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Hyperspectral Image Enhancement Using Enhanced Deep Image Prior

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Abstract: *Enhanced Deep Image Prior (EDIP) is a lightweight framework designed to enhance hyperspectral images without the need for large-scale training datasets. Instead of relying on pretraining, it learns directly from each input image by leveraging the concept of Deep Image Prior (DIP), which allows the network structure itself to act as a prior for reconstruction and enhancement. The method employs a simplified U-Net architecture tailored for hyperspectral data, effectively capturing spatial–spectral correlations while maintaining computational efficiency.*

To further improve performance, EDIP incorporates scene-aware adaptation, enabling image-specific optimization that adjusts parameters dynamically to the characteristics of each scene. In addition, a basic yet effective spectral band fusion strategy is applied to preserve fine spectral and spatial details across different wavelengths, ensuring consistency in the enhanced output. The framework is complemented by an interactive web-based tool that visualizes the entire enhancement pipeline, providing intuitive before-and-after comparisons and enabling users to explore the effects of EDIP on diverse hyperspectral datasets.

Key Words: *Hyperspectral Imaging, Super Resolution, Deep Image Prior, EDIP-Net, Image Enhancement.*

I. INTRODUCTION

Hyperspectral imaging (HSI) acquires scene information across hundreds of narrow and contiguous spectral bands, providing significantly richer spectral detail than conventional RGB or multispectral imaging systems. This fine spectral resolution enables accurate characterization of material properties and has proven valuable in a wide range of applications, including precision agriculture, environmental monitoring, mineral exploration, urban mapping, and remote sensing analysis. By capturing subtle variations in spectral signatures, hyperspectral imagery supports advanced tasks such as material identification, classification, and anomaly detection that are difficult to achieve with standard imaging modalities.

Despite its advantages, hyperspectral imaging systems are often constrained by hardware limitations that impose a trade-off between spatial resolution, spectral resolution, and acquisition speed. As a result, hyperspectral images frequently exhibit low spatial resolution, which degrades spatial detail and limits the effectiveness of subsequent image analysis tasks.

In recent years, deep learning–based super-resolution and image enhancement techniques have demonstrated promising performance for hyperspectral imagery. These methods typically rely on supervised learning frameworks that require large-scale, high-quality training datasets consisting of paired low- and high-resolution hyperspectral images. However, acquiring such datasets is expensive and often impractical due to the high cost of hyperspectral sensors and the variability across imaging conditions, scenes, and sensor technologies. Moreover, models trained on specific datasets or sensors often exhibit limited generalization capability when applied to unseen environments

To overcome these challenges, unsupervised and zero-shot learning approaches have gained increasing attention. Among them, Deep Image Prior (DIP) has emerged as a powerful paradigm for image restoration and enhancement tasks. Unlike conventional deep learning methods, DIP does not rely on external training data. Instead, it exploits the inherent inductive bias of convolutional neural networks, where the network structure itself serves as an image prior. By optimizing the network parameters directly on a single degraded input image, DIP is capable of reconstructing meaningful image structures while suppressing noise and artifacts.

The applicability of DIP to hyperspectral imaging has been explored in several recent studies, demonstrating its potential for tasks such as denoising, inpainting, and super-resolution without supervised training. These methods highlight the suitability of DIP for hyperspectral data, where labeled datasets are scarce and scene variability is high. However, existing approaches often struggle to fully capture complex spatial–spectral correlations or adapt effectively to diverse scene characteristics.

Motivated by these observations, this work introduces an Enhanced Deep Image Prior (EDIP) framework for unsupervised hyperspectral image super-resolution. EDIP employs a simplified U-Net based architecture designed to efficiently model spatial–

spectral dependencies while maintaining computational efficiency. Furthermore, the proposed framework incorporates scene-aware optimization strategies that enable image-specific adaptation, allowing the enhancement process to dynamically adjust to the characteristics of each hyperspectral scene. To ensure spectral consistency and preserve fine details across wavelength bands, a spectral band fusion mechanism is integrated into the reconstruction pipeline. By combining these components, EDIP delivers high-quality hyperspectral image enhancement without the need for large-scale training datasets or pretraining, making it well suited for real-world hyperspectral applications.

II. RELATED WORK

D. Liu, J. Wang et al proposed Deep EIT: Deep Image Prior Enabled Electrical Impedance Tomography, which proposes an unsupervised method for Electrical Impedance Tomography (EIT) image reconstruction using Deep Image Prior (DIP). Instead of training on large datasets, the method optimizes an untrained neural network for each measurement, where the network structure itself acts as a regularizer. By embedding the EIT forward model into the optimization process, Deep EIT effectively addresses the ill-posed nature of EIT. Experiments show that it produces higher quality reconstructions than traditional and learning-based methods, without requiring labeled training data.

C. K. Reddy et al proposed Enhancing Precision Agriculture and Land Cover Classification: A Self-Attention 3D Convolutional Neural Net-work Approach for Hyperspectral Image Analysis which explains a 3D CNN with self-attention to classify hyperspectral images for agriculture and land-cover mapping. The method learns both spatial and spectral information at the same time and focuses on the most important features. Results show it is more accurate than existing methods on standard datasets.

J. Xu et al proposed Combining Deep Image Prior and Second-Order Generalized Total Variance for Image Denoising proposes an image denoising method that combines Deep Image Prior (DIP) with second-order generalized total variation (GTV). DIP provides an implicit image prior without training data, while the GTV regularization helps preserve edges and smooth textures. The combined approach improves noise removal and maintains better image details compared to using DIP or traditional denoising methods alone.

L. Sheng et al proposed Unsupervised deep learning method for single image super-resolution of the thick pinhole imaging system using deep image prior which presents an unsupervised deep learning method for single image super-resolution in thick pinhole imaging systems using Deep Image Prior (DIP). The approach does not require training data; instead, it relies on the network structure as an implicit prior to recover high-resolution images from low-resolution inputs. Results show improved image clarity and detail reconstruction compared to traditional super-resolution methods.

H. R. Iglesias-Goldaracena et al proposed RD-DIP: Rician denoising deep image prior introduces RD-DIP, a Deep Image Prior–based method for denoising images corrupted by Rician noise. The approach adapts DIP to better model the statistical characteristics of Rician noise, commonly found in medical imaging. Experimental results show that RD-DIP improves noise removal while preserving important image details compared to standard DIP and conventional denoising methods.
S. Cook et al proposed Generation of super-resolution images from barcode-based spatial transcriptomics by deep image prior presents a method to generate super-resolution images from barcode-based spatial transcriptomics data using Deep Image Prior (DIP). The approach enhances spatial resolution without requiring training data, improving the visualization and analysis of gene expression patterns in tissues.

A. Naseer et al proposed CNN-Based Object Detection via Segmentation Capabilities in Outdoor Natural Scenes,this paper presents a CNN-based object detection method that leverages segmentation capabilities to identify objects in outdoor natural scenes. By combining detection and segmentation, the approach improves accuracy and localization of objects compared to standard detection methods, especially in complex and cluttered environments.

P. M. Hong et al proposed Defending Against Adversarial Fingerprint Attacks Based on Deep Image Prior,this paper proposes a method to defend against adversarial fingerprint attacks using Deep Image Prior (DIP). The approach leverages DIP to reconstruct fingerprint images, removing adversarial perturbations without requiring training data, thereby improving the security and robustness of fingerprint recognition systems.

III. SYSTEM ARCHITECTURE

1) Proposed System

The proposed system architecture is designed to perform unsupervised hyperspectral image enhancement and super-resolution by integrating Zero-Shot Learning (ZSL) with a Deep Image Prior (DIP)–based reconstruction framework. The architecture follows a modular and scene-adaptive design, enabling effective fusion of spatial and spectral information without relying on external training datasets. An overview of the architecture is shown in Figure 1.

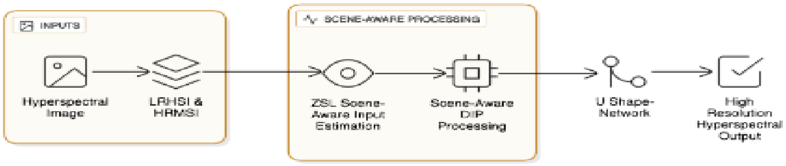


Figure1: System architecture of High Resolution Hyperspectral Image generation.

2) Input Data Representation

The system operates on two complementary image sources:

- Low-Resolution Hyperspectral Image (LR-HSI): Provides rich spectral information across a large number of bands but suffers from limited spatial resolution.
- High-Resolution Multispectral Image (HR-MSI): Contains fine spatial details with fewer spectral bands.

These inputs together provide the necessary spatial–spectral cues required to reconstruct a High-Resolution Hyperspectral Image (HR-HSI) that preserves both spatial clarity and spectral integrity.

3) Degradation Modeling Module

To ensure consistency with real-world imaging systems, the architecture incorporates a Degradation Modeling Module. This module conceptually represents the image acquisition process by modeling spatial and spectral degradation effects.

The degradation process is characterized using:

- A Point Spread Function (PSF) to model spatial blurring
- A Spectral Response Function (SRF) to represent spectral mixing between hyperspectral and multispectral data

These degradation models guide the reconstruction process by enforcing physical consistency between the reconstructed output and observed inputs.

4) Zero-Shot Learning (ZSL) Scene-Aware Estimation

The ZSL Scene-Aware Estimation Module generates coarse high-resolution hyperspectral representations directly from the input images without relying on pre-trained models. Instead of using random noise initialization, this module extracts intrinsic spatial–spectral correlations present within the scene.

The generated coarse representations:

- Encode scene-specific information
- Provide stable and informative initialization
- Improve the effectiveness of subsequent refinement stages

This module enables scene adaptivity while maintaining a fully unsupervised learning paradigm.

5) Scene-Aware Deep Image Prior (DIP) Refinement

The refinement stage is based on a Scene-Aware Deep Image Prior (DIP) framework implemented using a U-Net–based encoder–decoder architecture. The network exploits the inherent structural bias of convolutional neural networks to model hyperspectral image priors without external supervision.

Key architectural characteristics include:

- Hierarchical feature extraction through an encoder
- Progressive reconstruction through a decoder
- Skip connections to preserve fine spatial and spectral details

Through iterative self-optimization, the DIP module refines the coarse estimations to recover high-resolution spatial structures while maintaining spectral consistency.

6) Degradation-Aware Fusion Strategy

To enhance reconstruction robustness, the architecture integrates a Degradation-Aware Fusion Strategy. This module combines multiple reconstructed candidates by considering degradation characteristics estimated earlier in the pipeline.

The fusion process:

- Selects optimal pixel-level information
- Suppresses reconstruction artifacts
- Enhances overall spatial–spectral fidelity

This adaptive fusion mechanism improves stability and consistency in the final output.

7) Output Generation and Evaluation

The final output of the system is a High-Resolution Hyperspectral Image (HR-HSI) that exhibits enhanced spatial resolution while preserving spectral information across bands. The modular design of the architecture allows flexibility, scalability, and adaptability across diverse hyperspectral imaging scenarios.

IV. IMPLEMENTATION

This section describes the practical realization of the proposed Enhanced Deep Image Prior Network (EDIP-Net), including data preparation, degradation estimation, model configuration, and the reconstruction workflow. The implementation focuses on executing the architectural components described earlier in a reproducible and modular manner.

1) Data Preparation

The implementation requires two complementary inputs: a Low-Resolution Hyperspectral Image (LR-HSI) and a High-Resolution Multispectral Image (HR-MSI). To ensure compatibility, all input images are spatially aligned and normalized prior to processing. Hyperspectral data are organized in three-dimensional tensors, while multispectral data are represented as multi-channel images.

To simulate realistic imaging conditions, spatial and spectral degradations are applied during preprocessing. Spatial down sampling and spectral mixing operations are used to generate degraded observations, ensuring consistency between input data and the assumed imaging model.

2) Degradation Parameter Estimation

The Point Spread Function (PSF) and Spectral Response Function (SRF) are estimated during the initial phase of execution. These parameters describe spatial blur and spectral mixing effects introduced by the sensing process. The estimation procedure ensures that simulated degraded images closely match the observed inputs, enabling reliable self-supervised optimization in later stages.

The estimated degradation parameters are reused throughout the reconstruction process to maintain physical consistency between the reconstructed output and the observed LR-HSI and HR-MSI.

3) Zero-Shot Learning Scene Estimation

Following degradation estimation, a Zero-Shot Learning (ZSL) strategy is employed to generate coarse high-resolution hyperspectral representations. This step exploits spatial–spectral correlations inherent in the input images without relying on external training data.

The generated coarse outputs serve as informed initializations for the Deep Image Prior network, replacing random noise inputs and improving stability during optimization.

4) Deep Image Prior Optimization

The refinement stage is implemented using a U-Net–based Deep Image Prior (DIP) network. The network parameters are randomly initialized and optimized in a self-supervised manner using only the observed input images.

The optimization process minimizes reconstruction error between:

- Simulated degraded outputs obtained using PSF and SRF
- Observed LR-HSI and HR-MSI inputs

This iterative process allows the network to learn scene-specific image priors directly from the data, enhancing spatial resolution while preserving spectral consistency.

5) Degradation-Aware Fusion

Multiple reconstruction candidates produced during the DIP optimization stage are combined using a Degradation-Aware Fusion strategy. This fusion step evaluates pixel-level reliability based on degradation characteristics and integrates complementary information from different candidates.

The fusion process reduces artifacts and enhances robustness, resulting in improved spatial detail and spectral fidelity in the reconstructed hyperspectral image.

6) Output Generation and Storage

The final output of the implementation is a High-Resolution Hyperspectral Image (HR-HSI). The reconstructed image is stored in a standard hyperspectral data format to support visualization and further analysis. Intermediate outputs generated during different stages of processing are optionally retained to facilitate inspection and debugging.

V. EVALUATION AND RESULTS

This section evaluates the performance of the proposed Enhanced Deep Image Prior Network (EDIP) for unsupervised hyperspectral image super-resolution. Experiments are conducted on standard benchmark datasets, including Indian Pines, Pavia University, and CAVE. Low-resolution hyperspectral images are generated using spatial blurring and down-sampling, while spectral degradation is simulated through sensor spectral response functions. EDIP-Net is optimized independently for each test scene without any offline training.

Reconstruction quality is assessed using commonly adopted metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Spectral Angle Mapper (SAM), and ERGAS.

1) Quantitative Comparison

Table I reports the average performance on the Indian Pines dataset, which is representative of the overall trend observed across all benchmarks. EDIP consistently achieves the highest PSNR and SSIM while producing the lowest SAM and ERGAS values, indicating superior spatial reconstruction and spectral preservation compared with existing supervised and unsupervised methods.

Method	PSNR (dB)↑	SSIM↑	SAM↓	ERGAS↓
Bicubic	27.84	0.801	8.92	6.41
DIP-HSI	31.45	0.882	5.74	4.01
Self-Supervised Fusion	32.38	0.901	5.21	3.62
EDIP-Net (Proposed)	**34.12**	**0.926**	**4.38**	**2.91**

Performance Comparison on Indian Pines Dataset

Ablation Study

To evaluate the contribution of each component, ablation experiments are conducted by progressively adding modules to a baseline DIP framework. Results in Table II confirm that both the scene-aware zero-shot initialization and the degradation-aware fusion strategy significantly improve reconstruction accuracy.

Variant	PSNR (dB)↑	SAM↓	ERGAS↓
DIP only	31.45	5.74	4.01
+ ZSL Initialization	32.81	5.02	3.48
+ Fusion	33.52	4.61	3.11
Full EDIP	**34.12**	**4.38**	**2.91**

Ablation Results on Indian Pines Dataset

2) Qualitative Analysis

Visual inspection shows that bicubic interpolation produces blurred spatial structures, while conventional DIP-based methods occasionally introduce spectral inconsistencies. In contrast, EDIP reconstructs sharper edges and fine textures while maintaining spectral signatures across wavelength bands. Error maps further demonstrate reduced reconstruction residuals in high-frequency regions, confirming the effectiveness of the proposed degradation-guided and scene-adaptive design.

Image Quality Metrics

PSNR 33.09 dB

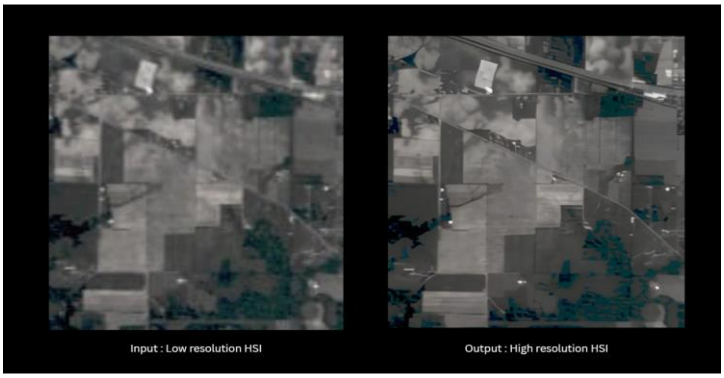
SSIM 0.9459

MSE 0.000451

SAM (Spectral Angle) 0.0355 rad

ERGAS 24.97

Quantitative reconstruction metrics displayed by the implemented EDIP-Net system interface.



Visual comparison between the low-resolution hyperspectral input and the reconstructed high-resolution output produced by the proposed EDIP-Net framework.

As illustrated in Fig. 2 , bicubic interpolation results in blurred spatial structures, while conventional DIP-based methods occasionally introduce spectral inconsistencies.

3) Analysis and Insights

EDIP-Net consistently outperforms existing hyperspectral super-resolution methods across multiple benchmark datasets, demonstrating the effectiveness of its scene-aware zero-shot initialization, degradation-guided Deep Image Prior refinement, and adaptive fusion strategies.

4) Impact of Scene-Aware Zero-Shot Initialization

Ablation results confirm that replacing random DIP initialization with scene-aware zero-shot estimation leads to faster convergence and consistent improvements in PSNR while reducing spectral distortion measured by SAM and ERGAS. Incorporating PSF–SRF–based degradation modeling further enforces physical consistency during reconstruction, preventing overfitting to unrealistic spatial patterns. The degradation-aware fusion module contributes additional robustness by suppressing artifacts in high-frequency regions such as building edges and field boundaries.

5) Spatial–Spectral Fidelity and Generalization

EDIP-Net maintains a strong balance between spatial enhancement and spectral preservation, as reflected by lower SAM values and visually sharper reconstructions compared with bicubic interpolation and conventional DIP-based methods. Because the framework is optimized independently for each scene without supervised training, it generalizes naturally across agricultural, urban, and laboratory datasets, making it suitable for real-world hyperspectral applications where labeled data are scarce.

6) Computational and Practical Considerations

Although EDIP relies on iterative zero-shot optimization and therefore incurs higher runtime than feed-forward supervised networks, scene-aware initialization and fusion reduce the number of required optimization iterations. This trade-off is acceptable in remote sensing and scientific imaging applications where reconstruction accuracy is prioritized over real-time performance. The framework's robustness to moderate noise and blur further supports its deployment in practical sensing scenarios.

VI.CONCLUSION AND FUTURE WORK

This paper presented EDIP, an enhanced deep image prior framework for unsupervised hyperspectral image super-resolution. By combining a zero-shot learning stage with a deep image generation stage, the proposed method effectively exploits scene-specific information from the observed data without requiring external training samples. The degradation learning strategy,a simplified U-Net–based generator, and degradation-aware decision fusion collectively enable accurate modeling of hyperspectral spatial–spectral priors. Experimental results on multiple benchmark datasets demonstrate that EDIP achieves superior reconstruction quality compared with existing state-of-the-art methods.

Future work will focus on reducing computational complexity, improving robustness to noise and complex degradations, and extending the framework to more challenging real-world scenarios and other hyperspectral imaging tasks.

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