ANALYZING NEURAL FLOW USING SIGNAL PROCESSING ON GRAPHS

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Motivation

- Analyzing communication and flow processes in the brain has received much attention in past years and better models may be crucial for developing treatments for neurological diseases.
- Graph signal processing (GSP) has been proposed as a way to study neural signals observed at the nodes of an underlying brain graph [1].
- Instead of focusing on node signals, **we propose a new framework that models neural communication as flow signals defined at the edges of a graph.**
- This new perspective allows to model neural communication flow on a finer temporal scale than other techniques such as Granger causality that are used in neuroscience to date.

Estimating Neural Flow from LFP Time Series

Goal:

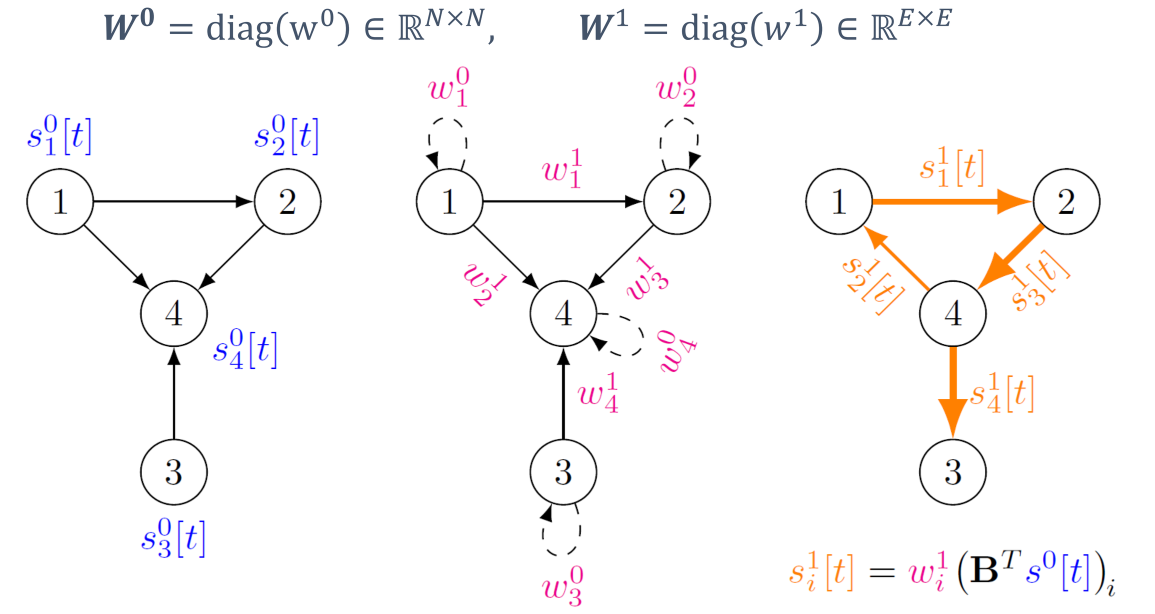
- Estimate neural flow along the edges of a graph (Fig. 1 – right) from local field potential (LFP) time series observed at the graph nodes (Fig. 1 – left)

Method:

1. Assume a graph with N nodes and E directed edges. Furthermore, time series of neural activity are measured at the nodes of the graph (Fig. 1 – left)
2. **Model neural flow through a parameterized diffusion process** (Fig.1 – middle):

$$s^0[t+1] = \left(\boldsymbol{W^0} - \boldsymbol{B}\boldsymbol{W^1}\boldsymbol{B^T}\right)s^0[t]$$

$$\boldsymbol{W^0} = \mathrm{diag}(w^0) \in \mathbb{R}^{N\times N}, \qquad \boldsymbol{W^1} = \mathrm{diag}(w^1) \in \mathbb{R}^{E\times E}$$



$$s_4^0[t+1] = \text{memory} + \text{inflow} - \text{outflow} = w_4^0 s_4^0[t] + s_3^1(t) - s_2^1(t) - s_4^1(t)$$

Fig. 1: Illustration of diffusion model. The graph shows from left to right the node signal, the model parameter, and the edge flow respectively. The equation at the bottom illustrated the diffusion model for Node 4.

Physical interpretation of flow term $\boldsymbol{B}\boldsymbol{W}^1\boldsymbol{B}^T s^0[t]$:

- $\boldsymbol{B}^T s^0[t]$: computes the voltage gradient for each edge
- $s^1[t] = \boldsymbol{W}^1\boldsymbol{B}^T s^0[t]$: computes the edge flow. w_i^1 can be interpreted as the conductivity between two nodes, so that conductivity times potential gradient yield the current
- $\boldsymbol{B}s^1[t]$: computes the net flow, i.e., the sum of all inflows minus sum of all outflows, for each node

Estimating Neural Flow in two Non-human Primates

- The neural flow is estimated from LFP measurements of neural activity of two rhesus macaque monkeys during a stimulation experiment [2].
- Location of stimulation varies between 63 experimental sessions.
- LFPs are measured by 96 electrode micro-electrocorticography (μ-ECoG) array.
- The ECoG array is used to construct sparsely connected graph, where each node is connected to approximately its 8 nearest neighbors.

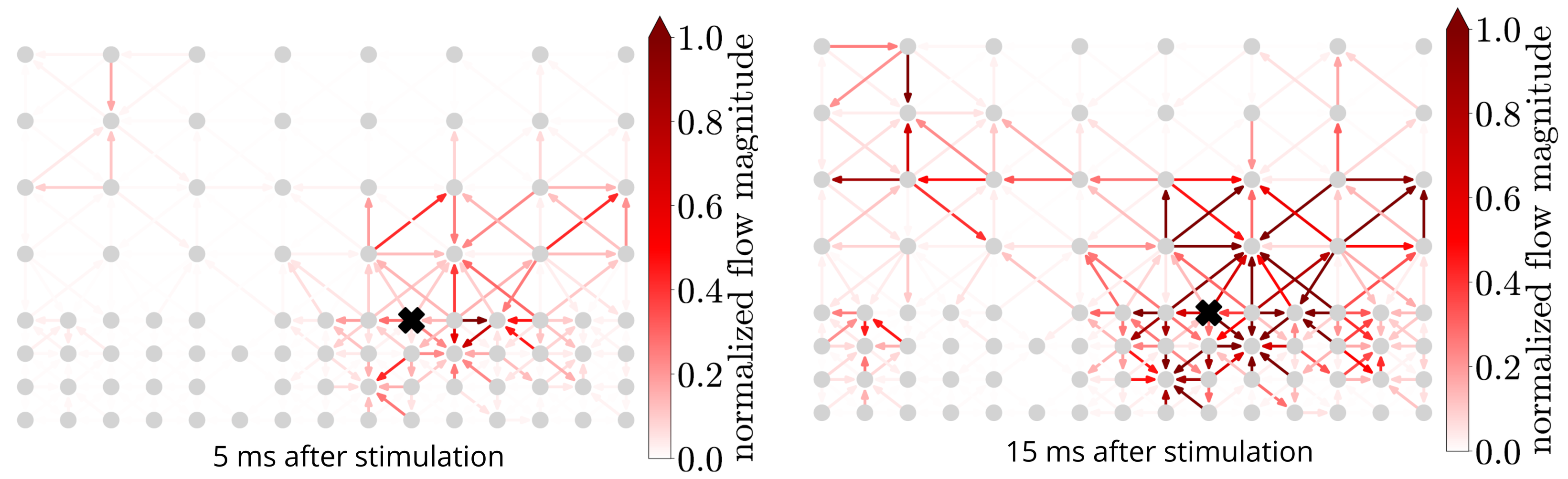


Fig. 2: Normalized neural flow of a single experimental session 5 and 15 ms after stimulation. The location of stimulation is indicated by the black cross.

Validation: Comparing Flow with No-flow Baseline Model

- *No-flow* baseline model: same as *flow* model but with constraint $w^1 = 0$
- *Flow* and *no-flow* model fitted to all 63 sessions to estimate w^1 and w^0
- Estimated model parameter used for one-step-ahead prediction on test dataset not included during model fitting.
- Compute root-mean square error (RMSE) between measured LFP $s[t+1]$ and predicted LFP $\hat{s}[t+1]$
- Relative improvement of *flow* over *no-flow* model for each session s:

$$I(s) = 100 \cdot \mathrm{median}_t\left\{\frac{RMSE_{s,no\ flow}[t] - RMSE_{s,flow}[t]}{RMSE_{s,no\ flow}[t]}\right\}$$

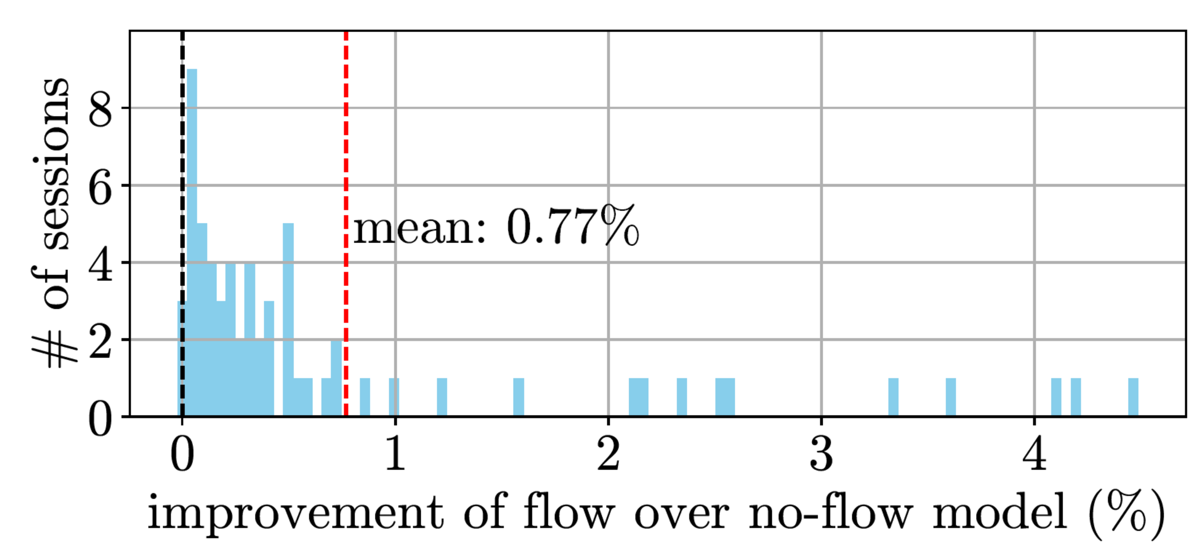
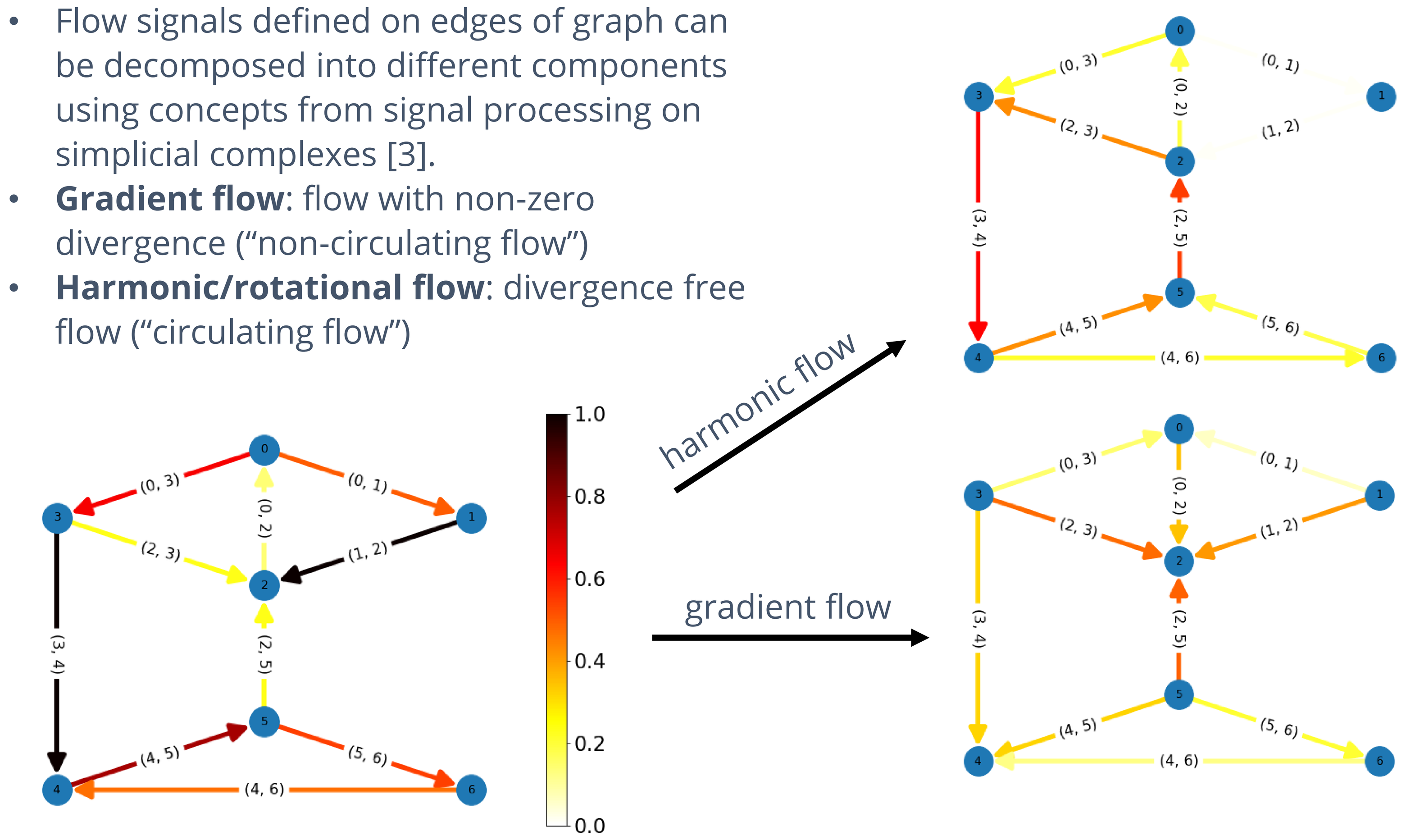


Fig. 3: Histogram of the improvement in LFP predictions of *flow* over *no-flow* model for all 63 experimental sessions. **For 62 out of 63 sessions, our proposed *flow* model performs better than the *no-flow* model.**

Decomposing Neural Flow

- Flow signals defined on edges of graph can be decomposed into different components using concepts from signal processing on simplicial complexes [3].
- **Gradient flow**: flow with non-zero divergence ("non-circulating flow")
- **Harmonic/rotational flow**: divergence free flow ("circulating flow")



Gradient and Harmonic Flow in Non-human Primates

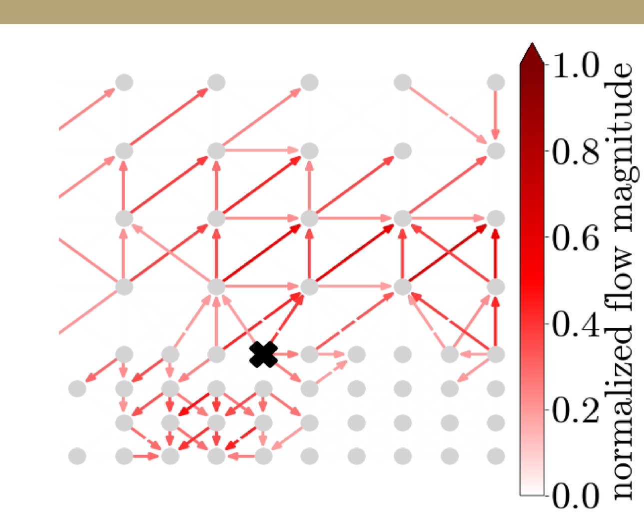


Fig. 4: Parts of gradient flow 15 ms after stimulation. Flow points away from stimulation site.

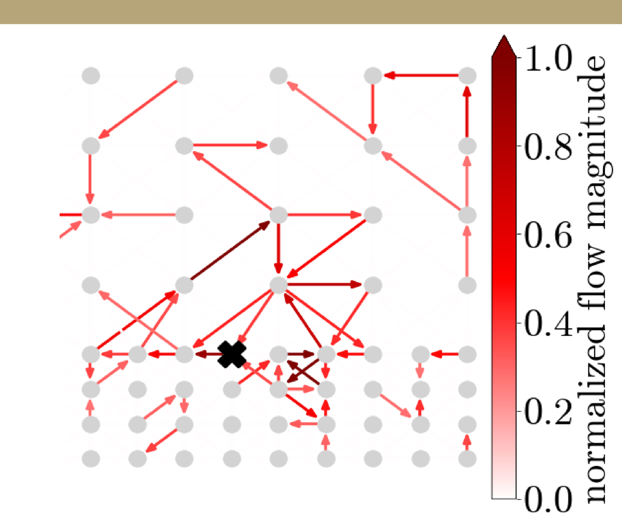


Fig. 4: Parts of harmonic flow 15 ms after stimulation. Flow circulates near stimulation site.

Future Work and References

- Build on these results and demonstrate how GSP can be further adapted to analyze flow signals.
- Investigate the relation between our estimated flow and other brain connectivity measures such as Granger causality.

[1] W Huang, T. A. W. Bolton, J. D. Medaglia, D. S. Bassett, A. Ribeiro, D. Van De Ville, "A graph signal processing perspective on functional brain imaging," *Proceedings of the IEEE*, vol. 106, no. 5, pp. 868–885, 2018.
[2] A. Yazdan-Shahmorad, D. B. Silversmith, V. Kharazia, P. N. Sabes, "Targeted cortical reorganization using optogenetics in non-human primates," *eLife*, vol. 7, pp. e31034, 2018
[3] M. T. Schaub, Y. Zhu, J. Seby, T. M. Roddenberry, S. Segarra, "Signal processing on higher order networks: Livin' on the edge... and beyond," *Signal Processing*, vol. 187, pp. 108149, 2021

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