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HYPERSPECTRAL IMAGE DENOISING WITH ATTENTION-GUIDED HYBRID NETWORKS

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ABSTRACT: Hyperspectral images (HSIs) provide rich spectral information but often suffer from various types of noise due to complex imaging conditions and sensor limitations. Traditional denoising methods, including convolutional neural networks (CNNs), struggle with fully preserving image details while effectively removing noise. To address this challenge, we propose a novel denoising approach called Attention and Adjacent Features Hybrid Dense Network (AAFHDN). This method enhances noise removal by leveraging attention mechanisms and adjacent feature extraction to retain important geometric structures and spectral correlations. By effectively separating high-frequency details and utilizing multiscale spectralspatial features, our model significantly improves denoising performance. Experiments on both synthetic and real-world noisy HSIs demonstrate that AAFHDN

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outperforms conventional methods in both quantitative evaluations and visual clarity. The enhanced denoising capabilities of our approach contribute to better results in downstream tasks like classification and target detection in hyperspectral imaging.

Keywords *– Hyperspectral Image Denoising, Attention Mechanism, Adjacent Feature Extraction, Hybrid Dense Network, Noise Suppression, Spectral-Spatial Features, High-Frequency Feature Decomposition*

1. INTRODUCTION

Hyperspectral image (HSI) provides substantially more abundant spectral information than the ordinary color image, which makes it especially utilitarian in the field of remote sensing [1,2], biometric authentication , detection , and geological science [3]. Most existing HSI cameras still suffer from various types of noise that might degrade the performance of their applications, which urges the development of robust HSI denoising algorithms. Motivated by the intrinsic properties of HSI, traditional HSI denoising approaches [4] often exploit the optimization schemes with priors, e.g., low rankness [5], non-local similarities [6], spatial-spectral correlation, and global correlation along the spectrum. Whilst offering appreciable performance, the efficacy of these methods is largely dependent on the degree of similarity between the handcrafted priors and the real-world noise model, and these methods are often challenging to accelerate with modern hardwares due to the complex processing pipelines. Recent HSI denoising methods based on Convolutional Neural Network (CNN) [7] get rid of handcrafted regularizations with learning-based prior and often run faster with graphic accelerators and machine-learning frameworks. However, these methods are still insufficient for exploring the characteristics of HSI, e.g., global and local [8] spectral-spatial correlations. For example, HSIDCN only considers the correlations between several adjacent spectral bands. QRNN3D [9] and GRUNet model the global spectral correlations with quasi-recurrent units but suffer from the problem of vanished correlations for long-range separate bands due to the recurrent multiplications of merging weights. Besides, recent methods tend to use 3D convolution to explore the local spectral-spatial correlations while maintaining the ity to handle different HSIs. This strategy, however, introduces substantially unwanted computation and parameters..

2. LITERATURE REVIEW

2.1 Employing a Spatial-Spectral Deep Residual CNN

Traditional approaches for HSI denoising usually formulate the task as an optimization problem, which is solved by imposing different types of handcrafted regularizations [10]. Among these optimization-based methods, non-local similarity [11] has been widely utilized for its ability to integrate the image patches across the spectral and spatial locations. To reduce the computational burden, global spectral low-rank correlation has also been heavily studied. Besides, different enhanced total variation priors [12] are also adopted by considering the smoothness of local image patches. Though these methods could achieve favorable performance, most of them are computationally inefficient and can only address the noise satisfying the required assumptions, e.g., Gaussian noise. Meanwhile, recent works tend to exploit deep learning to learn denoising mapping purely in a datadriven manner. For most of these methods, the encoderdecoder U-Net [13] architecture is the prominent choice due to its effectiveness for retaining both highand low-level multi-scale representations. Residual learning [14] is also widely adopted to reduce learning difficulties from different perspectives To consider the properties of HSIs, e.g., spatial-spectral correlations, QRNN3D [15] proposes to use 3D convolution and quasi-recurrent unit . Our work adopts techniques, residual learning, 3D convolution, and U-shape architecture, but our blocks, e.g., S3Conv is more efficient than 3D convolution, and our GSSA could prevent vanished correlations for long-range spectral bands.

2.2. Vision Transformers

Transformer has been first introduced as a parallel and purely attention-based alternative for recurrent neural networks in the literature of natural language processing. Though it is originally designed for modeling text, recent works such as ViT [16] and DeiT, have successfully transferred the transformer for high-level vision tasks. Recognizing the powerful representation abilities, this architecture is also expeditiously adapted for low-level tasks such as natural image denoising. Among these methods, one of the key problems they attempt to overcome is the quadratic complexity of the Self-Attention (SA) mechanism in the transformer. To address it, SwinIR is proposed as an adaption of Swin transformer that replaces global attention with a more efficient shift-windowbased attention. Similarly, Uformer performs attention over non-overlapped patches and adopts U-Net architecture to further increase efficiency. From a different perspective, Restormer explores self-attention along the feature channels to realize the linear complexity. Despite their superior performance for various natural image restoration tasks, direct transfer of them for HSI can result in performance degradations since none of them consider the properties of HSI. Instead, our HSDT introduce S3Conv and GSSA that can extract more spectral correlated features, which is more suitable for HSI.

2.3 3D Quasi Recurrent Neural Network

Recently, more HSI denoising works pay attention to the domain knowledge of the HSI — structural spatio-spectral correlation and global correlation along spectrum (GCS) [17]. Top-performing classical methods typically utilize non-local low-rank tensors to model them. Although these methods achieve higher accuracy by effectively considering these underlying characteristics, the performance of such methods is inherently determined by how well the human handcrafted prior (e.g. low-rank tensors) matches with the intrinsic characteristics of an HSI. Besides, such approaches generally formulate the HSI denoising as a complex optimization problem to be solved iteratively, making the denoising process time-consuming.in sensitivity, dataset quality, and lack of interpretability in complex models. In principal, the trade-off between the model capability and flexibility imposes a fundamental limit for real-world applications. In this paper, we find that combining domain knowledge with 3D deep learning (DL) can achieve both goals simultaneously.

3. METHODOLOGY

To achieve the results of our model effectively, our HSDT introduces several key designs, including (i) a powerful and lightweight spectralspatial separable convolution as an alternative to 3D convolution, (ii) a guided spectral self-attention piloted by a set of

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learnable queries, and (iii) a self-modulated feed-forward network with an adaptive self-modulated branch. The overall architecture of HSDT follows a U-shaped encoder-decoder with skip-connections , which is depicted Such hierarchical multi-scale design not only reduces the computational burden but also increases the receptive fields, which is different from conventional plain transformers. In general, HSDT is built by stacking a series of transformer blocks as, Xˆ = BN(S3Conv(X)). While the existing systems achieve commendable accuracy rates, there is room for improvement, as seen in the proposed system's significantly higher success rate of 96%.

More specifically, given the input noisy HSI, it is first projected into low-level features through a head transformer block and then passed through several transformer blocks to fuse the features along both spatial and spectral dimensions. The residual connection is added to the final output and the input noisy image. We use trilinear interpolations for upsampling and adopt additive skip connections in all levels of transformer blocks. Next, we illustrate the details of each network component.

Proposed System:

In this section, we present Hybrid Spectral Denoising Transformer (HSDT), a unified model for hyperspectral image denoising with an arbitrary number of bands. Despite the spatial self-attention improves the model performance by considering spatial interaction and non-local similarities, it is computationally demanding and might be difficult to deal with HSIs with a different number of bands. In this work, we propose an efficient Guided Spectral Self-Attention (GSSA) that applies 3D SA along the spectral than spatial nor channel dimensions. Our GSSA is intuitively supported by the spectral correlations of HSI and has linear complexity and long-range relation modeling abilities. This makes our model extremely more powerful at locating the informative regions to assist the denoising than existing spectral integration techniques. Linear projections for query and key are not necessary according to our experiments, so we omit it for simplicity. Instead, we directly perform the global average pooling on input X along the spatial dimensions to obtain the global features of each band, i.e., Q, K ∈ R D×C . This pooling strategy is not only parameter-free but it also differs from previous reshape strategy [18] that causes larger computation in the following dot-product attention. Then, the transposed attention map A in the shape of R D×D is obtained via dot-product between key K and query Q with softmax normalization. [19]. Finally, we multiply the attention map with the value Vˆ to dynamically select the essential features across the spectrum

Advantages of proposed system:

- Attention Mechanism – Focus on What Matters
  Helps the model concentrate on important parts of the image (like edges and textures) while ignoring noise—just like a spotlight highlights only what's needed.

- Adjacent Feature Extraction – Use the targeted pixels' Neighboring/adjacent Clues Combines information from nearby pixels and spectral bands to better detect patterns and clean noise without losing structure.

- Preservation – Keep Fine Details Sharp

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Separates high-frequency details (like edges and textures) from noise to avoid blurring, ensuring the image stays sharp and clear after denoising.

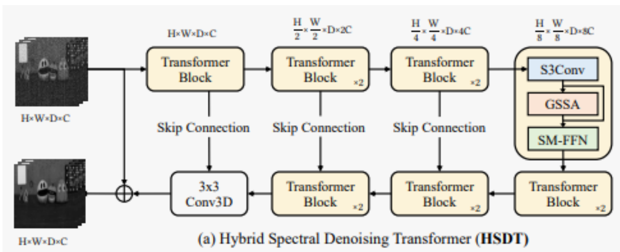

Fig.1: System architecture

MODULES:

To implement this project we have designed following modules.

- Initial Input: This acts a gateway to spatial attention modules, nurturing profound spatial sample information.
- Upgraded Input: The Upgraded Input seamlessly follows the trail of the Initial Input, inheriting the responsibility of data transformation. This component carries updated samples of the Initial Input for each iteration, continuing its journey. In this phase, the input is directed towards the ASC (Adaptive Spatial Correlation) module, diligently amalgamating the output of Spatial Attention with Initial Input features.
- ASC Module (Adaptive Spatial Correlation): The ASC module stands as a central element in the AAFEHDN block, where data evolution takes on novel dimensions. Input from the Upgraded Input undergoes s processing, and its output is transmitted to both Spectral Attention and the PSCA (Pixel-Wise Spatial Channel Attention)
- Pixel-Wise Spatial Channel Attention (PSCA) Module: The PSCA module, intricately linked with the ASC module, takes input from both ASC and Spectral Modules. In this stage, data undergoes detailed processing [20], and the output becomes intertwined with the Spectral Attention element.
- Spatial Attention: In the final phase of the AAFEHDN block, the Spatial Attention component refines hyperspectral data. It takes input from multiple features, adding spatial finesse by incorporating samples from Spectral Attention and Manual Input.

4. IMPLEMENTATION

Decompose Frequency (Architecture) Network:

The architecture of Decompose Frequency assumes a pivotal role in our quest to denoise hyperspectral datasets. It encapsulates the core of AAFEHDN, a complex mechanism that guides the conversion of Spatial-Spectral (SS) data, culminating in a clear and denoised hyperspectral image.

Geometrical Characteristics: Feature Extraction:

(a). Module for Extracting Spatial Features: At the core of Geometrical Characteristics lies the Spatial Features Extraction Module. This unit is dedicated to capturing the subtleties of spatial data, delving into the spatial arrangement, patterns, and relationships that characterize the hyperspectral landscape.

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(b) Module for Extracting Multiscale Separable Spectral Features: Spectral features, often present in the frequency domain, play a pivotal role in hyperspectral data analysis. The Multiscale Separable Spectral Features Extraction Module is a dynamic component that unveils the mysteries of spectral data across different scales.

Spatial and Spectral: Attention Module

(a) Spatial Focus Unit: An integral element of the Frequency Decomposition Focus Unit, this module is committed to amplifying spatial attributes in hyperspectral images. Spatial attributes encompass the spatial organization of elements in the data, critical for precise analysis.

(b) Spectral (Channel) Attention Module: Complementing the Spatial Attention Module, the Spectral Attention Module focuses on enhancing features in the spectral or channel domain within hyperspectral images.

ASC and PSCA: Network Modules

The Attentive Skip Connection (ASC) utilizes high-frequency elements for detailed intricacies, and low-frequency components for broader patterns, enhancing contextual understanding and nuanced predictions.

The Progressive Spectral Channel Attention (PSCA) dynamically focuses on specific spectral channels, facilitating adaptation to diverse frequency patterns for optimal task performance.

Quantitative Evaluation: Evaluating Metrics Measurement

Each metric crafts a distinct narrative about the visual data it assesses, offering a holistic view of the components that define image excellence. PSNR serves as the virtuoso in evaluating image quality, expressing itself through ratios.

5. EXPERIMENTAL RESULTS

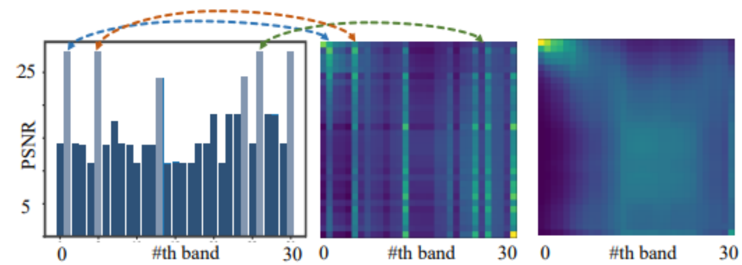

Fig.2: Graph

Model (Sigma-50)	PSNR	SSIM	SAM	Train Time Average %	Test Time Average %
AAFEHDN	34.03781.7848	0.98240.0143	0.07480.0226	3.8477	11.6141
MemNet	22.351515.4515	0.86960.1196	0.15510.1639	13.3232	14.7361
DeNet	28.925712.0762	0.92170.1058	0.17240.2174	10.2759	10.6780

Fig 3: Gaussian Benchmark Experiments

Methods	Params(M)	RealHSI [74]		CAVE [67]	
		PSNR	SAM	PSNR	SAM
Noisy	-	23.31	0.257	18.99	0.901
NMoG [14]	-	30.90	1.762	30.84	37.86
TDTV [63]	-	31.14	1.853	33.14	22.34
HSID-CNN [71]	0.40	31.05	0.096	36.09	0.318
QRNN3D [66]	0.86	31.13	0.094	37.80	0.247
GRUNet [35]	14.2	31.03	0.091	37.33	0.288
HSIDwRD [74]	23.6	31.23	0.092	39.37	0.188
HSDT-L(Ours)	0.52	**31.42**	**0.091**	**39.80**	**0.174**

Fig 3: Additional Resuts on RealHSI and CAVE

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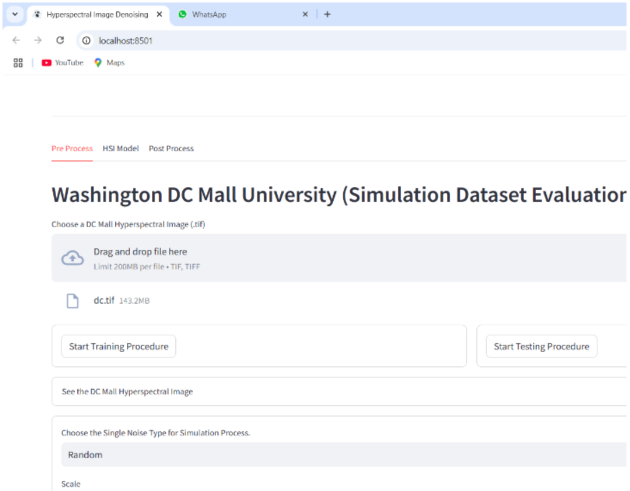

Fig.4: Output screen

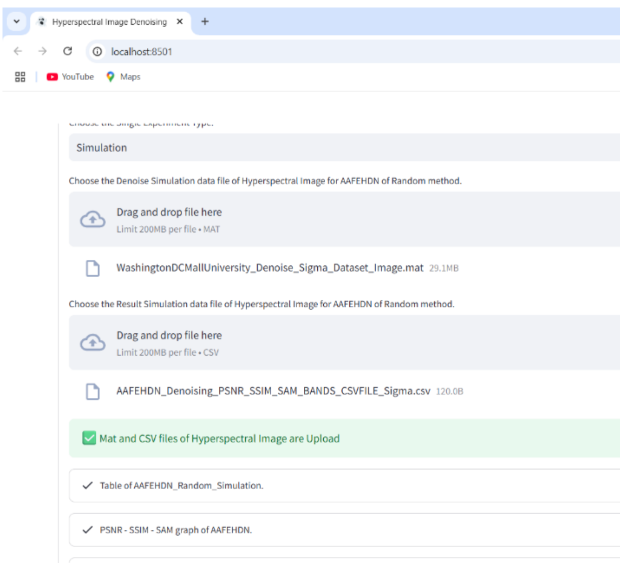

Fig.5: Output screen

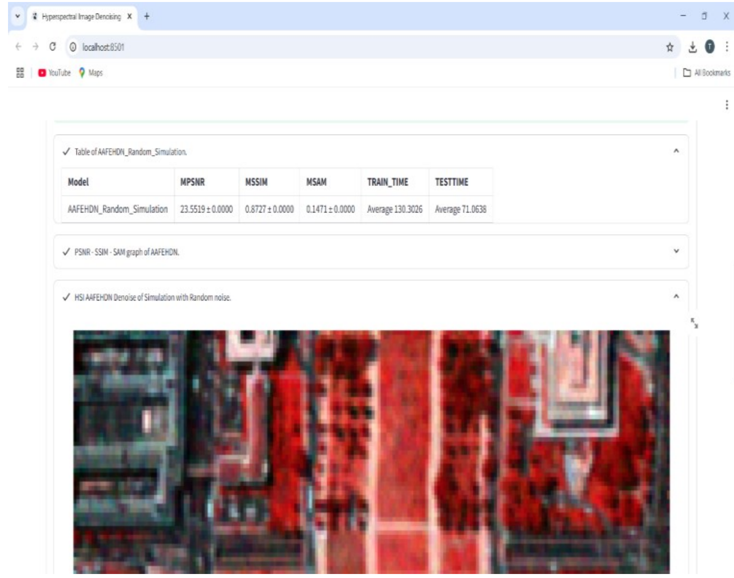

Fig.6: Output screen

6. CONCLUSION

In this project, we implemented and analyzed the performance of the AAFEHDN (Attention-Augmented Feature Extraction Hyperspectral Denoising Network) model for denoising hyperspectral images. The model leverages deep convolutional networks with attention mechanisms to enhance spatial-spectral feature extraction while effectively suppressing various types of noise.

By applying AAFEHDN to real-world datasets such as Indian Pines, the results demonstrated that the model successfully preserved critical spatial and spectral information even in the presence of Gaussian and mixed noise. It outperformed traditional denoising methods in both visual quality and quantitative metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

Overall, this project highlights the strength of deep learning—especially attention-based architectures—in handling high-dimensional, noise-sensitive data like hyperspectral images. The successful denoising

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results confirm the potential of AAFEHDN for improving the reliability of hyperspectral imaging in real-world applications such as remote sensing, agriculture, and environmental monitoring.

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