Adapting temporal tensor decomposition for spatiotemporal pattern extraction in functional neuroimaging

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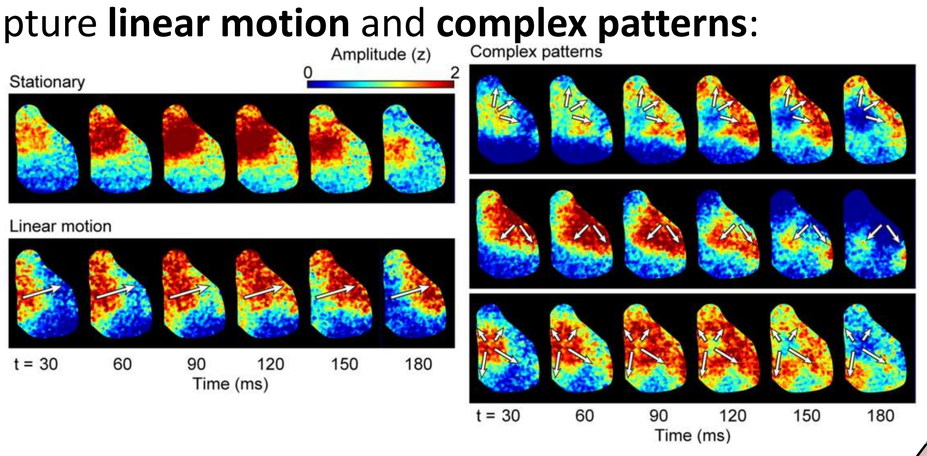
Context

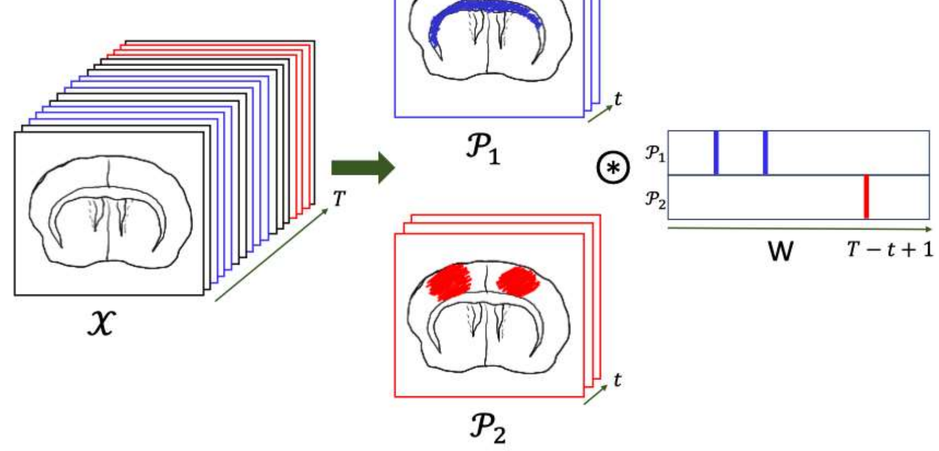
- **Brain activity** requires tools to analyse **signal dynamics**
- **Existing methods** (eg QPP[1] , ICA[2],…) rely on **strong assumptions** (recurrence, independance, spatial priors,…)
- **Song et al. [3]** classify spatiotemporal patterns into three families, beyond **stationary** ones, we need methods that also capture **linear motion** and **complex patterns**:



[1] Majeed W. et al. Spatiotemporal dynamics of low frequency BOLD fluctuations in rats and humans. NeuroImage, 2011
[2] Meyer-Bäse L. et al. Spatiotemporal patterns of spontaneous brain activity: a mini-review. Neurophotonics, 2022
[3] Song M. et al. Classification of spatiotemporal neural activity patterns in brain imaging data. Scientific Reports, 2018

Sliding Window for Temporal Tensor Decomposition - $SWoTTeD$[4] -

- Given χ , a 3D **brain imaging** stack containing T **2D** frames
- SWoTTeD extracts K **temporal patterns**, $\mathcal{P}$, of **duration t**
- $\mathcal{W}$ exhibits **the occurrences** of patterns $\mathcal{P}$ in the stack χ



[4] Sebia H. et al. : an extension of tensor decomposition to temporal phenotyping. Machine Learning, 113(9):5939–5980, 2024. Swotted

1 Adapt SWoTTeD model

Adaptation of «**SWoTTeD** » for **spatiotemporal pattern** extraction in **functional neuroimaging** capturing both recurrent and rare neural events

2 Orthogonality constraint

Introduce $SWoTTeD^{\perp}$: a new **orthogonality regularization** on patterns to enforce **diverse and non-redundant** spatiotemporal motifs

3 Validate on rat fUS data

Applied to **functional ultrasound (fUS)** recordings of rat brains under **visual stimulation**; compared against **Block Tensor Decomposition (BTD)**

Minimisation Problem

$$\ell = \mathcal{L}(\widehat{\mathcal{X}}, \mathcal{X}) + \alpha\|\mathcal{P}\|_1 + \beta\, \mathcal{S}(\mathcal{W}) + \gamma\ \mathcal{R}_{\perp}(\mathcal{P})$$

- $\mathcal{L}(\widehat{\mathcal{X}}, \mathcal{X})$ is the **reconstruction error** described as the **distance** between the **ground-truth** $\mathcal{X}$ and the **reconstruction** $\widehat{\mathcal{X}} = \mathcal{P} \circledast \mathcal{W}$
- $\|\mathcal{P}\|_1$ enforces **sparsity regularization** on **patterns** to focus on relevant signal changes
- $\mathcal{S}(\mathcal{W})$ is a pattern **non-succession regularization** term, penalizing reconstructions that **reuse** the **same** pattern within the **same window t**
- $\mathcal{R}_{\perp}(\mathcal{P})$ is an **orthogonality regularization** to enforce patterns to be as **distinct** as possible

Validation Framework

- Applied on **functional ultrasound** imaging (fUS) acquired from **rat brain** under **visual stimulation**
  - **Number of extracted patterns K** in {2, 5, 10)
  - **Duration of extracted patterns t** in {50, 75,100) frames
- Compared to **Block Tensor Decomposition (BTD)**

Evaluation Metric

$$FIT = 1 - \frac{\sum_{i=1}^{T}\|X^{(i)} - \widehat{X}^{(i)}\|}{\sum_{i=1}^{T}\|X^{(i)}\|}$$

Quality of Recontruction

K	ω	SWoTTeD$^{\perp}$	SWoTTeD	BTD
2	50	0.0028 ± 0.007	-0.005 ± 0.0101	0.030 ± 0.001
	75	0.0030 ± 0.005	-0.004 ± 0.007	
	100	0.0036 ± 0.001	0.007 ± 0.001	
5	50	0.0034 ± 0.01	-0.003 ± 0.008	0.038 ± 0.001
	75	0.0042 ± 0.004	-0.001 ± 0.008	
	100	0.0051 ± 0.006	0.004 ± 0.008	
10	50	0.0043 ± 0.006	-0.0039 ± 0.009	0.042 ± 0.001
	75	0.0054 ± 0.001	-0.0147 ± 0.015	
	100	0.0063 ± 0.008	-0.0160 ± 0.020	

- $SWoTTeD^{\perp}$ systematically outperforms classic SWoTTeD, the orthogonality regularization **consistently improves reconstruction** across all K, ω.
- **Increasing** the number of patterns **K**, or their duration **t**, **improves** the recontruction
- The reconstruction of **BTD** is **significantly better**

Quality of Spatiotemporal Patterns

- **Both** SWOTTED and BTD **detect activation** in **the superior colliculus** and **visual cortex** during **visual** stimulation
- **BTD** provides **static spatial maps** and their associated **temporal signals**
- **SWOTTED** extracts full spatiotemporal patterns as **sequences** of frames
- It reveals **dynamic propagation**: activation starts in the colliculus and spreads to the visual cortex

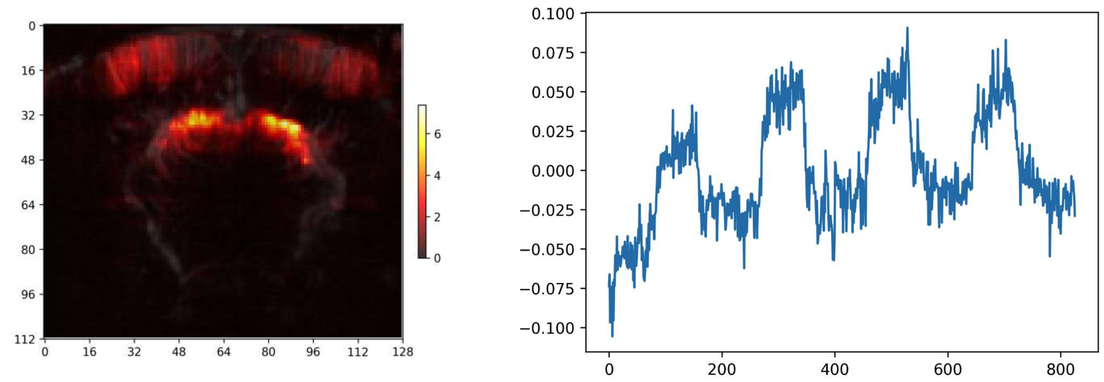


Figure 1: One of the extracted patterns using BTD, exhibiting the response to visual stimulation.

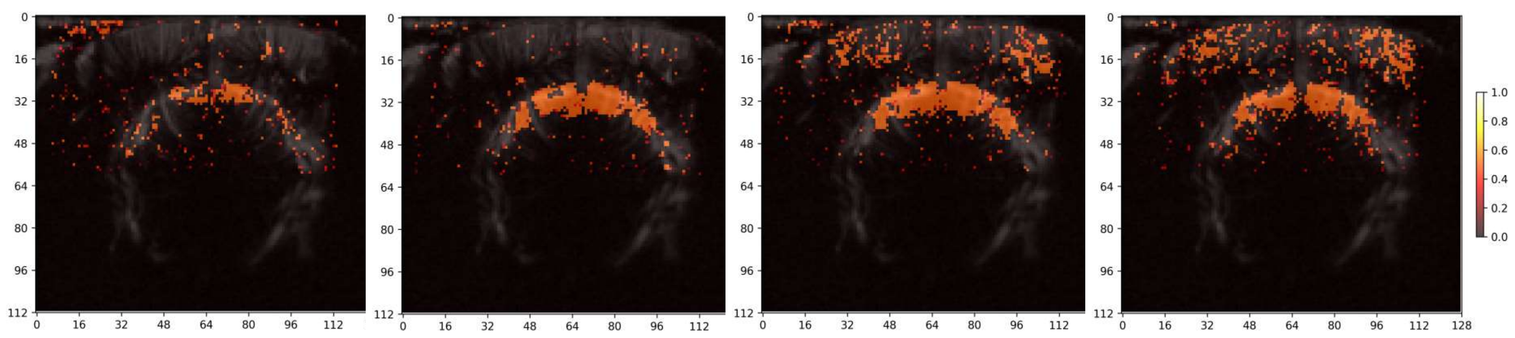


Figure 2: Four frames of a spatiotemporal pattern extracted, using SWoTTeD, from fUS under visual stimulation, showing signal evolution from left to right in response to the stimulus across different brain regions.

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