

Spatiotemporal pattern extraction in functional neuroimaging

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SWoTTed

Context

- Brain activity requires tools to analyse signal dynamics
- Existing methods (eg QPP[1], ICA[2],...) rely on **strong assumptions** (recurrence, independance, spatial priors,...)

[1] Majeed W. et al. Spatiotemporal dynamics of low frequency BOLD fluctuations in rats and humans. NeuroImage, 54:1140–1150, 2011
[2] Meyer-Bäse L. et al. Spatiotemporal patterns of spontaneous brain activity: a mini-review. Neurophotonics, 9:032209, 2022

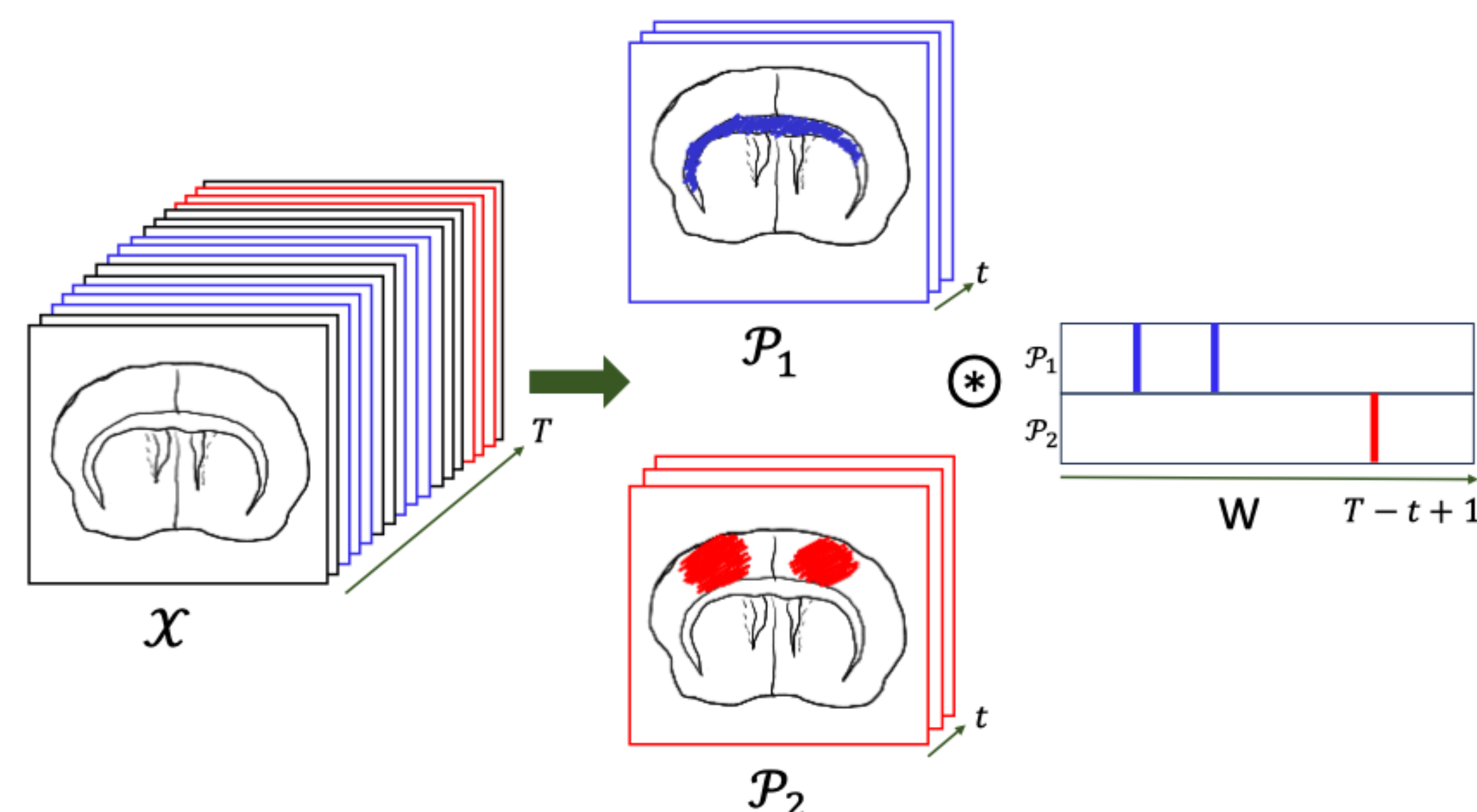
Contribution

- Adaptation of a **tensor decomposition** framework «SWoTTed» for **spatiotemporal pattern** extraction in functional neuroimaging
- SWoTTed operates **without prior assumptions**, detecting both **recurrent** and **rare** neural events
- Applied to functional ultrasound (fUS), it reveals **activation patterns linked to visual stimulation**

Sliding Window for Temporal Tensor Decomposition

- SWoTTed* -

- 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



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

Minimisation Problem

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

- $\mathcal{L}(\hat{\chi}, \chi)$ is the **reconstruction error** described as the **distance** between the **ground-truth** χ and the **reconstruction** $\hat{\chi} = \mathcal{P} \circledast \mathcal{W}$
 - \circledast is a **convolutional** operator
- $\|\mathcal{P}\|_1$ 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**
- Varied the **number of extracted patterns K** in {2, 5, 10}
- Varied the **duration of extracted patterns t** in {50, 75, 100} frames
- Compared to **Block Tensor Decomposition (BTD)**

Evaluation Metric

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

Quality of Reconstruction

K	SWoTTed		BTD Mean FIT
	t	Mean FIT	
2	50	0.0028 ± 0.007	0.030 ± 0.001
	75	0.0030 ± 0.005	
	100	0.0036 ± 0.001	
5	50	0.0034 ± 0.01	0.038 ± 0.001
	75	0.0042 ± 0.004	
	100	0.0051 ± 0.006	
10	50	0.0043 ± 0.006	0.042 ± 0.001
	75	0.0054 ± 0.001	
	100	0.0063 ± 0.008	

➤ Increasing the number of patterns K, or their duration t, improves the reconstruction

➤ 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

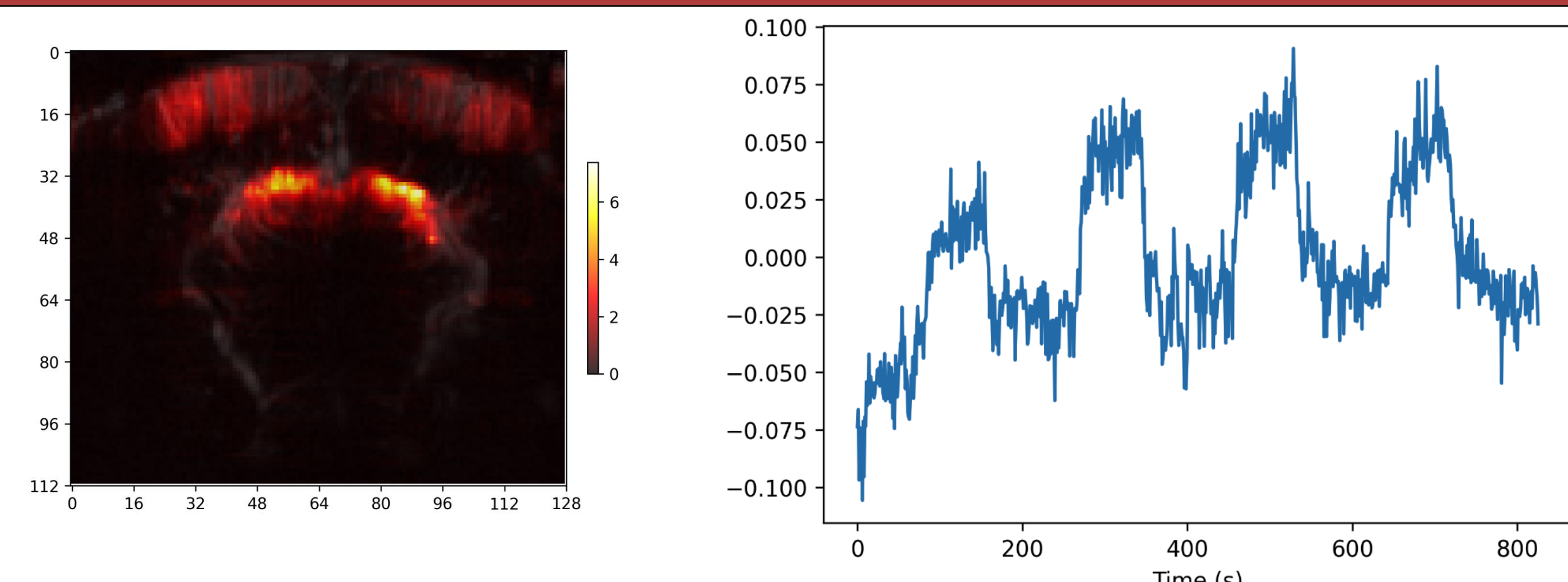


Figure 1: One of the extracted patterns using BTD, exhibiting the response to visual stimulation.

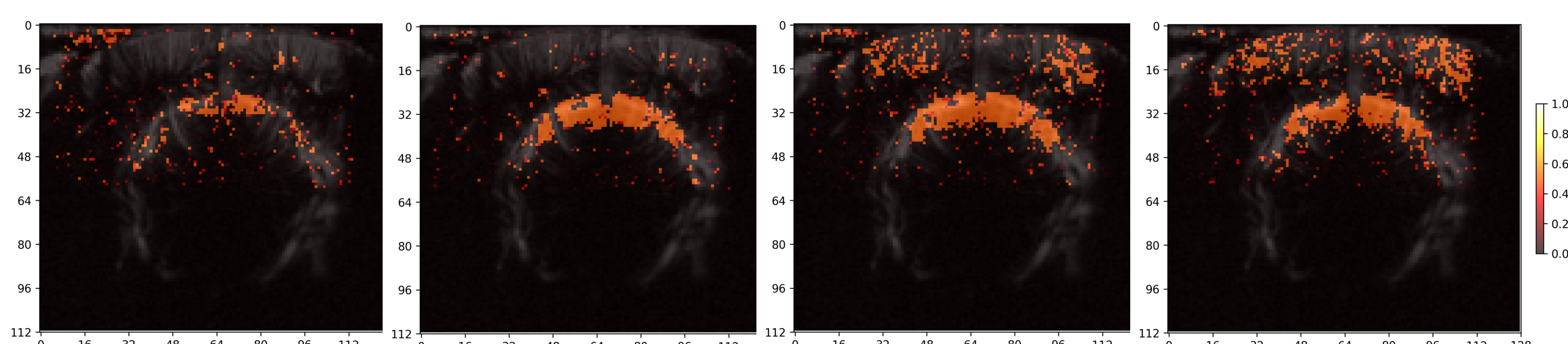


Figure 2: Four frames of a spatiotemporal pattern extracted, using SWoTTed, from fUS under visual stimulation, showing signal evolution from left to right in response to the stimulus across different brain regions.