Relating slow waves from different measurement techniques through an adaptable pipeline

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Motivation

Slow waves (SW) are spatially arranged transitions from low- (Down) to high-activity (Up) states, in the range of 0-5 Hz.

- **Heterogeneity of data**
  SW activity is observable
  - across species,
  - across scales,
  - across methods.
- **Requisites for comparability**
  SW analysis approaches need
  - reproducibility,
  - reusability,
  - generality.
- **Enablement of cross-domain comparisons**
  Joint analyses of diverse data empower
  - integration of multiple data sources,
  - model calibration & validation,
  - quantifying experimental variability.

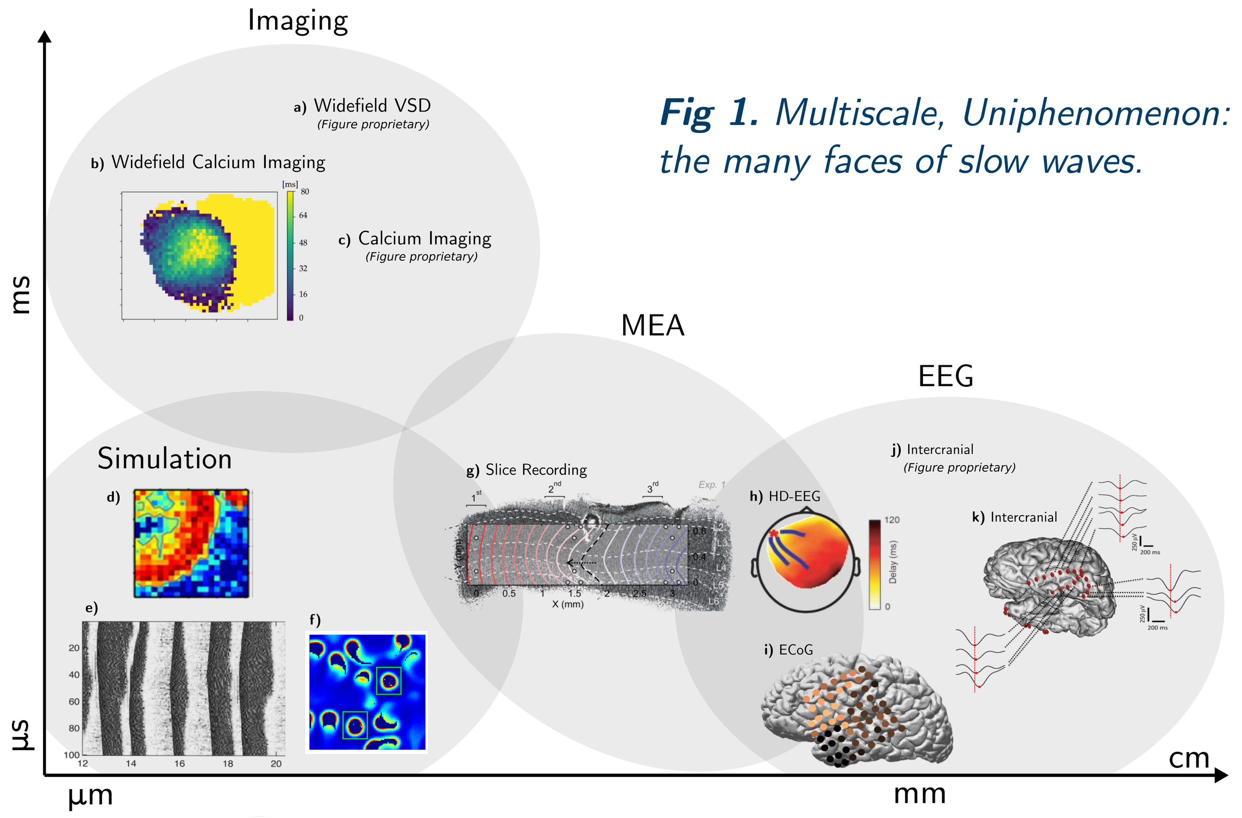

Fig 1. Multiscale, Uniphenomenon: the many faces of slow waves.

Resources

Introduction video at *www.youtube.com/watch?v=uuAiY6HScM0*
More details at *github.com/INM-6/wavescalephant*

Approach

- **Integrating existing methods, algorithms, tools & standards**
  Structuring data & metadata in the Neo [1] format, adopting methods from the literature, using standard implementations (e.g. in Elephant [2]), and relying on open-source solutions (e.g. Snakemake [3] for workflow management)
- **Challenge 1: Common slow-wave description & evaluation**
  Having a common phenomenon description makes the methods agnostic of the data origin. So, comparison metrics can be computed identically.
- **Challenge 2: Modularity & adaptability**
  Clearly defining the input-output relationships, as well as checking the input requirements for each step makes the pipeline adaptable, and each element reusable.

The implementation of an analysis workflow in a modular, adaptable, and reproducible pipeline enables the comparison of slow-wave activity across diverse datasets.

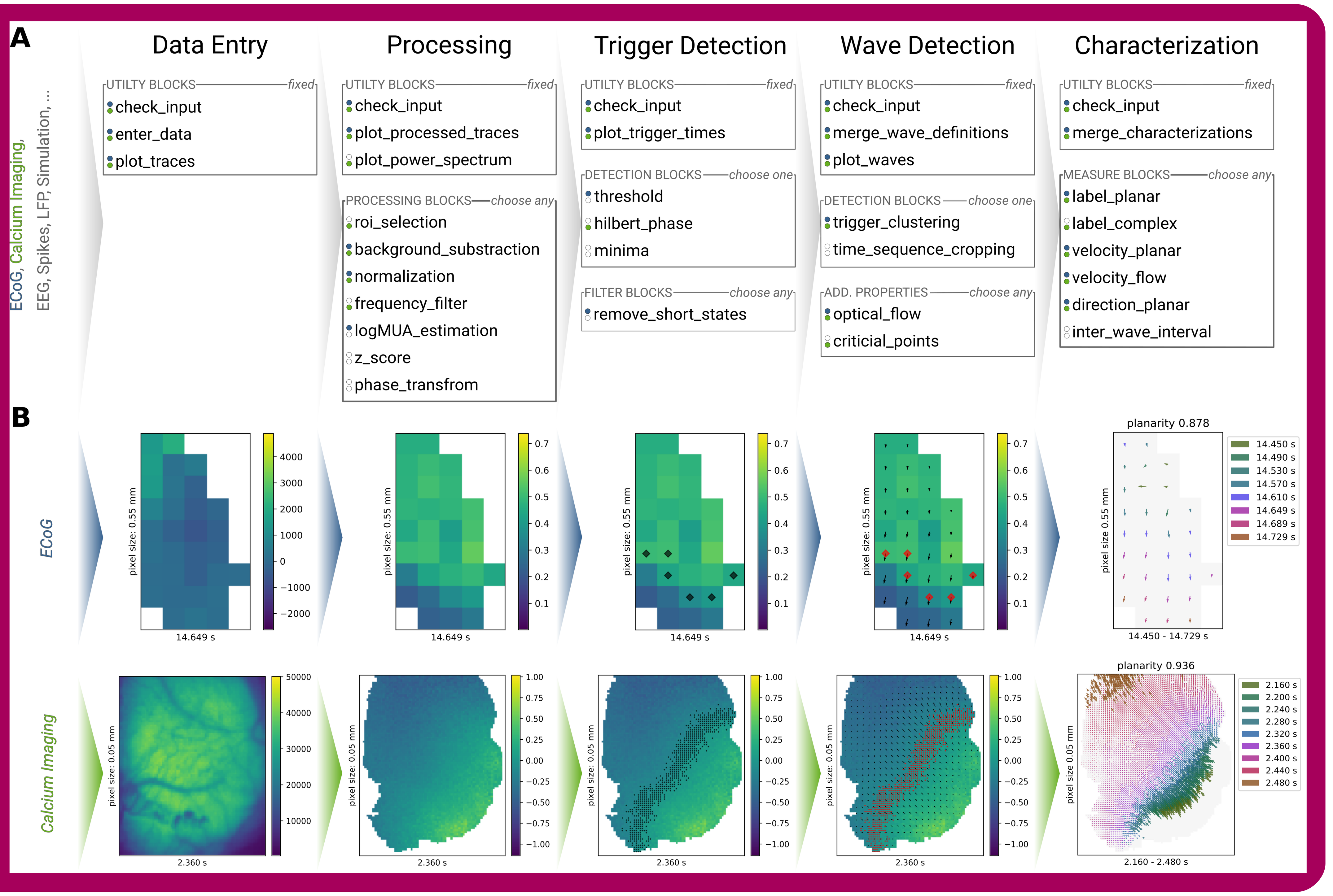

Fig 2. Illustration of the sequential stages (columns) and modular method blocks of the analysis pipeline (A), and example intermediate results for two datasets (B).

Results

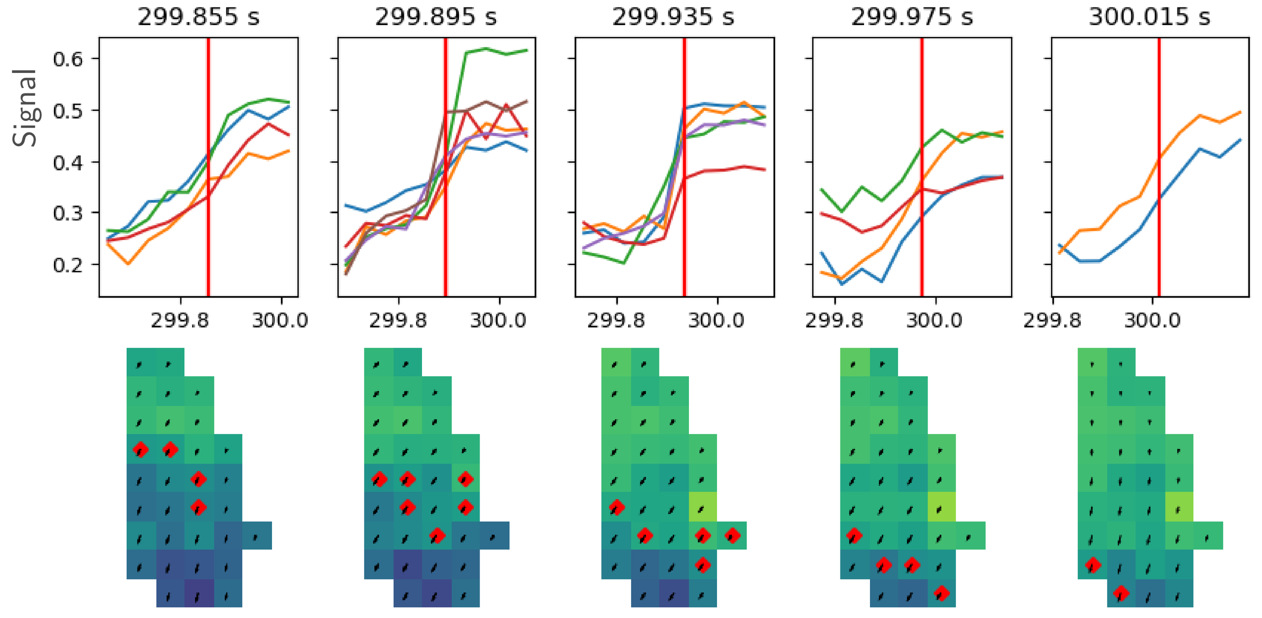

Fig 3. Example wave in an EcoG recording. The transition times from Down to Up state (red line & dot) are grouped to define the wavefronts.

We analyze *56* recordings of anesthetized mice, varying in
- measurement technique,
- genetic strain,
- anesthetic,
- and anesthesia level.

The pipeline detects *5551* waves & characterizes them. Now, they can be compared within & between categories.

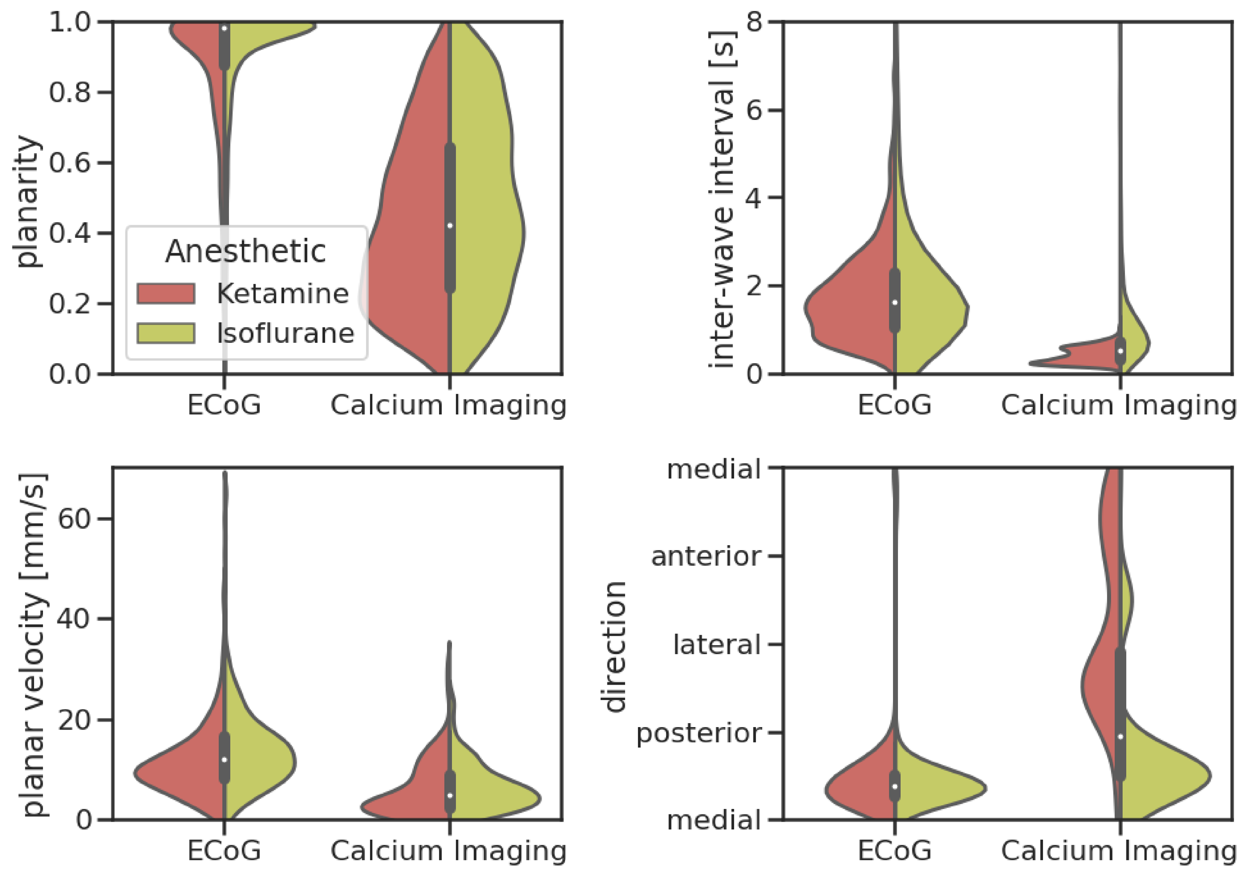

Fig 4. Comparing wave characteristics across datasets w.r.t. measurement technique and anesthetic.

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[3] https://snakemake.github.io/

Datasets

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