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Inference of Global States Stability in Cortical Networks

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The Default Global State of the Cerebral Cortex [1]

Phenomenology

▶ Slow Oscillations (≤1Hz)
 ▷ at the neuron level (membrane potential and firing rate)
 ▷ at the network level



Cortical Slices Recordings





(extracellular electrical activity: LFP and MUA)

Observed in:

slow wave sleep
deep anaesthesia
deafferentation
cortical slices

Key Features

Bistability

Motivation

- existence of two attractors:UP state and DOWN state
- Intrinsic fluctuations between these attractors
- Regularity of the UP/DOWN states alternance
- \rightarrow behaves as a relaxation oscillator



Figure 1: Slow oscillations recorded from the frontal cortex of an anaesthetized mouse [1]

Advantages

- Resilience to perturbances:
 the relaxation-oscillator regime acts as an equilibrium of the network.
- Facilitation of the transition towards more connected, awake-like states.

Figure 2: Cortical slice recording setup: (A) cortex, (B) white matter, (C) infragranular layers' electrodes and (D) supragranular layers' electrodes

Experimental Conditions [2]

- ▶ Pharmacological Modulations
 ▷ adding Carbachol (0.5 µM) + Norepinephrine (50 µM)
 - reducing extracellular Calcium (to 0.8-0.9 mM)
 - ▷ Reducing temperature (to 31-32 °C)
- Electrical Stimuli
 - \triangleright 150 $\mu \rm A$ pulses every 10 s at layer 5.
 - \rightarrow Experimental model to explore the transitions from a state of slow oscillations towards a higher complexity state (awake-like asynchronous state).



Figure 3: Schematic of the 16-channel SU-8-based flexible microprobe used for the recordings

Can we detect and characterize other global network states apart from the SO regime?

Cortical Networks Parameters: Literature Review

In fact, the dynamics of the network states are not fully understood [3]. The stability of such states seems to be strongly influenced by:

- the input stimulus [4]
- the connectivity properties of the network
 - either unshaped or structured in clusters [5]
- the excitatory-inhibitory balance
 [6]
- the network architecture
 - either predominantly feedforward or recurrent [7]
- the kind of noise
 - ▷ intrinsic or extrinsic [8]

Problem: Although multiple mechanistic hypotheses have been proposed in models, the current analysis tools do not enable us to discern empirically the dynamics of the network states.

Figure 4: Example of extracellular activity (LFP and logMUA) issued from recordings at two different layers under two different experimental conditions

Our Approach

Aims

To identify the stability of the global network states in isolated cortical networks under experimental manipulations that alter key network parameters (excitability, input, connectivity, etc.).

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- To develop a novel theoretical tool which empirically captures the metastable regions of the network, i.e. transient states that temporarily behave as attractors.

Methodology

- With the aid of kernel mean embedding techniques for clustering [9], we will detect the convergence regions of the system.
- By studying how the phase portrait of the system evolves when the slow-oscillation regime is perturbed, we will map the bifurcations or transient states with the network parameters.

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