TranCIT: Transient Causal Interaction Toolbox

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Summary

The study of complex systems, particularly neural circuits and cognitive functions, requires understanding causal interactions during brief, transient events (Logothetis et al., 2012; Lundqvist et al., 2024; Nitzan et al., 2022; Safavi, 2022; Safavi et al., 2023; Womelsdorf et al., 2014). Traditional causality methods, such as Granger causality (GC) (Granger, 1969) and Transfer Entropy (TE) (Schreiber, 2000), assume stationarity and require long data segments, making them suboptimal for event-driven analysis (Mitra, 2007).

We present `trancit` (Transient Causal Interaction Toolbox), an open-source Python package implementing advanced causal inference methods for transient dynamics (Nouri et al., 2025a, 2025b). `trancit` provides a comprehensive pipeline for dynamic causal inference on multivariate time-series data, extending a robust causal learning algorithm originally introduced in MATLAB (Shao et al., 2023). Built on NumPy (Harris et al., 2020) and SciPy (Virtanen et al., 2020), it integrates seamlessly into modern data science workflows.

The package offers an integrated solution for end-to-end causal analysis, including:

- **Advanced causal inference methods:** GC, TE, and robust Structural Causal Model(SCM)-based Dynamic Causal Strength (DCS) and relative Dynamic Causal Strength (rDCS)
- **Event-based preprocessing:** Automated event detection, data alignment, and artifact rejection pipeline
- **Simulation tools:** Synthetic autoregressive (AR) time-series data generation with known causal structures for validation and exploring scenarios.

Statement of need

While many statistical methods focus on correlation, the ability to infer directed causal relationships offers deeper, more mechanistic insights into how complex systems function (Seth et al., 2015). A critical challenge is analyzing transient dynamics where interactions occur in brief, intense bursts. Existing methods are primarily implemented in proprietary software, such as MATLAB (Shao et al., 2023), which limits accessibility.

`trancit` bridges this gap with a fully open-source Python implementation. While general-purpose causality libraries, such as `causal-learn` (Zheng et al., 2024) and `tigramite` (Runge, 2022), exist, they lack specialized features for analyzing transient, event-related data, including integrated event detection and alignment workflows.

`trancit` provides a tailored solution that implements GC, TE, DCS, and rDCS, with configurations for non-stationary signals. This promotes reproducible research, lowers barriers to advanced causal inference, and supports applications in neuroscience, climatology, and economics.

Functionality

Causal inference methods

`trancit` implements four primary methods for detecting and quantifying causal relationships. A brief overview is provided here; for complete mathematical derivations and theoretical background, please refer to our main methodology papers (Nouri et al., 2025a; Shao et al., 2023).

- **Granger Causality (GC):** Vector autoregressive model-based method assessing whether the history of one time series improves the prediction of another.
- **Transfer Entropy (TE):** Non-parametric, information-theoretic measure quantifying directed information flow between signals, and reduction of uncertainty between two signals.
- **Dynamic Causal Strength (DCS):** SCM-based method overcoming the "synchrony pitfall" where TE fails during high synchronization periods. Since it quantifies time-varying causal influence through a principled interventional approach.
- **relative Dynamic Causal Strength (rDCS):** Event-based extension quantifying causal effects relative to baseline periods. It quantifies causal effects relative to a pre-defined baseline or reference period, making it exceptionally sensitive to the deterministic shifts in signal dynamics that often characterize event-related data.

`trancit` provides integrated preprocessing for event detection, data alignment, and artifact rejection, as well as simulation tools for generating synthetic AR data with known causal structures for validation and education.

Example

We validated `trancit` by replicating key results from Shao et al. (2023). As shown in Figure 1, our simulation illustrates the "synchrony pitfall," where TE fails during high-synchronization periods, while DCS correctly identifies the underlying causal link.

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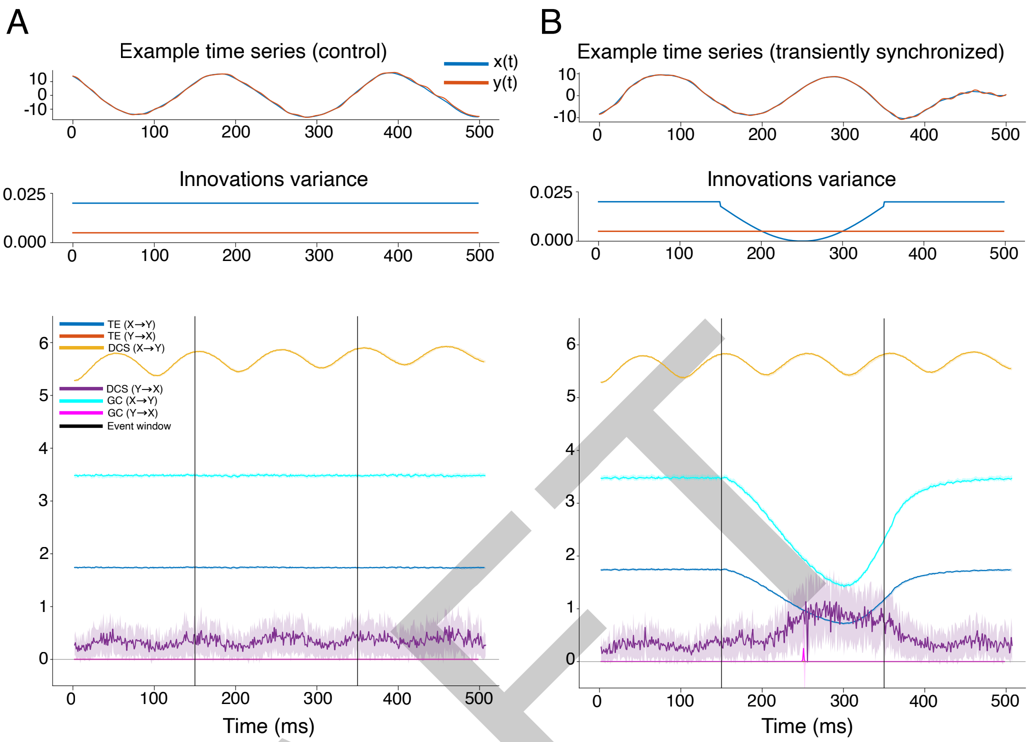

Figure 1: Replication of Shao et al. (2023) Figure 4 using `trancit` package. Shows successful detection of directed influence from X to Y using simulated data and causality measures (e.g., TE, DCS) implemented in the package.

To demonstrate its utility on real-world scientific data, `trancit` is used to analyze hippocampal LFP recordings during sharp wave-ripple events. As shown in **Figure 2**, rDCS correctly identifies transient information flow from CA3 to CA1, demonstrating the importance of proper event alignment facilitated by our package.

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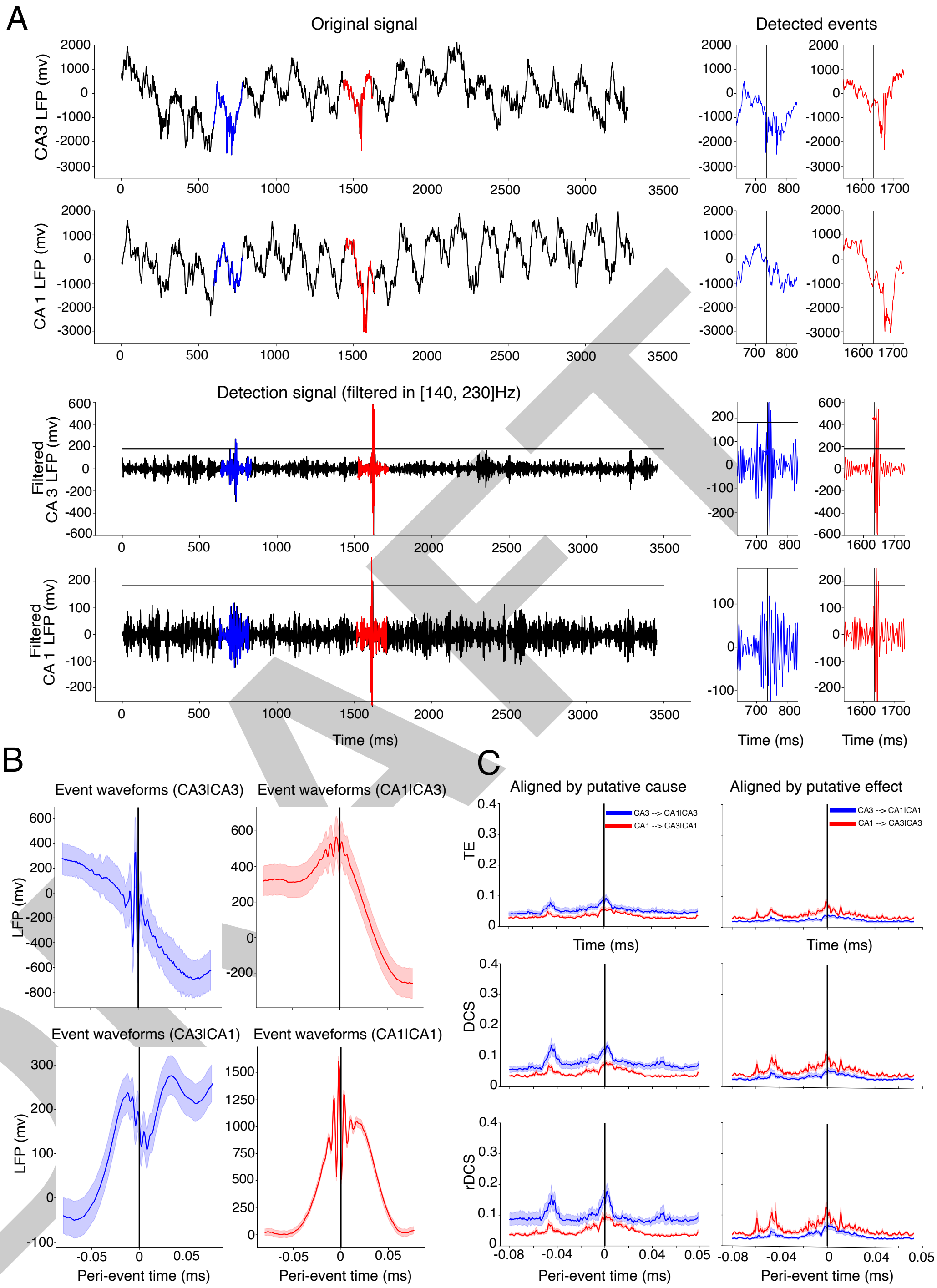

Figure 2: Demonstration of `trancit` on real-world LFP data showing directed causality from hippocampal area CA3 to CA1. The analysis successfully identifies transient information flow during sharp-wave ripple events using the package's built-in rDCS method.

Implementation details

`trancit` is distributed under the BSD-2 license. The package features a modular architecture separating causality, modeling, simulation, and utilities (Nouri et al., 2025a, 2025b). It includes robust error handling, a comprehensive `pytest` test suite, and GitHub Actions continuous integration. Community contributions are welcome with detailed guidelines in the repository.

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References

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424–438.

Harris, C. R., Millman, K. J., Van Der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., & others. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362.

Logothetis, N. K., Eschenko, O., Murayama, Y., Augath, M., Steudel, T., Evrard, H. C., Besserve, M., & Oeltermann, A. (2012). Hippocampal–cortical interaction during periods of subcortical silence. *Nature*, *491*(7425), 547–553. https://doi.org/10.1038/nature11618

Lundqvist, M., Miller, E. K., Nordmark, J., Liljefors, J., & Herman, P. (2024). Beta: Bursts of cognition. *Trends in Cognitive Sciences*. https://doi.org/10.1016/j.tics.2024.03.010

Mitra, P. (2007). *Observed brain dynamics*. Oxford university press.

Nitzan, N., Swanson, R., Schmitz, D., & Buzsáki, G. (2022). Brain-wide interactions during hippocampal sharp wave ripples. *Proceedings of the National Academy of Sciences*, *119*(20), e2200931119. https://doi.org/10.1073/pnas.2200931119

Nouri, S., Shao, K., & Safavi, S. (2025a). TranCIT: Transient causal interaction toolbox. *arXiv Preprint arXiv:2509.00602*. https://doi.org/10.48550/arXiv.2509.00602

Nouri, S., Shao, K., & Safavi, S. (2025b). *TranCIT: Transient causal interaction toolbox*. Zenodo. https://doi.org/10.5281/zenodo.16998396

Runge, J. (2022). *Jakobrunge/tigramite: Tigramite 5.0*.

Safavi, S. (2022). *Brain as a Complex System, harnessing systems neuroscience tools & notions for an empirical approach* [PhD thesis, Universität Tübingen]. https://doi.org/10.15496/publikation-69434

Safavi, S., Panagiotaropoulos, T. I., Kapoor, V., Ramirez-Villegas, J. F., Logothetis, N. K., & Besserve, M. (2023). Uncovering the organization of neural circuits with Generalized Phase Locking Analysis. *PLOS Computational Biology*, *19*(4), e1010983. https://doi.org/10.1371/journal.pcbi.1010983

Schreiber, T. (2000). Measuring information transfer. *Physical Review Letters*, *85*(2), 461–464. https://doi.org/10.1103/PhysRevLett.85.461

Seth, A. K., Barrett, A. B., & Barnett, L. (2015). Granger causality analysis in neuroscience and neuroimaging. *Journal of Neuroscience*, *35*(8), 3293–3297. https://doi.org/10.1523/JNEUROSCI.4399-14.2015

Shao, Y., Logothetis, N. K., & Besserve, M. (2023). Information theoretic measures of causal influences during transient neural events. *Frontiers in Network Physiology*, *3*, 1085347.

Virtanen, P., Gommers, R., Oliphant, T., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., & others. (2020). Fundamental algorithms for scientific computing in python and SciPy 1.0 contributors. SciPy 1.0. *Nat. Methods*, *17*, 261–272.

Womelsdorf, T., Ardid, S., Everling, S., & Valiante, T. A. (2014). Burst firing synchronizes prefrontal and anterior cingulate cortex during attentional control. *Curr Biol*, *24*, 2613–2621. https://doi.org/10.1016/j.cub.2014.09.046

Zheng, Y., Huang, B., Chen, W., Ramsey, J., Gong, M., Cai, R., Shimizu, S., Spirtes, P., & Zhang, K. (2024). Causal-learn: Causal discovery in python. *Journal of Machine Learning Research*, *25*(60), 1–8.