

# Compute heatmap embeddings

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## Function space generated by the composition of embedding, wavelet band reconstruction, and nonlinear ICA

Let  $X \in \mathbb{R}^{I \times J \times T}$  denote a time series of facial heatmaps with spatial size  $I \times J$  and temporal length  $T$ . We consider three operators applied in cascade:

- **Spatial embedding (framewise)**  
 $\mathcal{E} : \mathbb{R}^{I \times J} \rightarrow \mathbb{R}^K$ , applied to each frame  $x_t$ , producing  $\mathcal{E}(X) \in \mathbb{R}^{K \times T}$ .
- **Per-channel 1D DWT and band reconstruction**  
 $\Omega : \mathbb{R}^{K \times T} \rightarrow \mathbb{R}^{K \times T}$ , applying a 1D discrete wavelet transform to each channel, selecting bands, and reconstructing.
- **Nonlinear ICA / dimensionality reduction**  
 $\Psi : \mathbb{R}^{K \times T} \rightarrow \mathbb{R}^{L \times T}$  with  $L < K$ , applied framewise or on short windows.

Define the composed map

$$f = \Psi \circ \Omega \circ \mathcal{E} : \mathbb{R}^{I \times J \times T} \rightarrow \mathbb{R}^{L \times T}.$$

The function space is

$$\mathcal{F} = \{ f : \mathbb{R}^{I \times J \times T} \rightarrow \mathbb{R}^{L \times T} \mid f = \Psi \circ \Omega \circ \mathcal{E} \text{ for admissible } \mathcal{E}, \Omega, \Psi \}.$$

## Typical assumptions

1. **Regularity of  $\mathcal{E}$ :** linear or smooth (PCA, moments, or differentiable neural embedding).
2. **Wavelet properties:**  $\Omega$  denotes the 1D discrete wavelet analysis followed by optional subband selection and synthesis. Selecting or zeroing coefficients (i.e., discarding subbands) is a projection in coefficient space and in general destroys invertibility; the reconstructed signal is then the band-limited approximation obtained from the retained subbands.
3. **Nonlinear ICA identifiability:**  $\Psi$  trained with auxiliary/temporal structure enabling identifiability.

## Analytic and geometric properties

- **Finite parameterization:**  $\mathcal{F}$  is a finite-dimensional manifold when operators are finitely parameterized:

Let  $\Theta \subset \mathbb{R}^p$  parameterize the stages  $\mathcal{E}_{\theta_E}, \Omega_{\theta_\Omega}, \Psi_{\theta_\Psi}$  and define

$$\Phi : \Theta \rightarrow \mathcal{M}, \quad \Phi(\theta) = \Psi_{\theta_\Psi} \circ \Omega_{\theta_\Omega} \circ \mathcal{E}_{\theta_E},$$

where  $\mathcal{M}$  is a Banach space of maps (for example  $C^0$  or  $L^2$  mappings). The induced function class is the image  $\Phi(\Theta) = \{f_\theta : \theta \in \Theta\} \subset \mathcal{M}$ . If  $\Phi$  is  $C^r$  and an immersion at  $\theta$ , then  $\Phi(\Theta)$  is a  $p$ -dimensional  $C^r$  submanifold of  $\mathcal{M}$ . Parameter redundancies reduce the effective dimension, and nonparametric or infinite-width stages may produce infinite-dimensional families.

- **Band-limited structure:** outputs after  $\Omega$  are localized in time–frequency.

### **i** Note

Time-localization is useful because it lets you detect, separate, and interpret short, emotion-related transients (micro-events) from background noise; it improves denoising, feature extraction, and interpretability for time-varying facial heatmaps, especially when emotions produce brief thermal signatures.

- **Dimensionality reduction:** effective dimension reduces from  $K \times T$  to  $L \times T$ .

We employ a sequencewise encoder

$$\Psi : \mathbb{R}^{K \times T} \rightarrow \mathbb{R}^{L \times T} \quad (\text{or } \Psi : \mathbb{R}^{K \times T} \rightarrow \mathbb{R}^{L \times T'} \text{ if temporal downsampling is used}),$$

so that the effective spatio-temporal degrees of freedom are reduced from  $K \times T$  to  $L \times T$  (or  $L \times T'$ ). This formulation lets  $\Psi$  exploit temporal dependencies for identifiability and for isolating emotion-relevant transients while compressing redundant or noisy dimensions.

- **Identifiability constraints:** independence assumptions carve out identifiable latent subspaces.

### **i** Note

Independence (or conditional-independence) assumptions are the mechanism that restrict the space of possible latent explanations and thereby make certain nonlinear-ICA problems identifiable: they “carve out” a subspace (or *quotient*) of latent solutions that can be uniquely recovered up to trivial indeterminacies.