Superpixel-informed Implicit Neural Representation for Multi-Dimensional Data

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Introduction of Implicit Neural Representation

Implicit Neural Representation (INR) (sometimes also called coordinate-based representation) is a new way to **parameterize various signals**.

- Traditional signal representations are usually discrete, while INR parameterizes the signal as a continuous function that maps the domain of the signal to the value of the attribute at that coordinate.

Image	Video	Pixel
$\mathbb{R}^2 \to \mathbb{R}^3,\ f(x,y) = (\mathrm{r},\mathrm{g},\mathrm{b})$	$\mathbb{R}^3 \to \mathbb{R}^3,\ f(x,y,t) = (\mathrm{r},\mathrm{g},\mathrm{b})$	$\mathbb{R}^3 \to [0,1],\ f(x,y,z) = p \in [0,1]$

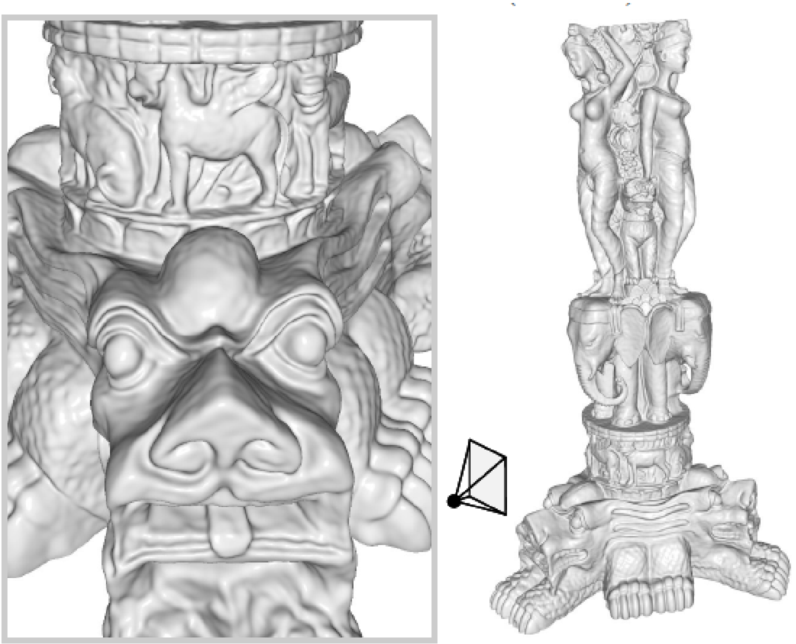
The neural network architecture [1] for INRs:

$$\Phi(\mathbf{x}) = \mathbf{W}_n (\phi_{n-1} \circ \phi_{n-2} \circ \ldots \circ \phi_0)(\mathbf{x}) + \mathbf{b}_n, \quad \mathbf{x}_i \mapsto \phi_i(\mathbf{x}_i) = \sin(\mathbf{W}_i \mathbf{x}_i + \mathbf{b}_i).$$

[1]Sitzmann, V., Martel, J., Bergman, A., Lindell, D., Wetzstein, G.: Implicit neural representations with periodic activation functions. Proceedings of the International Conference on Neural Information Processing Systems, NeurIPS, 2020.

Examples and Application

Point Cloud



Image

INRs have potential in multi-dimensional data recovery.

[1]Sitzmann, V., Martel, J., Bergman, A., Lindell, D., Wetzstein, G.: Implicit neural representations with periodic activation functions. Proceedings of the International Conference on Neural Information Processing Systems, NeurIPS, 2020.

Limitations of Traditional INRs

•**Simple Mapping**: Traditional INRs map spatial coordinates to corresponding values using Multi-Layer Perceptrons (MLPs).

•**Lack of Semantic Understanding**: These methods often treat the data as a collection of points in space, ignoring the rich semantic information inherent in the data.

•**Consequences**: As a result, traditional INRs may fail to effectively capture and represent complex structures and meaningful patterns, leading to suboptimal data representation.

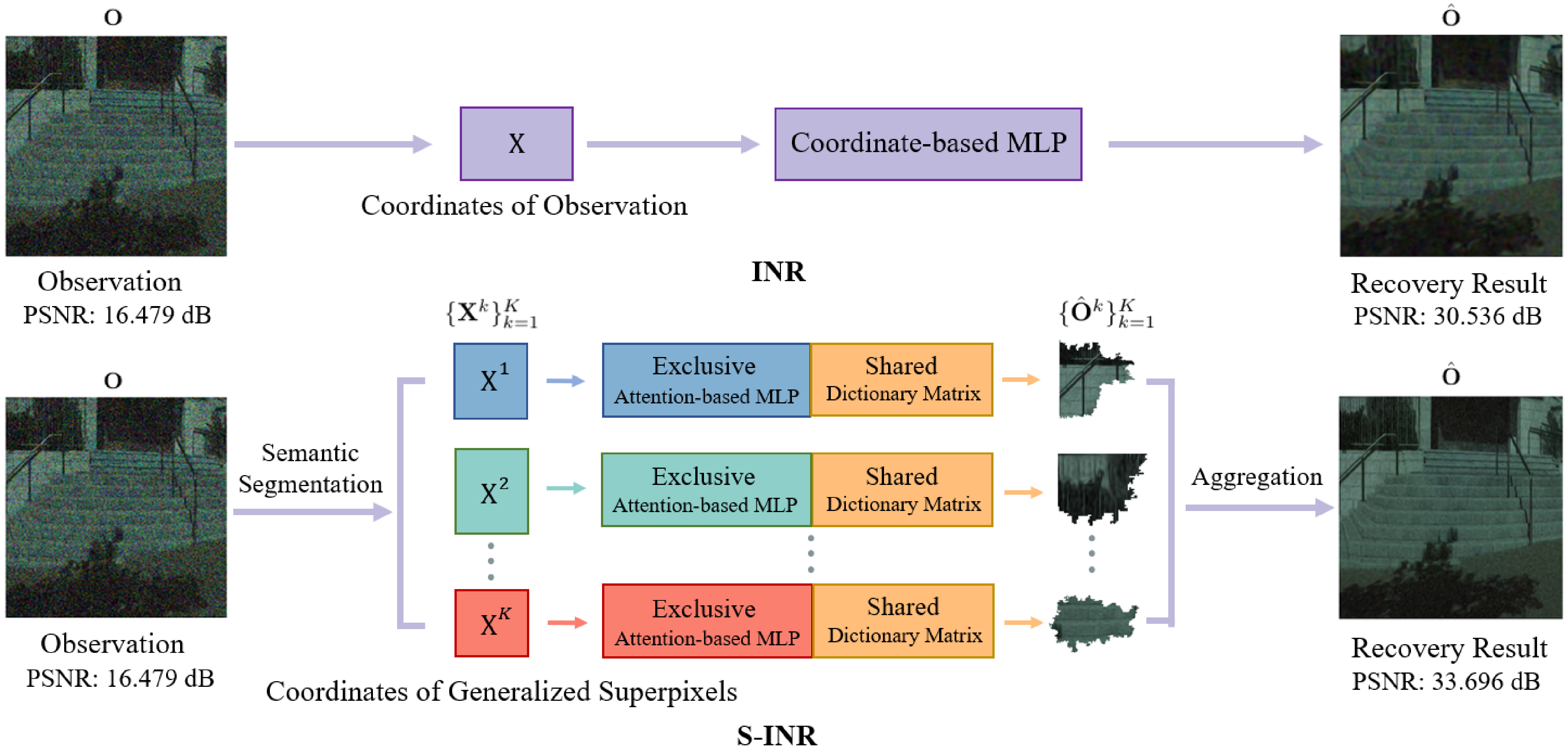
To leverage semantic priors from the data, we propose a novel Superpixel-informed INR (S-INR).

Background & Motivation

Experiments

Discussions

Method Framework



Generalized Superpixel Segmentation

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Discussions

(a) Image data (b) 3D surface data (c) Weather data

The segmentation results by our Generalized Superpixel Segmentation Algorithm (GSSA).

Results on Image Completion and Denoising

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Background
&
Motivation

Experiments

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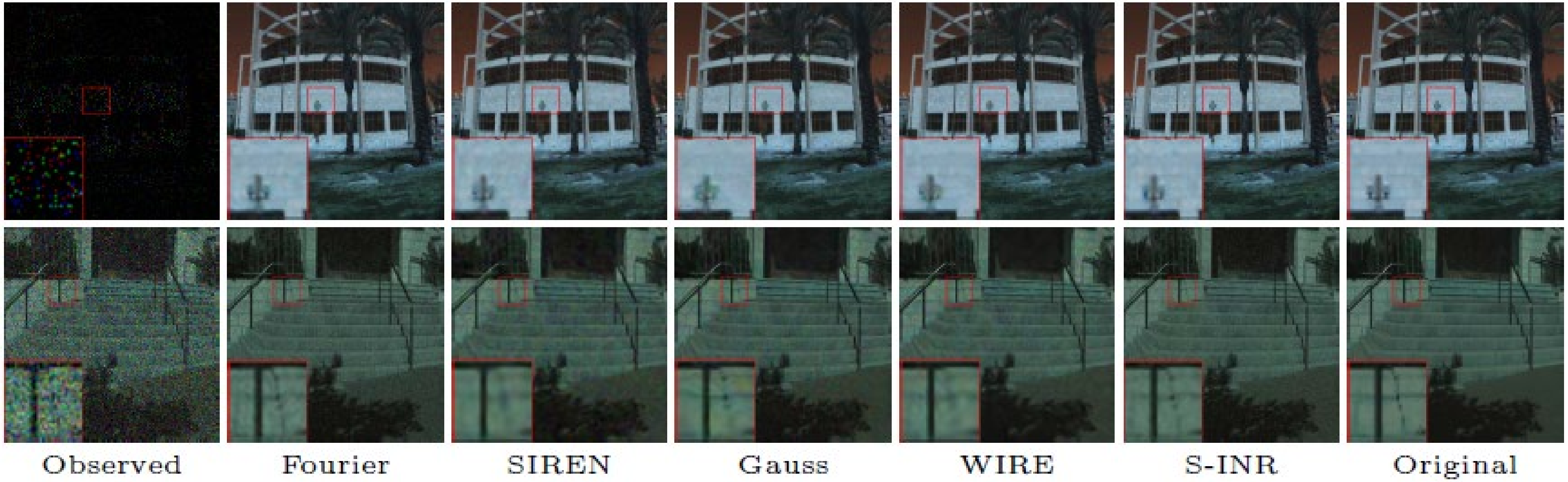
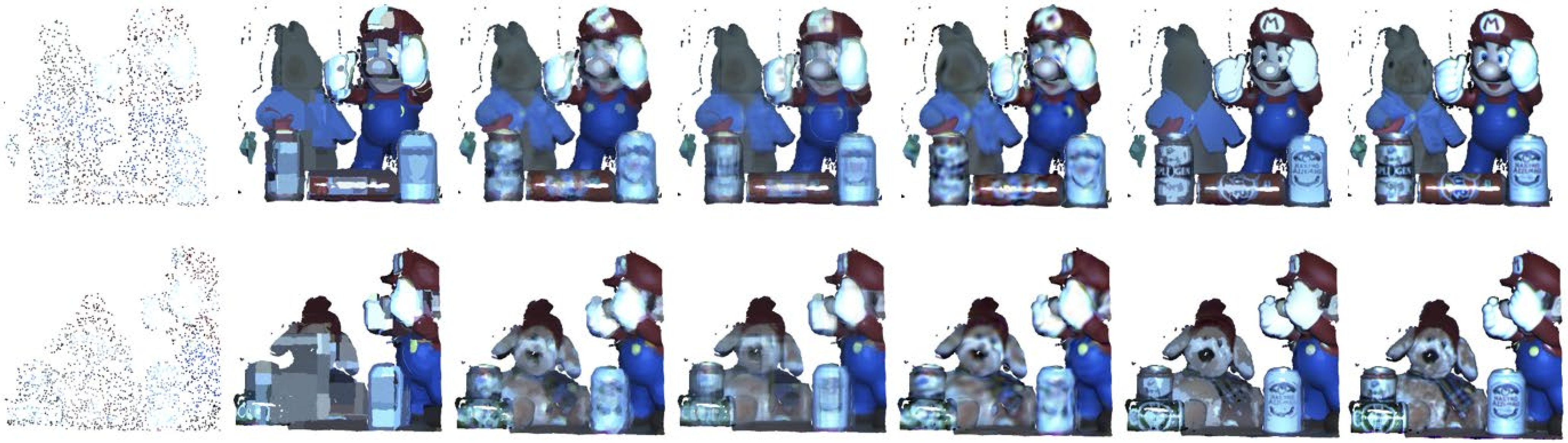


The results of image completion and image denoising recovery

Results on 3D Surface Completion



Observed DT KNR RF SIREN S-INR Original

The results of 3D surface completion recovery

Results on Weather Data Completion

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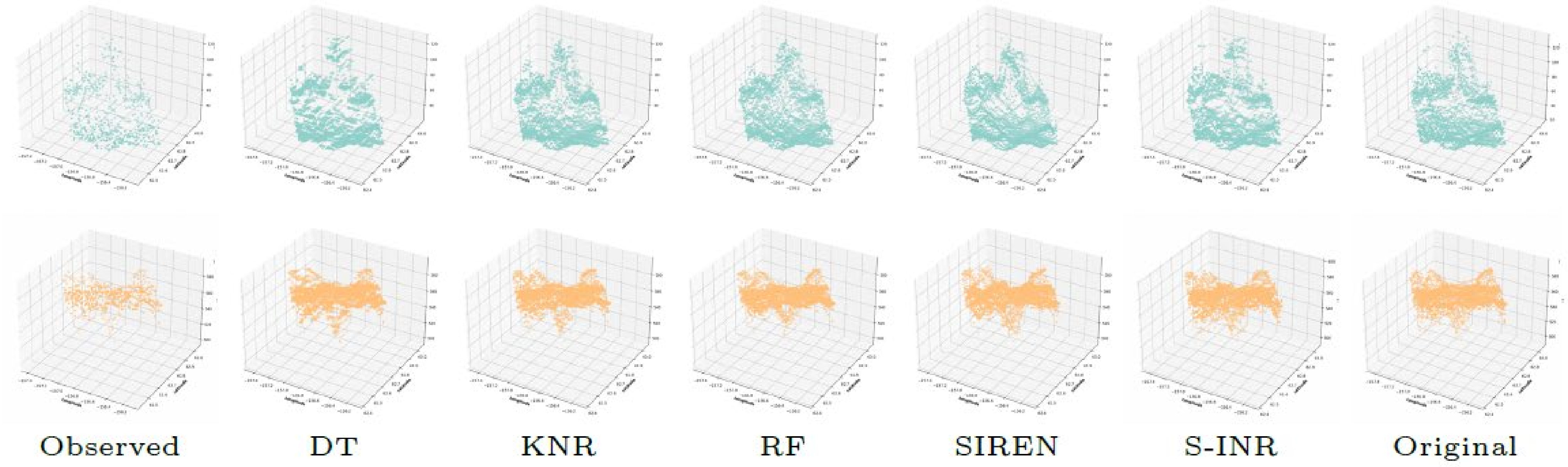

The results of weather data completion recovery

The roles of basic units

Comparison of Basic Units: Pixels vs. Generalized Superpixels

Observed	Pixel-based INR	Superpixel-based INR	Original
PSNR: 13.977 dB	PSNR: 29.348 dB	**PSNR: 31.475 dB**	PSNR: Inf

The results of image denoising recovery by pixel-based INR [1] and superpixel-based INR

Ablation Study

Components			*Lehavim*		Parameters (Mb)
Generalized Superpixels	Exclusive MLPs	Shared Dictionary Matrix	PSNR	SSIM	
✗	✗	✗	29.348	0.745	0.786
✓	✗	✗	31.475	0.817	**0.741**
✓	✗	✓	31.997	0.818	0.797
✓	✓	✗	31.012	0.787	0.902
✓	✓	✓	**32.394**	**0.831**	0.995

The quantitative results of image denoising recovery comparisons with different components in S-INR.

Thanks for your listening!

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