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HADF: a hash-adaptive dual fusion implicit network for super-resolution of turbulent flows

Key words: Turbulence reconstruction; Deep learning; Unpaired data; Low-resolution consistency loss; Hash adaptive spatial encoding; Dynamic feature fusion; Implicit neural representations

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Motivation

Background:

- High-resolution (HR) turbulence data are critical for understanding physical mechanisms but expensive to acquire (computational/experimental costs).
- Super-resolution (SR) via deep learning is a promising solution.

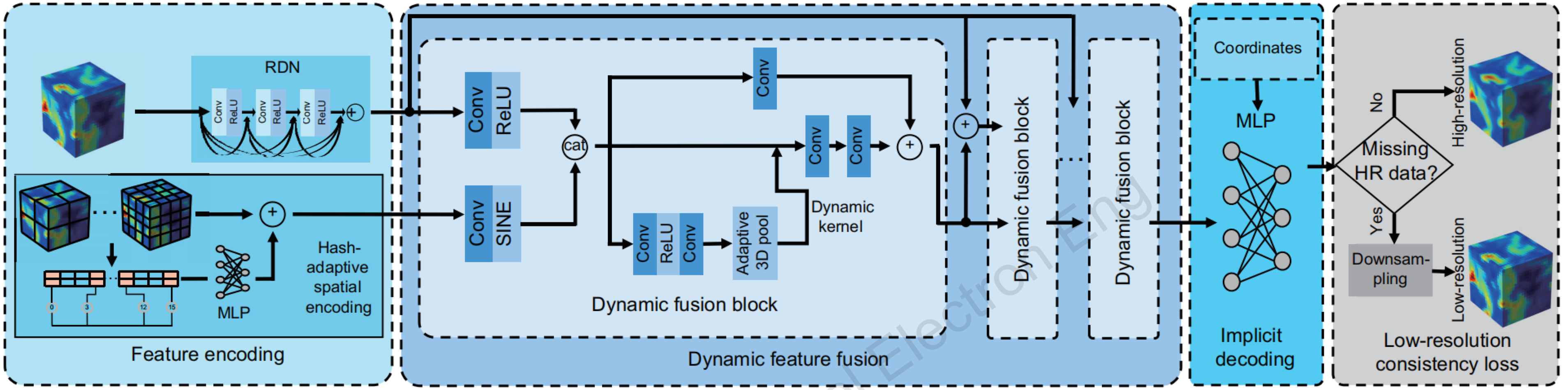
Current challenges:

- Paired data dependency: Existing models rely on perfectly matched low-resolution (LR) and HR data, which are often unavailable in practice.
- Fixed resolution: CNN-based models are typically tied to fixed upsampling ratios, lacking flexibility.

Our goal:

- Develop a unified framework for multi-scale reconstruction that works with unpaired data and maintains physical fidelity.

Main idea



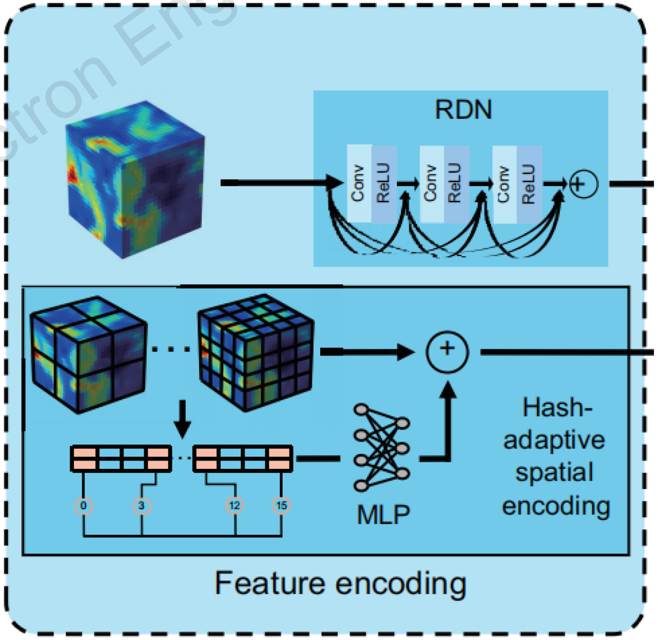
The HADF framework. The proposed HADF model is designed to process a low-resolution input field alongside spatial coordinates to predict high-resolution turbulence details.

- The workflow begins by extracting content and spatial features via a residual dense network and a hash-adaptive encoder, respectively.
- These features are integrated through a dynamic fusion module and processed by an implicit decoder to query arbitrary high-resolution coordinates.
- Uniquely, the framework incorporates a low-resolution consistency loss loop, allowing the model to self-supervise using downsampled predictions, thereby eliminating the conventional need for fully paired datasets.

Method

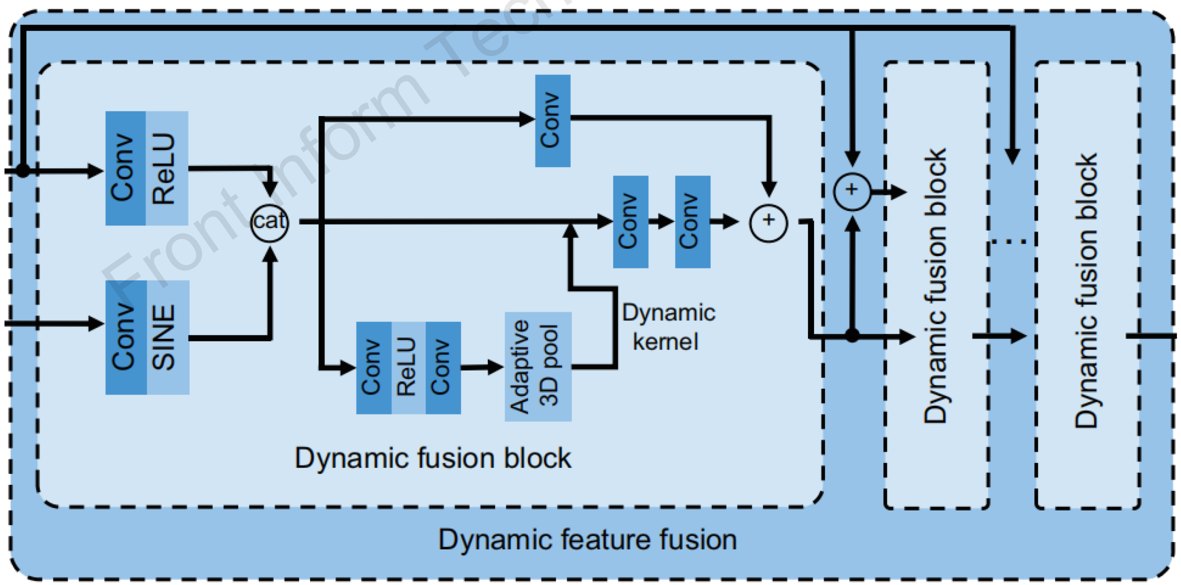
1. Feature encoding

The model uses a dual-path strategy: a 3D RDN extracts content features from the data, while a hash-adaptive spatial encoding module maps coordinates to a multi-resolution grid. This allows the network to efficiently capture fine-scale details and prioritize critical turbulent regions.



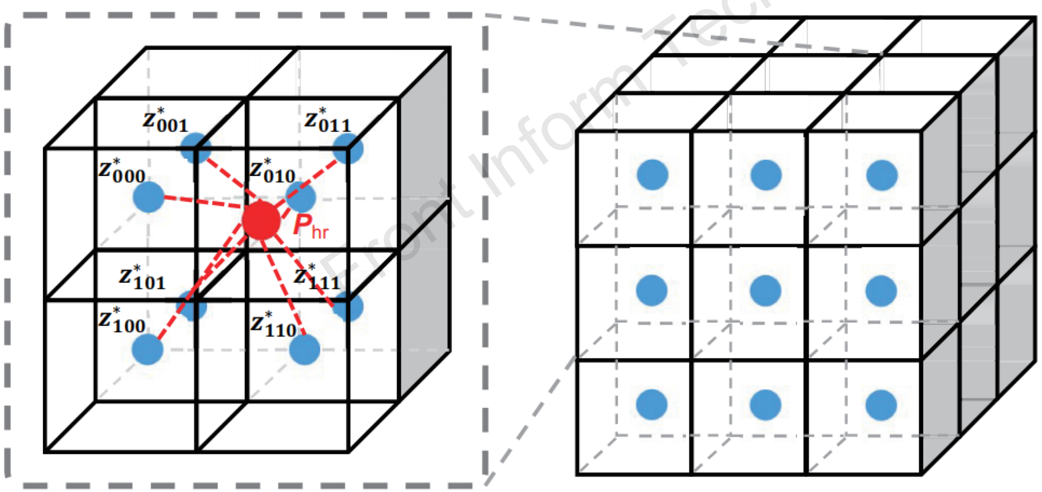
Method

2. Dynamic feature fusion: Instead of fixed weights, this module integrates content and spatial features using dynamic convolution kernels. This adaptive mechanism allows the network to actively capture complex, nonlinear turbulent structures based on the specific feature distribution.

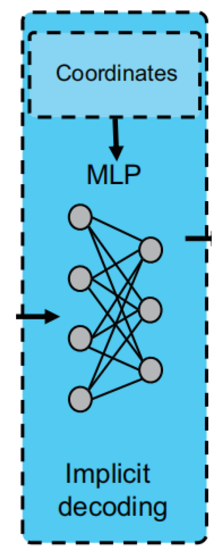


Method

3. Implicit decoding with local ensemble: This module reconstructs flow fields at arbitrary resolutions by mapping features to physical values. It employs a 3D local ensemble strategy that aggregates predictions from eight neighboring voxels, ensuring spatial continuity and minimizing artifacts across diverse scales.



Local ensemble

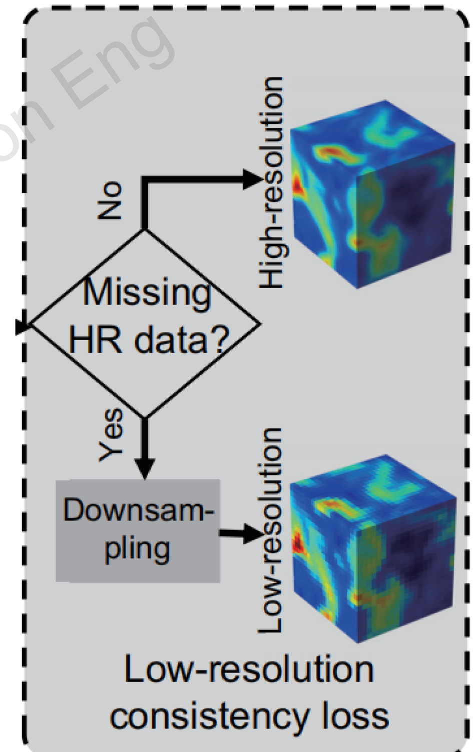


Feature encoding

Method

4. Unpaired data training strategy

To handle real-world scenarios where paired data are scarce, we introduce the LR consistency loss. This enables robust training on unpaired data by strictly enforcing that the downsampled high-resolution prediction matches the original low-resolution input.



Major results

Qualitative comparison: The visual results demonstrate that HADF successfully recovers fine-scale turbulent structures, such as sharp flame fronts and small eddies, in both interpolation and extrapolation scenarios.

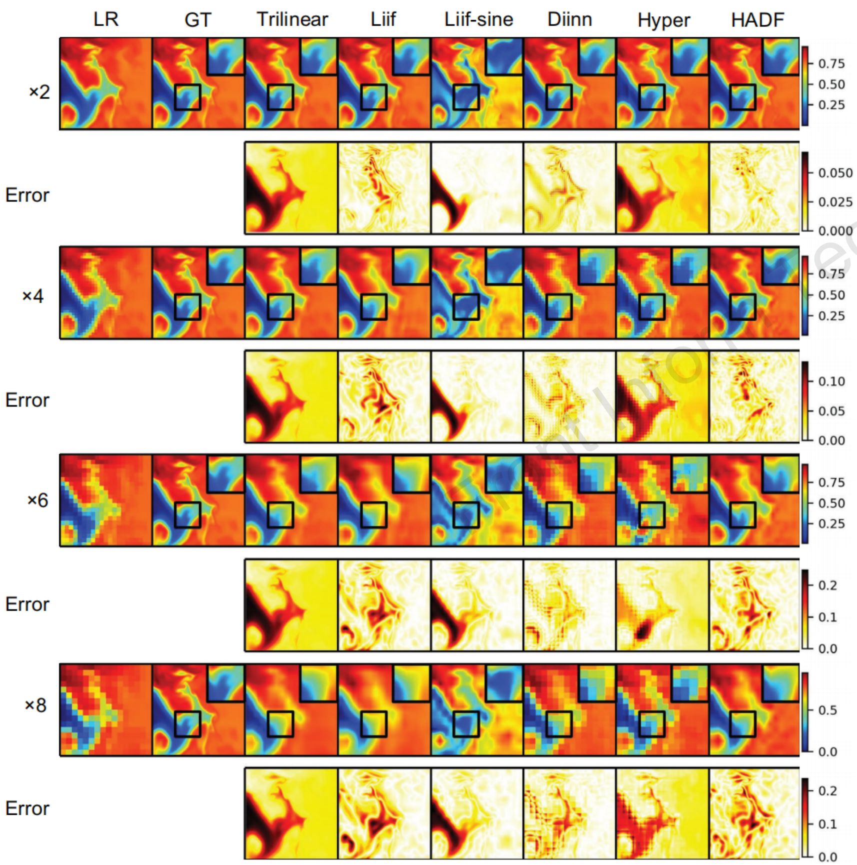


Fig. 7 Qualitative comparison of interpolation testing

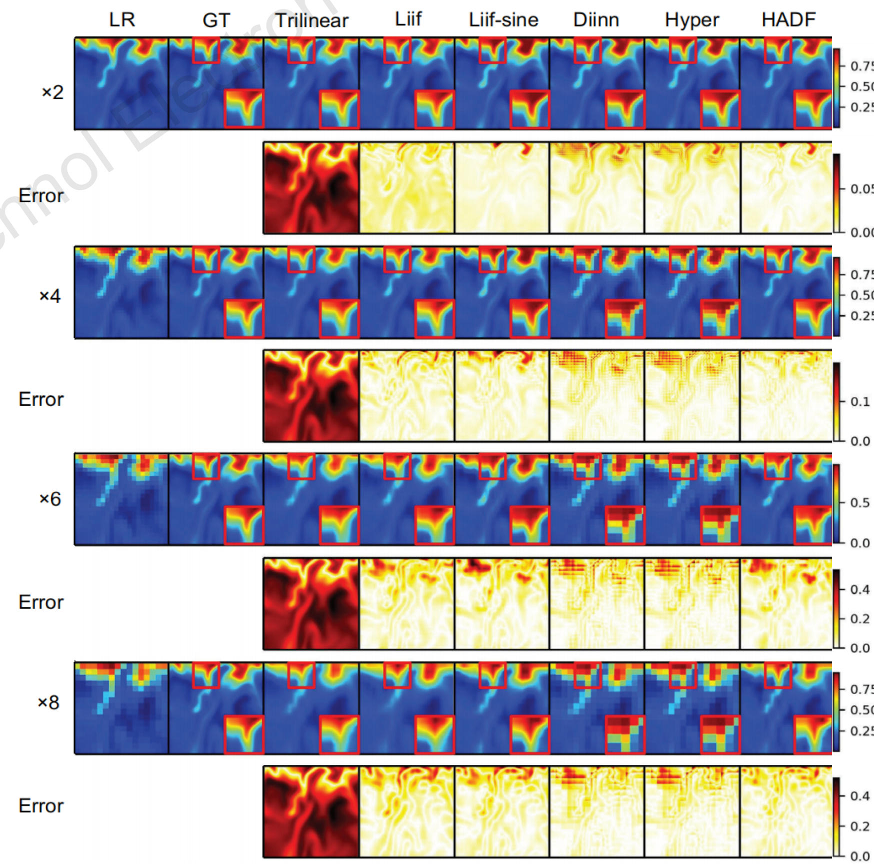


Fig. 9 Qualitative comparison of extrapolation testing

Major results

Performance with unpaired data: A key advantage of HADF is its robustness when paired HR data are unavailable. Experiments show that HADF consistently outperforms all baselines in PSNR even when 30% of HR data are missing.

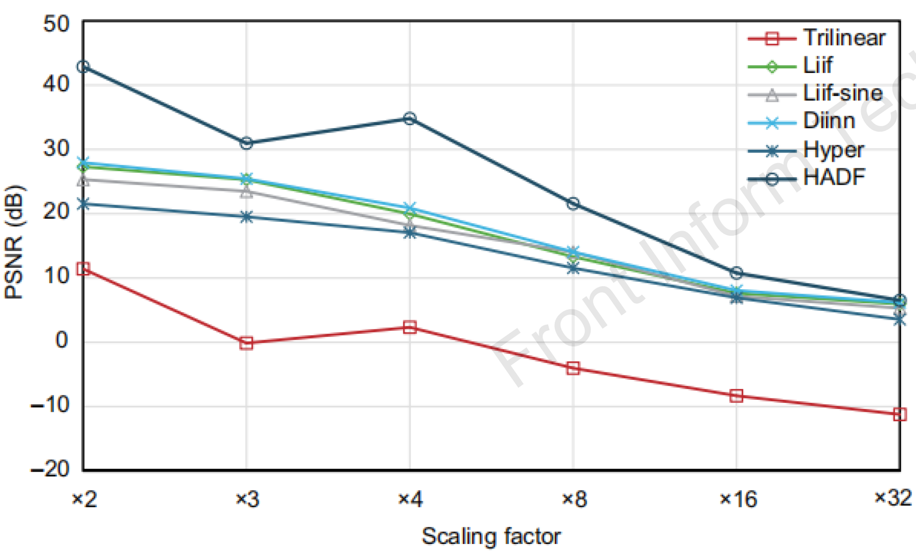


Fig. 11 PSNR performance comparison with 30% HR data unavailable

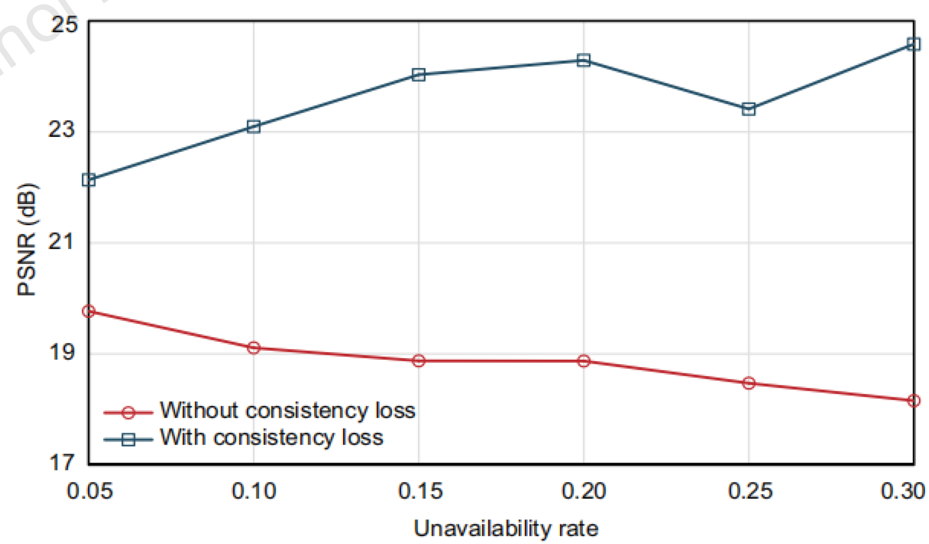


Fig. 12 Impact of the HR data unavailability rate on average PSNR

Conclusions

- Unified framework: We proposed HADF, a novel network incorporating hash-adaptive spatial encoding and dynamic feature fusion to capture complex turbulent structures.
- Flexible reconstruction: The model achieves arbitrary resolution reconstruction (multi-scale) after being trained only once, significantly reducing computational costs compared to traditional simulations.
- Data efficiency and robustness: By introducing the LR consistency loss, HADF eliminates the strict reliance on paired data, enabling robust training even when HR data are partially unavailable or noisy.
- Superior performance: Experimental results demonstrate that HADF outperforms state-of-the-art baselines in global reconstruction accuracy, preservation of local physical properties (energy spectrum), and visual detail recovery.