Unsupervised Self-Prior Embedding Neural Representation for Iterative Sparse-View CT Reconstruction

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AAAI-25 PHILADELPHIA, USA

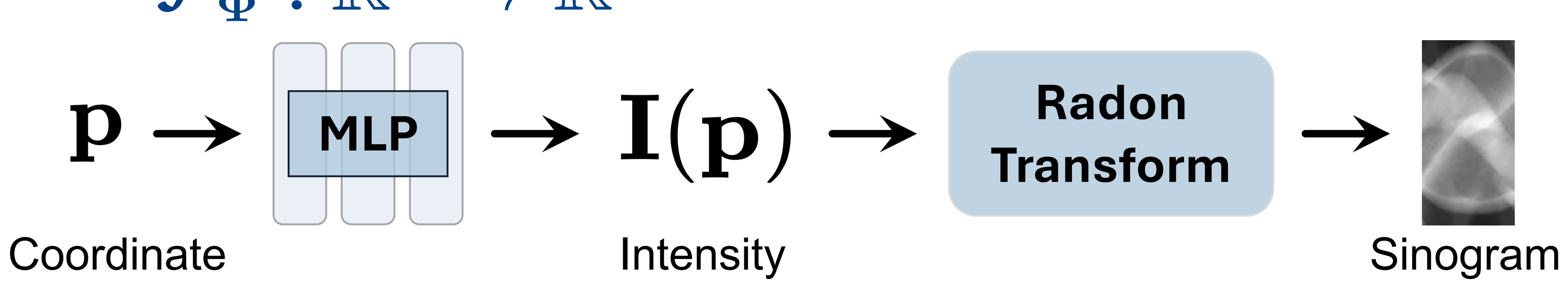
1. Overview

- **Motivation:**
  Current unsupervised INR-based methods struggle with sparser or noisier SV-CT reconstruction
- **Method:** An **unsupervised** framework "**Spener**"
  1. Utilize image domain prior with INR
  2. Integrate iterative framework to stabilize solution
- **Results:** Matched supervised methods in-domain data & outperform at out-of-domain; Outperform INR-based methods in noise robustness
- **Contributions:**
  INR: Utilize explicit regularization for INR optimization
  PnP: Integrate powerful solver to achieve data consistency

2. Preliminaries

- **Implicit Neural Representation for CT**

$$\mathcal{F}_\Phi : \mathbb{R}^2 \rightarrow \mathbb{R}$$



- **Plug-and-Play HQS for Solving Inverse Problem**

$$\mathbf{y} = \mathcal{A}\mathbf{x} + \epsilon$$

Measurement Target Image Noise

Solve Data Consistency Subproblem

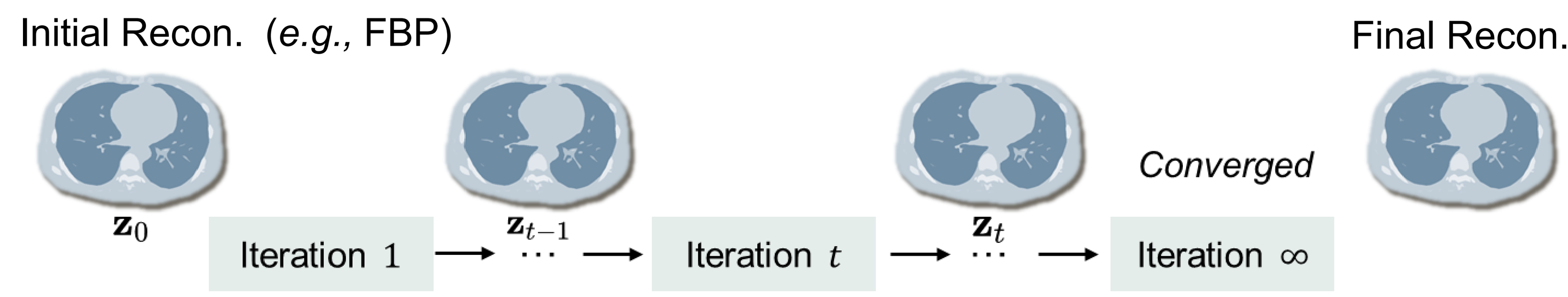
$$\mathbf{x}_t = \underset{\mathbf{x}}{\text{argmin}} \|\mathbf{y} - \mathcal{A}\mathbf{x}\|^2 + \frac{\mu}{2}\|\mathbf{z}_{t-1} - \mathbf{x}\|^2$$

Solve Prior Subproblem with Denoiser $\mathcal{D}_\sigma$

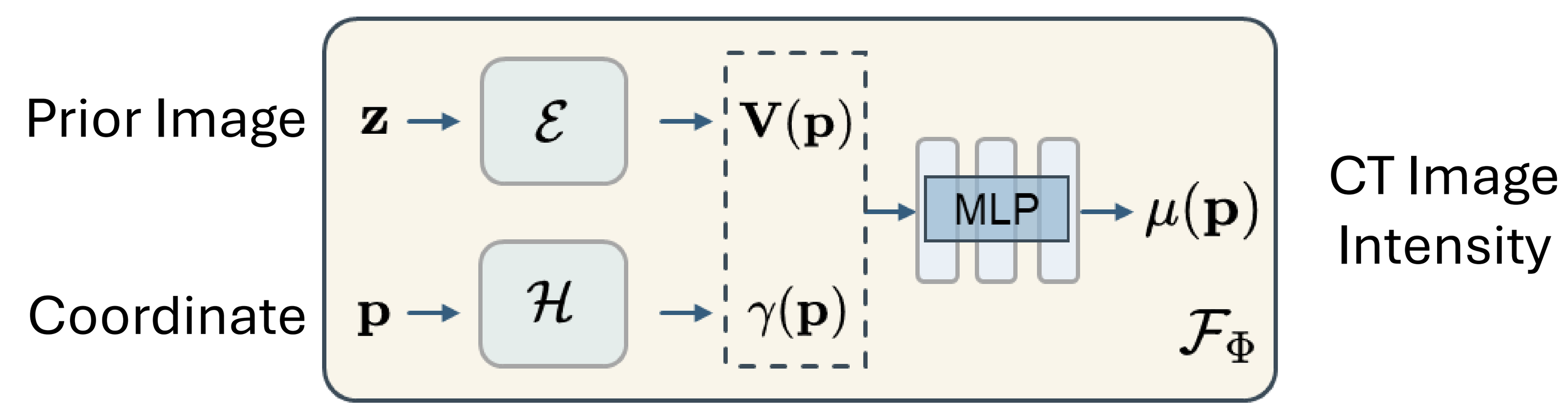
$$\mathbf{z}_t = \mathcal{D}_\sigma(\mathbf{x}_t)$$

3. Method

➢ **Iterative Reconstruction Process**

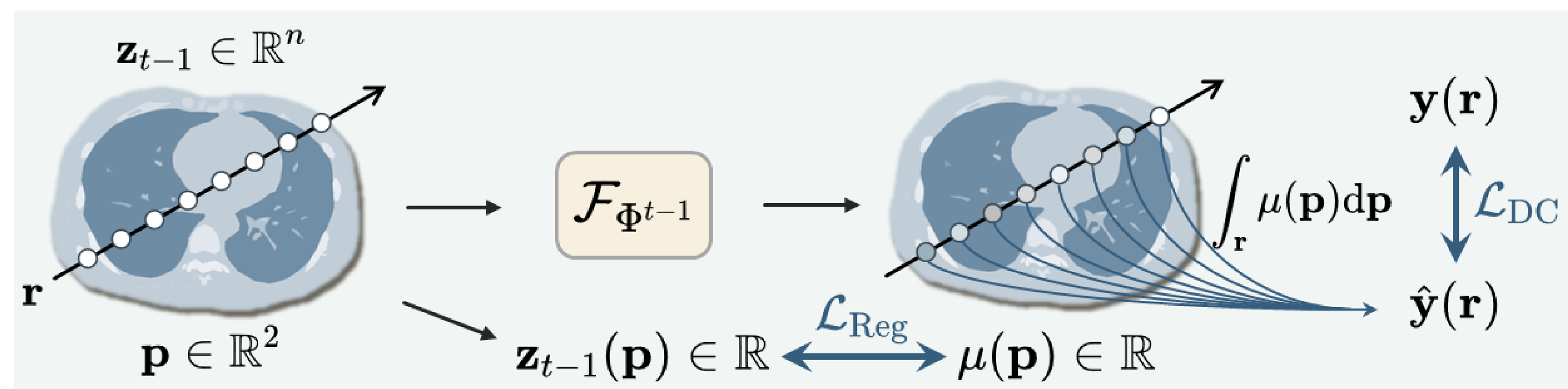


➢ **Image Prior Embedding Neural Representation**



In Iteration t: Solve **Data Consistency** & **Prior** Subproblems

a. Data Consistency Solving via Image Embedding INR



1) Sampling of **a set of coordinates** along any X-ray
2) Prediction of Intensity feeding the **coordinates and image** into network
3) Optimize network through minimizing the **loss function**

$$\Phi^t = \underset{\Phi^{t-1}}{\text{argmin}} \mathcal{L}_{\text{DC}} + \lambda \cdot \mathcal{L}_{\text{Reg}}$$

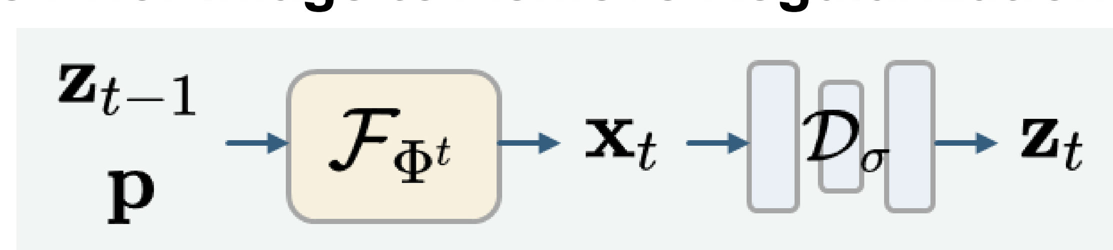
Data Consistency Term

$$\sum_{\mathbf{r} \in \mathcal{R}} |\mathbf{y}(\mathbf{r}) - \hat{\mathbf{y}}(\mathbf{r})|$$

Regularization Term

$$\sum_{i=1}^{N} \|\mathcal{F}_{\Phi^{t-1}}(\mathbf{z}_{t-1}(\mathbf{p}_i), \mathbf{p}_i) - \mathbf{z}_{t-1}(\mathbf{p}_i)\|^2$$

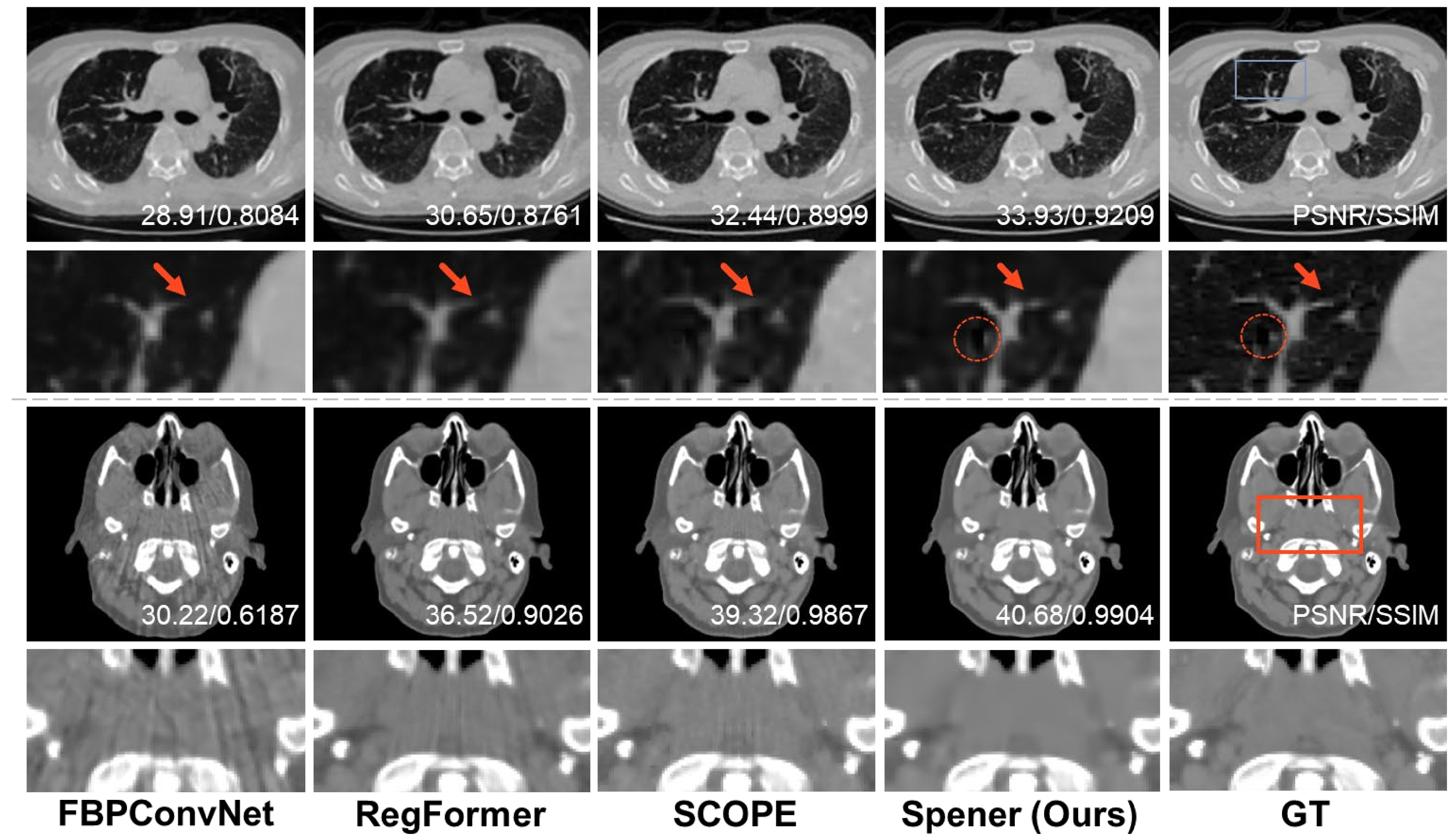
b. Update Prior Image to Achieve Regularization



1) Feed **all coordinates** and last iteration recon image into network
2) Regularize the current recon image via **powerful denoiser**
3) Update the **prior image** from the denoised recon image

4. Experimental Results

- Outperform SOTA Supervised Methods on **OOD** Data



- Supervised DL methods (FBPConvNet, RegFormer).
- Unsupervised INR-based methods (CoIL, SCOPE, our **Spener**).

- Outperform with INR Baselines on **Low-Dose Settings**

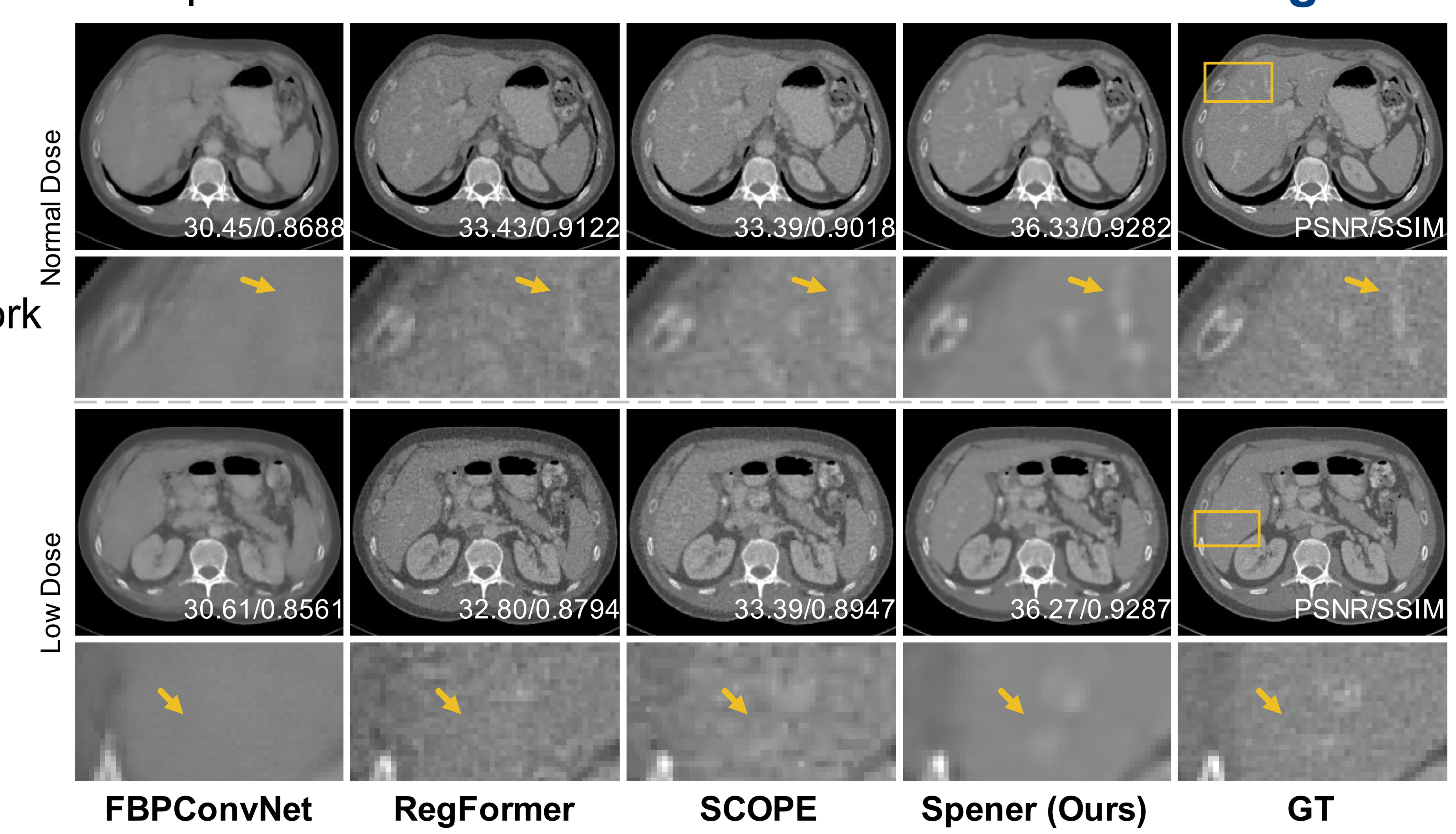


Table 1. Effectiveness of Iteration in Spener Optimization

Strategy	PSNR	SSIM
w/o iteration	36.28±0.69	0.9342±0.0060
w/ iteration	**37.35±0.54**	**0.9484±0.0062**

For addition details please contact: tianxy@shanghaitech.edu.cn

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Reference

[1] Zhang, K.; Li, Y.; Zuo, W. et al. 2021. Plug-and-play image restoration withdeep denoiser prior. IEEE TPAMI, 44(10): 6360–637
[2] Wu, Q.; Feng, R.; Wei, H et al . 2023. Self-Supervised Coordinate Projection Network for Sparse-View Computed Tomography. IEEE TCI, 9: 517–529.
[3] Kamilov, U. S.; Bouman, C. A.; Buzzard, et al. 2023. Plug-and-play methods for integrating physical and learned models in computational imaging: Theory, algorithms, and applications. IEEE SPM, 40(1): 85–97.