An efficient unfolding network with disentangled spatial-spectral representation for hyperspectral image super-resolution

Abstract

Objective: The paper introduces an efficient unfolding network, EUNet, which integrates domain knowledge (like spectral correlation degradation models and structural priors) with deep learning to tackle the challenges of hyperspectral image super-resolution (HSI SR), especially issues like high spectral dimensionality, insufficient spatial resolution, and limited training samples.

Method: EUNet employs a multi-stage network that unfolds the optimization process of the super-resolution prior-driven Maximum A Posteriori (MAP) framework. It includes a disentangled spatial-spectral representation and a lightweight spectral attention mechanism, reducing the difficulty and computational complexity of feature learning.

Significance: EUNet's design balances model interpretability and performance. Through specific structural design and the integration of deep learning techniques, it effectively enhances the quality of hyperspectral image super-resolution reconstruction while maintaining lower computational complexity.

key components

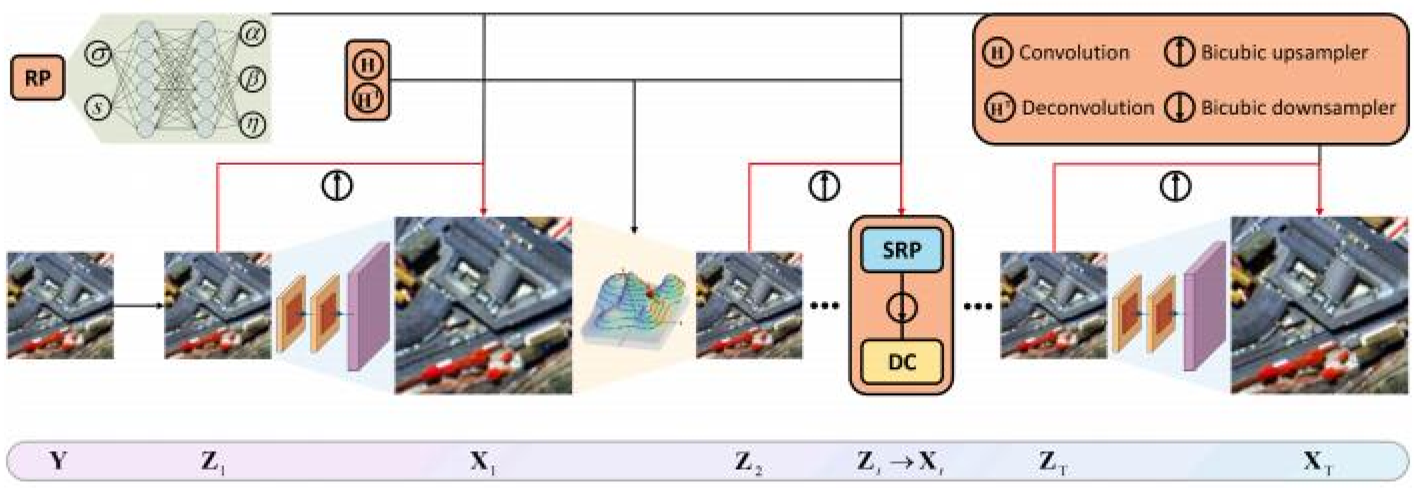

Fig. 2. The overall architecture of our proposed EUNet for HSI SR.

- **Feature Extraction:** Captures primary features from low-resolution images, like edges and textures.
- **Deep Feature Extraction:** After initial extraction, the network delves deeper to extract complex features using Efficient Sub-pixel Spectral Blocks (ESSB) and Groups (ESSG) to analyze high-dimensional data in hyperspectral images
- **Attention Mechanism:** A crucial part of the process, focusing selectively on features that hold more information for reconstructing a high-resolution image.
- **Reconstruction:** Rebuilds the extracted features into a high-resolution image while preserving spectral integrity and enhancing spatial detail.
- **Iterative Refinement:** The network likely includes a gradual image quality enhancement process to ensure the super-resolution image is as accurate and detailed as possible.

HSRPN (Hyperspectral Image Super-Resolution Prior Module)

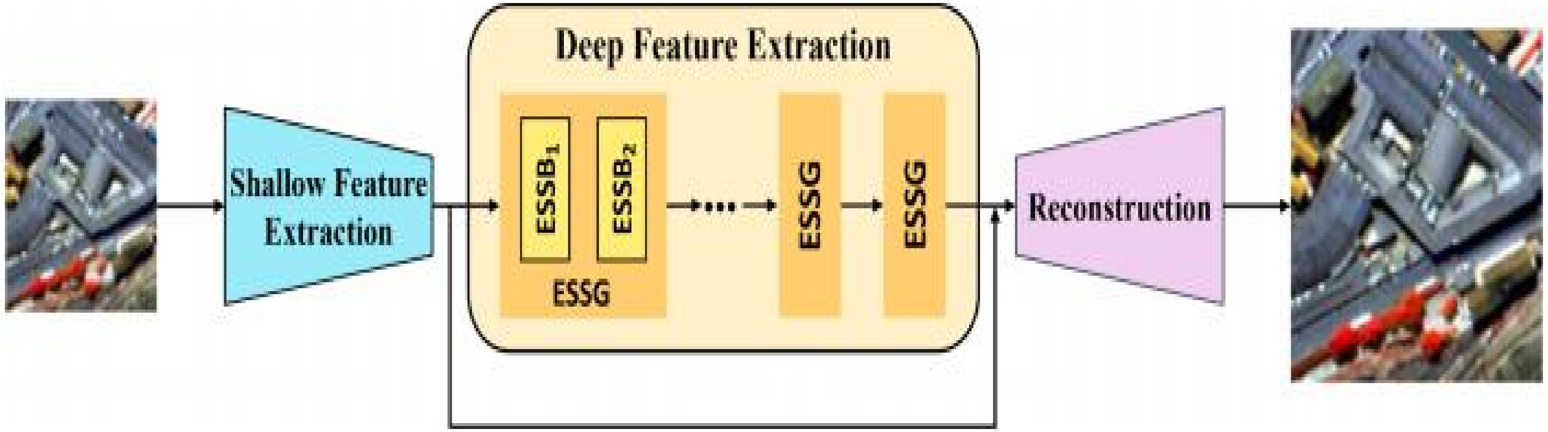

Fig. 3. The architecture of HSRPN for super-resolution prior module.

- **Shallow Feature Extraction：** The initial step aims to extract low-level features, typically including edges and corners, which lays the groundwork for the extraction of deeper features.
- **Deep Feature Extraction：** In this phase, a series of layers, namely Efficient Sub-pixel Spectral Blocks (ESSB1, ESSB2, ..., ESSG), extract more complex features. Each ESSB is a specialized network module designed for effective spectral data processing. The arrows between ESSBs indicate sequential connections, where the output of one layer becomes the input to the next. ESSG, or Efficient Sub-pixel Spectral Group, is a collection of such blocks working together to extract high-quality features.
- **Reconstruction：** After deep features are extracted, they are fed into a reconstruction module. This module synthesizes the extracted features into a high-resolution image, completing the super-resolution reconstruction process.

ESSG

（ **Efficient Sub-pixel Spectral Blocks**）

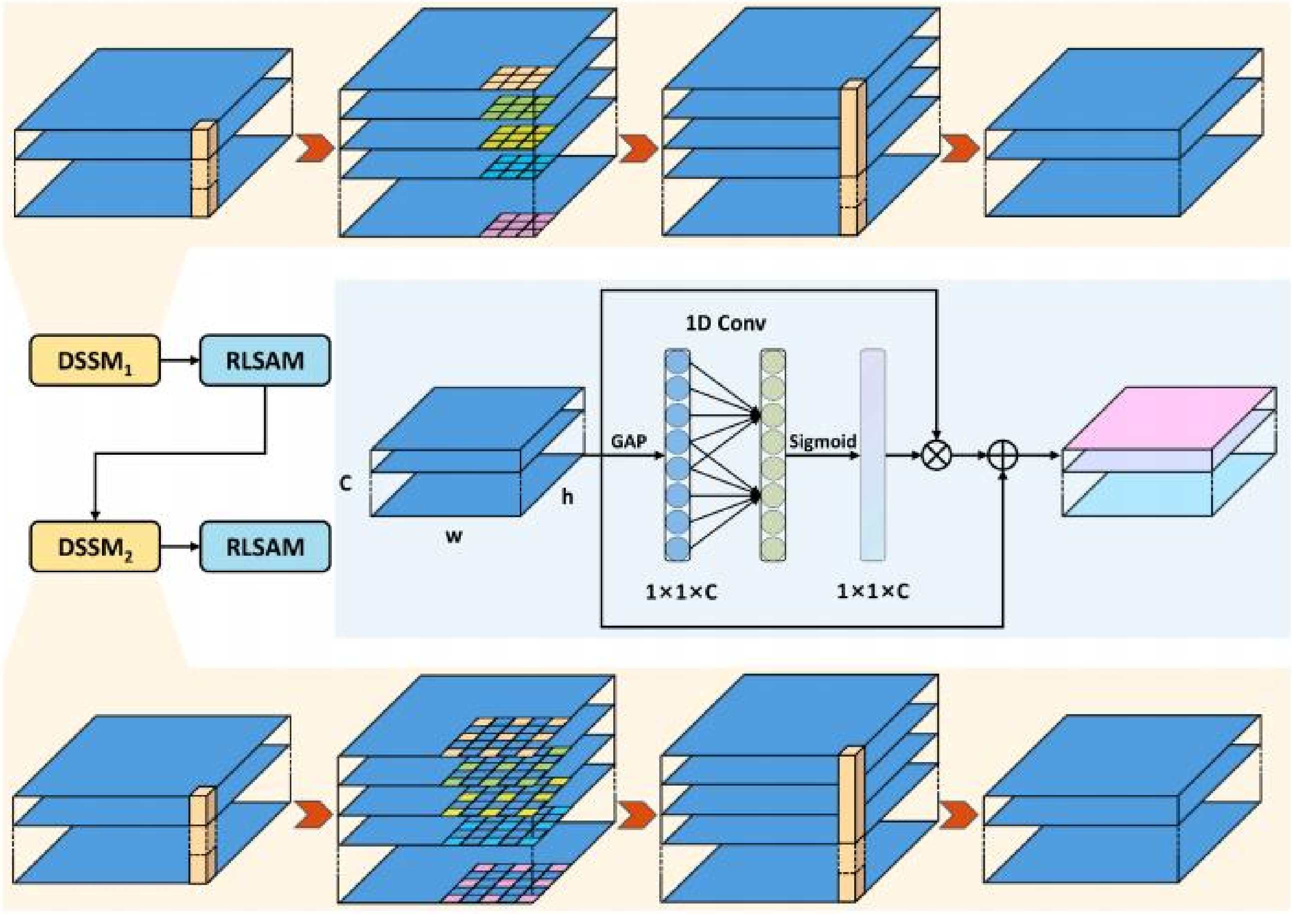

Fig. 4. The structure of ESSG in HSRPN.

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- 1.DSSM: Modules that convert spatial to spectral domain data, extracting deep spectral features.
- 2.RLSAM: An attention module focusing on important spectral features for image reconstruction.
- 3.GAP: Reduces spatial dimensions and summarizes features globally.
- 4.1D Conv: Prepares features post-GAP for attention weighting.
- 5.Sigmoid: Adjusts feature map focus with weights between 0 and 1.

summary

- Reducing Computational Complexity: EUNet lowers feature learning difficulty and computational complexity through disentangled spatial-spectral representation and a lightweight spectral attention mechanism, valuable for projects with limited hardware resources.

- Preserving Spectral Information: Essential for analyzing and identifying material characteristics, EUNet focuses on maintaining spectral information while enhancing spatial resolution, crucial for preventing spectral data loss during the super-resolution process.