MSc in Computational Cognitive Neuroscience

Goldsmiths
UNIVERSITY OF LONDON

Computational modelling of variance in local field potentials and machine-learned multivariate patterns using information theory

Dr. Andres Canales-Johnson and Louis Roberts

Background

Time-generalized multivariate pattern analysis (TG-MVPA) is a popular technique for the analysis of how well a timepoint in a signal associated with an experimental condition, like participant attention, predicts that condition in conjunction with another timepoint. **TG-MVPA quantifies temporal aspects of representations in neural signals** as the performance of a linear classifier *(Fig 1, a).* Though this methodology has produced interesting findings, like sustained representation of signals associated with stimuli maintained in conscious awareness[1], the non-parametric and classifier-specific nature of classifier performance restricts the interpretability of TG-MVPA outputs for below-chance performance and the comparison of outputs for recordings within and between participants.

To address this, Dr. Canales-Johnson developed **TG-CoI,** an analytical pipeline which replaces TG-MVPA's classifiers with a Gaussian-Copula Mutual Information (GCMI) estimator which quantifies the amount of **co-information (Co-I)** between two timepoints and a condition *(Fig 1,b).* TG-CoI measures **mutual information (MI);** if **negative,** this is the MI present in both signals, a **redundancy,** while if **positive,** this is the MI which emerges through their interaction, a **synergy** present only when both signals are examined together. Applying **TG-CoI** to electrocorticography (ECoG) **local field potentials (LFP)**, Dr. Canales-Johnson found synergy off-diagonal in **generalized time,** indicating that two timepoints of the signal are a better predictor of participant attention under an **"oddball" paradigm** than those timepoints alone. To better understand this finding among others, this project proposes to **apply TG-CoI to simulated ECoG event-related potentials (ERP) with trial-wise variation and noise** *(Fig 1, c).*

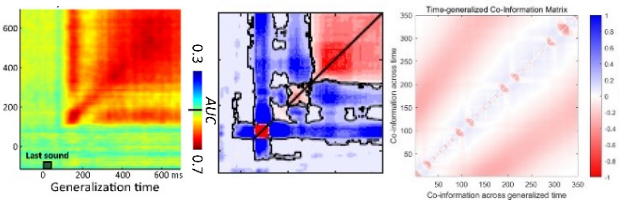

Figure 1: a) TG-MVPA b) experimental TG-CoI, c) simulated TG-CoI outputs

Objectives

Simulate LFP data as vectors of trials of one or two damped harmonic oscillators with parametric and noise- based forms of variance over trials.

Analyze how **waveform parameters and variance contribute to time-generalized patterns of redundancy and synergy** characteristic of experimental data, both for within-channel and between-channel TG-CoI.

Simulate LFPs using a neurobiologically-grounded neural-field theory model of LFPs with attentional gain dynamics implemented through local feedbacks.

Analyze how variation of neurophysiological parameters controlling **oscillatory band activity contributes to the same experiment-like TG-CoI patterns**.

Primary Hypotheses

H1) Trial-wise parametric variance in simulated ERP waveforms results in off-diagonal patterns of synergy in the TG-CoI matrix.

H2) Trial-wise variance in **alpha and theta oscillatory activity** results in off-diagonal patterns of synergy in TG-CoI between early (N1, ~100ms) and late (P2-P3, ~250ms) components of a simulated ERP.

Preliminary Findings

When simulating an MMN within a channel as one damped oscillator, varying the restoring force results in systematic differences in the frequency of the waveform across trials, leading to synergy in later generalized timepoints similar to that found in experimental data.

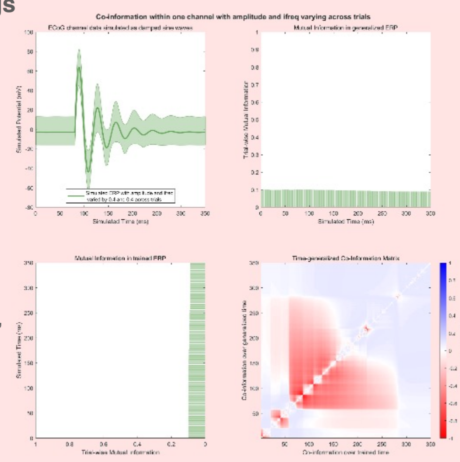

Figure 2: Within-channel simulation with amplitude and restoring force varied across trials

Methods

The differential equation describing a simple damped harmonic oscillator is:

$$m\frac{d^2x}{dt^2} + 2\gamma\frac{dx}{dt} + kx = 0$$

where m determines the **amplitude** of the oscillation, 2γ controls the **damping**, and k the **restoring force**.

Condition-difference, or **mismatch negativity (MMN)** waveforms can be simulated either as a single oscillator or as a difference, computed though MI, between two oscillators.

ERP waveforms are varied over trials to some proportion of the original parameter value. Other trial-wise distributions can be examined alongside post-simulation addition of noise and latency effects.

Summary

Preliminary results indicate support for H1; trial-by-trial variance may be the source of synergistic co-information in later stages of a recorded ERP.

1 King, J-R. et al. (2014) Two distinct dynamic modes subtend the detection of unexpected sounds. PLoS ONE http://dx.doi.org/10.1371/journal.pone.0085
2 Ince, R. A., Giordano, B. L., Kayser, C., Rousselet, G. A., Gross, J., & Schyns, P. G. (2017). A statistical framework for neuroimaging data analysis based on mutual information estimated via a gaussian copula. Human brain mapping, 38(3), 1541–1573. https://doi.org/10.1002/hbm.23471