Fast Amortized Fitting of Scientific Signals Across Time and Ensembles via Transferable Neural Fields

Supplementary Material

7. Additional Training Details

7.1. Model Considerations

In addition to **SIREN** [15] and **K-Planes** [6], we use a modified **fhash** encoder [18] as our spatial encoding-based model. Fhash builds on multi-resolution hash encodings (e.g., tiny-cuda-nn [11]) and has been shown to be effective for representing spatiotemporal data. We adapt the fhash implementation to support 5D inputs for our experiments. We summarize the training settings for one dataset per category below.

7.2. Time-Evolving Toy Signal

We summarize training configurations for the Schwefel experiments described in Section 3.1 below (Table 7).

7.3. Rayleigh–Taylor Instability

We summarize training configurations for the Rayleigh–Taylor instability experiments described in Section 3.2 below (Table 8).

7.4. Deep Water Asteroid Impact

We summarize training configurations for **Deep Water Asteroid Impact** experiments described in Section 4.3 below (Table 9)

8. Dataset Visualization: Time-Evolving Toy Signal

We visualize the time-evolving Schwefel function under the transformations described in Section 3.1. Each transformation produces a sequence of signals with progressively increasing variation over time while preserving underlying structure. These controlled evolutions provide an interpretable setting for analyzing how representations capture and transfer structure across timesteps.

Table 7. Model and training settings for the time-evolving **Schwefel** dataset.

Component	**Value**
Compression Ratio	$\sim 2\times$
Training Iterations	4,000
Batch Size	65,536 coordinates
Optimizer	Adam
Learning Rate	1×10^{-4}
Loss	ℓ_1
ω_0 (for SIREN)	10

Table 8. Shared training settings for the **Rayleigh–Taylor instability** dataset.

Component	**Value**
Compression Ratio	$\sim 53\times$
Training Iterations	100,000
Batch Size	200,000 coordinates
Optimizer	Adam
Learning Rate	1×10^{-3}
Loss	ℓ_1
ω_0 (for SIREN)	30

Table 9. Shared training settings for the **Deep Water Asteroid Impact** dataset.

Component	**Value**
Compression Ratio	$\sim 10\times$
Training Iterations	100,000
Batch Size	2,000,000 coordinates
Optimizer	Adam
Learning Rate	1×10^{-4}
Loss	ℓ_1
ω_0 (for SIREN)	30

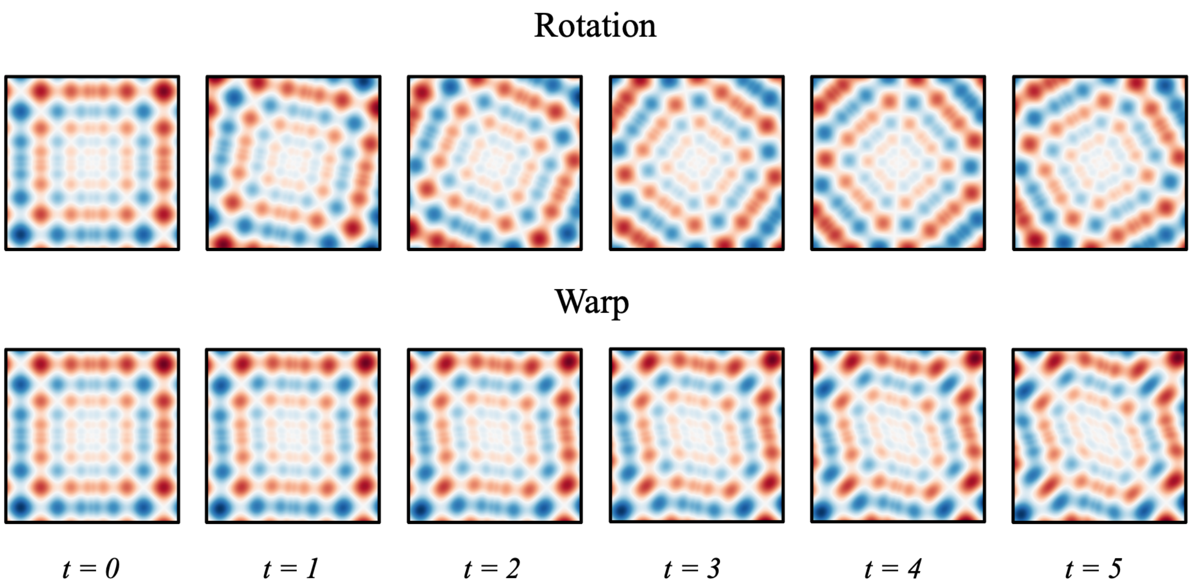

Figure 8. **Geometric transformations over six timesteps.** Each row corresponds to a different transformation: **Rotation** (top) (Eq. 4) and **Warp** (bottom) (Eq. 5). Time progresses from left to right. These transformations preserve underlying signal structure while altering spatial configuration, enabling evaluation of feature transfer under spatial misalignment.

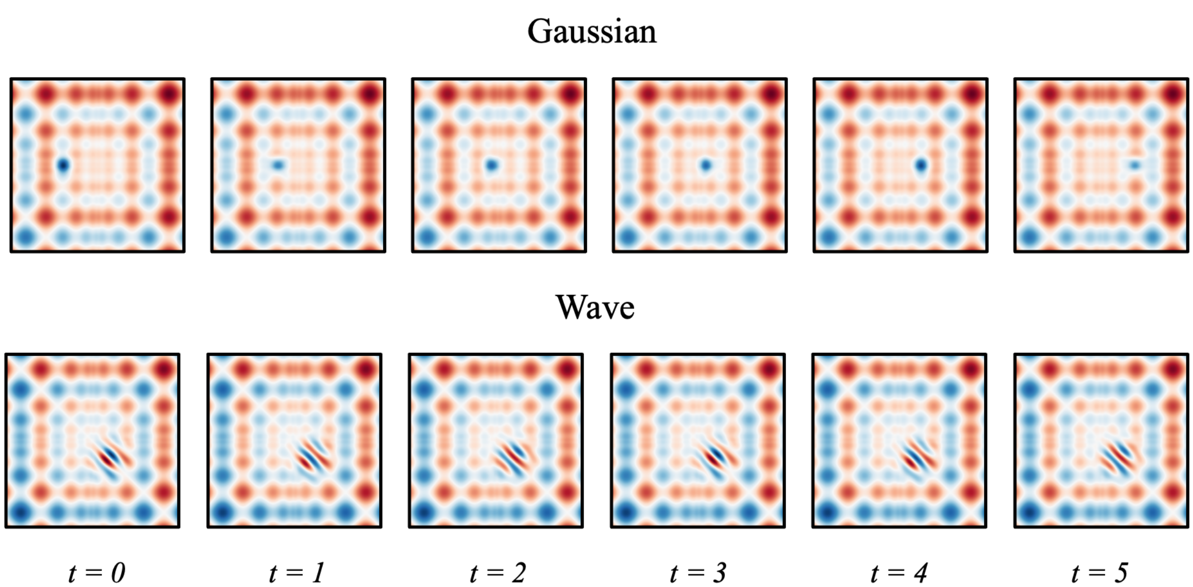

Figure 9. **Local transformations over six timesteps.** Each row corresponds to a different transformation: **Gaussian** (top) (Eq. 6) and **Wave** (bottom) (Eq. 7). Time progresses from left to right. These transformations emulate localized, time-evolving structures found in scientific systems, providing a controlled setting to assess transferability under known structural variations.