

PyGPLA: A Python Toolbox for Generalized Phase Locking Analysis

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Summary

PyGPLA is a Python implementation of Generalized Phase Locking Analysis (GPLA) for multivariate analysis of coupling between spikes and local field potentials (LFPs) (Safavi et al. 2023). For a given frequency, GPLA constructs a complex coupling matrix $\hat{C}(f) \in \mathbb{C}^{N_c \times N_u}$ between LFP channels (N_c) and spike units (N_u), then applies singular value decomposition (SVD) to reduce the dimensionality of data. The leading singular value (gPLV) summarizes population-level coupling strength, while the corresponding singular vectors describe dominant LFP and spike coupling modes. PyGPLA provides a full analysis workflow including LFP preprocessing, coupling-matrix construction, SVD-based decomposition, and diverse statistical significance testing (Safavi, Logothetis, and Besserve 2021).

Statement of need

Neural recordings are becoming increasingly high-dimensional and multimodal, demanding more sophisticated analysis tools. Simultaneous analysis of spiking activity and LFPs is among the most informative multi-modal approaches in systems neuroscience, providing insight into the multi-scale mechanisms underlying cognitive functions such as attention and memory (Buzsaki, Anastassiou, and Koch 2012; Einevoll et al. 2013; Herreras 2016). LFP oscillatory activity partly reflects subthreshold processes shared by neuronal ensembles, and the synchronization between this activity and spiking is hypothesized to coordinate neural populations during cognitive processes (Buzsaki, Anastassiou, and Koch 2012; Hagen et al. 2016).

However, commonly used spike-LFP coupling measures are pairwise, making them suboptimal for modern multichannel recordings (Zeitler, Fries, and Gielen 2006; Vinck et al. 2010, 2012; Jiang et al. 2015; Li, Cui, and Li 2016; Zarei, Jahed, and Daliri 2018). As modern electrophysiological techniques allow simultaneous recordings from hundreds or even thousands of sites, pairwise analyses generate high-dimensional covariance matrices whose size grows rapidly with the number

of channels, limiting interpretable extraction of large-scale collective dynamics (Dickey et al. 2009; Jun et al. 2017; Juavinett, Bekheet, and Churchland 2019; Buzsaki 2004).

GPLA was developed to address these challenges by providing an efficient multivariate framework together with statistical routines (Safavi, Logothetis, and Besserve 2021) for characterizing spike-LFP coupling at the population level (Safavi et al. 2023). However, the original algorithm was implemented in MATLAB, limiting its accessibility. PyGPLA bridges this gap as an open-source Python implementation, aligning with the extensive use of Python in neuroscience as solidified by libraries such as MNE-Python (Gramfort et al. 2013), Nilearn (contributors, n.d.), and TranCIT (Nouri, Shao, and Safavi 2025).

Existing spike-field coupling methods - including the phase-locking value (PLV), pairwise phase consistency (PPC) (Vinck et al. 2010), and spike-field coherence - operate on individual spike-LFP channel pairs. While informative for small-scale recordings, these pairwise approaches face combinatorial scaling with modern high-density probes, and do not directly capture the population-level structure of coupling. GPLA addresses this gap by providing a multivariate method that summarizes all spike-LFP interactions simultaneously, analogous to how PCA summarizes covariance structure. To our knowledge, no other Python package implements this multivariate approach to spike-field coupling analysis.

Functionality

Core analysis pipeline

PyGPLA provides a comprehensive solution for multivariate spike-field coupling analysis, including:

- **LFP preprocessing:** Band-pass filtering, Hilbert transform for analytic signal extraction, and optional reduced-rank whitening to decorrelate channels while avoiding noise amplification (Chavez et al. 2006).
- **Coupling-matrix construction:** Assembly of the complex-valued coupling matrix $\hat{C}(f) \in \mathbb{C}^{N_c \times N_u}$, where each entry sums the analytic LFP evaluated at all spike times of a given unit.
- **SVD-based decomposition:** Extraction of the gPLV (leading singular value) and associated LFP and spike spatial vectors, with rotational phase alignment, unwhitening of LFP vectors, and spike-vector rescaling.
- **Statistical testing:** Significance assessment via two complementary approaches: (1) surrogate-based testing using multiple spike-jittering schemes, and (2) an analytical test based on Marchenko–Pastur Random Matrix Theory (RMT) (Anderson, Guionnet, and Zeitouni 2010; Safavi et al. 2023).
- **Simulation tools:** Synthetic data generators for phase-locked and transient-coupling scenarios, supporting reproducibility and method validation.

Normalization options

The package supports two normalization modes for the coupling matrix: PLV-type normalization ($1/N_m^{\text{tot}}$) for phase-only analysis, and unit-variance normalization ($1/\sqrt{N_m^{\text{tot}}}$) required for the theoretical RMT-based significance test.

Example

We illustrate PyGPLA on synthetic transient-coupling simulations generated with the script `paper/figures/figure2.py`. As shown in Figure 1, the figure compares four coupling models and reports their recovered gPLV values, together with representative LFP and spike-train windows and the associated spike-vector structure.

Code snippets and detailed instructions for reproducing these results are available in the package documentation and example scripts in the repository.

Implementation details

The `pygpla` package is distributed under the BSD-2-Clause license. PyGPLA follows a layered architecture separating preprocessing (`pygpla.preprocessing`), core computation (`pygpla.core`), statistical testing (`pygpla.stats`), simulation utilities (`pygpla.simulations`), and configuration (`pygpla.config`). The high-level API (`pygpla.api.gpla`) orchestrates the full pipeline in a single call, keeping default usage compact while preserving access to lower-level components for advanced analyses. The package is built on NumPy (Harris et al. 2020) and SciPy (Virtanen et al. 2020), and includes a `pytest` test suite with continuous integration via GitHub Actions.

Use of generative AI

Generative AI tools were used to assist with auxiliary development tasks such as drafting documentation, refactoring code for style, and generating boilerplate for tests and continuous-integration configuration. All AI-assisted output was reviewed, tested, and validated by the authors, who take full responsibility for the correctness of the software and the content of this paper. The scientific method, algorithmic design, and numerical implementation of GPLA were carried out by the authors.

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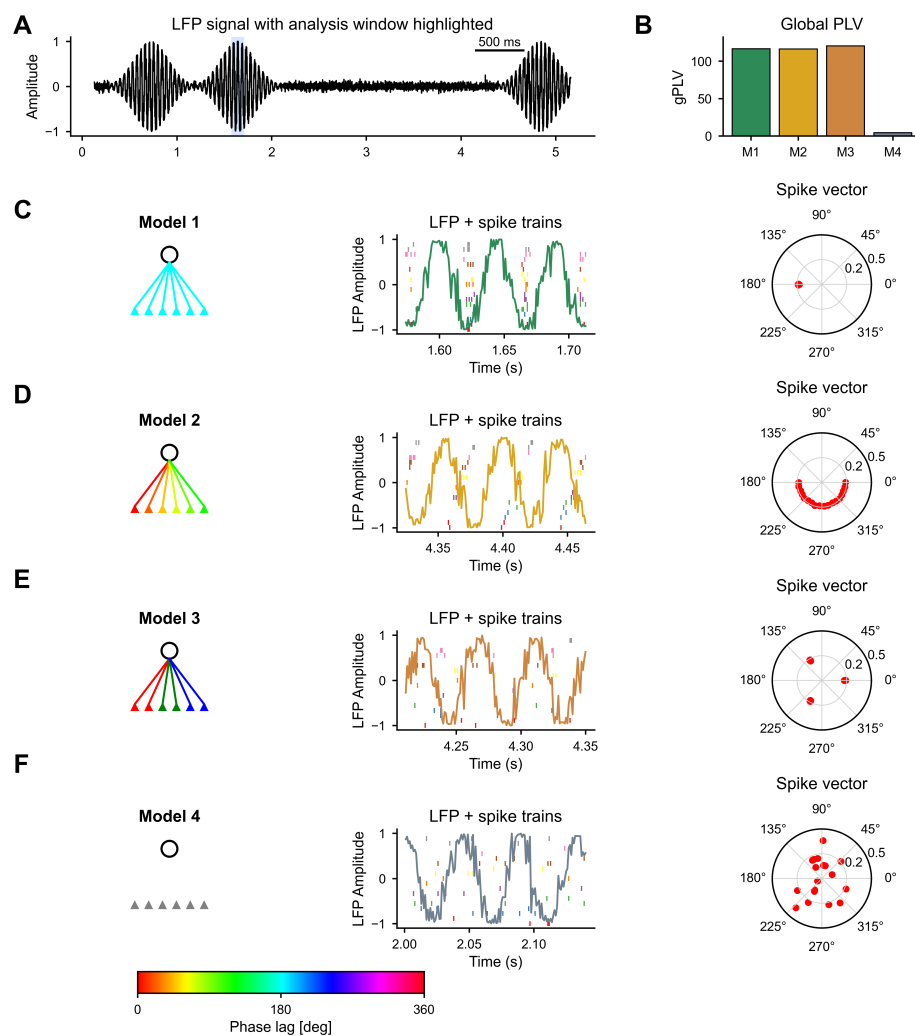


Figure 1: Illustrative PyGPLA simulation example produced by `paper/figures/figure2.py`. Panel A shows an LFP trace with the analysis window. Panel B shows gPLV values across four simulated coupling models (M1-M4). Panels C-F display, for each model, a schematic, LFP plus spike-train segment, and the recovered spike vector in polar coordinates.

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