainty. State space models can be ubiquitous even when neural signals exhibit time-varying activity, precluding adequate model specification with stationary parameters. One flexible approach to model such time-varying signal is by using switching state-space models. A set of parallel state-space models with different linear dynamics are constructed from domain knowledge, capturing multiple target neural states of interest, while a switching process determines the presence of a particular dynamics at a given point of time. We show that these switching state-space models provide numerous analytical advantages and enable more rigorous characterization of time-varying neural signals.

Lastly, we demonstrate how state-space modeling provides a convenient and compact way to model signals simultaneously recorded at multiple sensors. With a generative model where an unknown number of hidden oscillation sources undergo linear mixing to produce multichannel recordings, we can effectively pool information across channels while taking the temporal (i.e. oscillatory) structure of neural data into consideration. That provides inference of oscillation source time-courses and their explicit distribution over the scalp as an interpretable dimensionality reduction. In a nutshell, This session offers a glimpse into how the state space modeling approach of linear dynamical systems can lead to significant methodological advancements in analyzing neural electrophysiology signals.

Keywords:

Oscillations, EEG, state space

Topics:

3.16: Machine learning algorithms for brain data analysis

3.26: Statistical analysis and pattern recognition in neuroimaging

3.8: Data brain modeling and formal conceptual models of brain data

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