

A Spectral-Spatial Attention Network for Hyperspectral Unmixing

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Abstract—Hyperspectral unmixing, an essential and fundamental task in remote sensing, focuses on estimating endmembers (spectrally pure components) and their fractional abundances within each mixed pixel of a hyperspectral image. With the advent of deep learning (DL), which provides powerful and automated feature representations, the field of hyperspectral unmixing has made significant progress. Among DL approaches, autoencoder-based models (widely used for unsupervised learning) have shown promising results. However, most unmixing methods do not consider the noise contained in hyperspectral images, and endmembers are usually estimated by the weights of the linear layers in the decoder of these models, and their performance may be highly dependent on weight initialization, which may limit their effectiveness. In this work, we propose an automatic spectral-spatial attention unmixing network (AS-SAUN) that performs unmixing using an innovative strategy. AS-SAUN includes a deep denoising module (DDM) to filter the noise contained in the hyperspectral images and an automatic unmixing module (AUM) to estimate abundances from the output, extract endmembers in an inversion strategy instead of the weight, and reconstruct images using the multiplication of estimated endmembers and abundances. Especially, a spectral-spatial attention module (SSAM) is designed in the AUM to learn the long-distance vertical and horizontal spatial dependencies in the hyperspectral images and capture the important differences between the spectral bands. Extensive experiments on a synthetic and three real datasets show that the proposed method significantly and consistently outperforms the compared state-of-the-art methods. The full code is available at <https://github.com/xuanwentao> for public evaluation.

Index Terms—Hyperspectral unmixing, automatic unmixing module, autoencoder, deep denoising module, attention module.

I. INTRODUCTION

HYPERSPECTRAL images provide rich spectral information and intricate spatial characteristics of target scenes, making them indispensable in a wide range of applications, including environmental monitoring, mineral exploration, and precision agriculture [1]–[4]. These images capture detailed spectral signatures comprising hundreds of contiguous spectral bands, allowing an accurate identification of materials and substances in the scene.

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However, one of the inherent challenges with hyperspectral images is their low spatial resolution. A single pixel in a hyperspectral image can cover a large physical area, often ranging from tens to thousands of square meters. This large footprint leads to mixed pixels, where multiple materials are captured within a single pixel, resulting in a blurred representation of the actual scene. This spatial ambiguity, where distinct materials are blended within individual pixels, poses a significant limitation for many applications that require high spatial precision. To overcome this critical obstacle, hyperspectral unmixing techniques [5] have been developed. These methods aim to solve the mixed pixel problem by decomposing each pixel into a set of spectrally pure components, known as endmembers, and estimating their corresponding proportions, referred to as abundances.

A. Classical Unmixing Methods

The most widely used mixing model is the nonlinear mixing model (NLMM) [6]–[9] and the linear mixing model (LMM) [10]–[13]. Nonlinear spectral unmixing assumes that materials undergo multiple scattering, LMM operates under the assumption that each incident light ray interacts with a single pure material within the pixel’s instantaneous field of view before reaching the sensor, making it possible to express the spectrum of each pixel as a linear combination of a set of endmembers and their corresponding abundances. Due to its simplicity and computational efficiency, the LMM is popular compared to more complex nonlinear mixing models [14]–[16]. Hyperspectral unmixing techniques that solve the LMM can be broadly categorized into three groups: geometry-based, statistical-based, and sparse regression-based methods.

Geometry-based unmixing methods operate under the assumption that the observed spectral vectors lie within a simplex, with vertices corresponding to the endmembers, ensuring that the resulting abundances are non-negative and sum to one to provide a physically interpretable solution. Two main categories exist: pure pixel-based methods [17]–[19] and minimum volume-based methods [20]–[22]. Pure pixel-based methods assume the existence of at least one pure pixel for each endmember in the image. For example, maximum distance analysis (MDA) [18] computes the maximum distance between any pixel and the affine hull formed by previously extracted endmembers, and selects the next endmember based on this criterion. When no pure pixels are present, minimum volume-based methods aim to estimate the endmembers as vertices of a simplex with minimal volume. As an example, minimum

volume simplex analysis (MVSA) [20] minimizes the volume of the simplex enclosing the data points while constraining the abundance fractions within a probability simplex, ensuring that the resulting abundances are non-negative and sum to one.

Statistical methods describe the unmixing problem as an inference task, often within a Bayesian framework [23]–[25]. These techniques model the uncertainty of both endmembers and abundances, allowing for a more flexible and probabilistic interpretation of the results. In [23], a hierarchical Bayesian model was proposed, selecting appropriate priors to enforce non-negativity and encourage sparsity in the abundance vectors. This helped to ensure that the solution is both physically meaningful and sparse, which is often desirable in hyperspectral unmixing. [25] presented a Bayesian model and a Markov Chain Monte Carlo (MCMC) algorithm for unsupervised hyperspectral unmixing. This approach simultaneously estimates endmembers and abundances, providing a robust statistical solution to the unmixing problem.

Sparse regression-based methods tackle hyperspectral unmixing by selecting endmember candidates from a spectral library [26]–[29]. These methods exploit the fact that, in many cases, only a small subset of materials from the spectral library are present in each pixel, leading to sparse abundance representations. In [28], a spectral-spatial weighted sparse unmixing framework was proposed, which leverages both the spectral characteristics of the data and the spatial dependencies between adjacent pixels to improve the sparsity and accuracy of the unmixing solution. Similarly, a local-global sparse regression unmixing method was introduced in [29]. This method incorporates a local sparsity regularization to enhance performance by considering both local and global sparsity patterns, addressing the limitations of purely global sparsity-based methods.

B. DL-based Unmixing Methods

Recently, neural networks [30]–[33] have been widely applied to hyperspectral image analysis due to their powerful generalization and modeling capabilities, which have been significantly improved by advances in DL technology. DL-based unmixing methods [34]–[36] have increasingly become the mainstream approach for addressing the mixed pixel problem in hyperspectral remote sensing. Traditional unmixing algorithms require manual parameter setting or rely on strict mathematical assumptions, but deep learning leverages the ability of neural networks to learn complex representations, making them particularly suitable for tasks such as hyperspectral unmixing. A notable unsupervised approach that has attracted attention is the autoencoder framework. Autoencoders are designed with an encoder-decoder architecture, where the encoder reduces the dimensionality of the input data and the decoder reconstructs the original data from the learned representations. This has proven successful in hyperspectral unmixing by automatically learning low-dimensional representations (i.e., the abundances) and reconstructing the original data using a corresponding basis (i.e., the endmembers). In [37], Hua *et al.* proposed an autoencoder network with adaptive abundance smoothing (AAS) that employs a

multi-layer encoder to infer the abundances, and a single-layer decoder to reconstruct the hyperspectral image. The approach incorporates spatial-contextual information to handle outliers and adaptively adjusting for each pixel. Similarly, in [38], Su *et al.* developed a deep autoencoder network that uses stacked autoencoders (SAEs) to provide a good initialization for the unmixing task. This model also integrates a variational autoencoder (VAE) to simultaneously estimate the endmember signatures and abundance fractions, offering a more robust unmixing solution. However, most autoencoder-based approaches tend to focus solely on capturing spectral information and overlook the spatial relationships between different pixels. This limitation may hinder the full exploitation of spatial-contextual information, which is crucial for accurate unmixing in scenarios where spatial continuity or homogeneity plays a significant role.

Recently, convolutional neural networks (CNNs) have shown significant progress in hyperspectral image processing by incorporating both 2D or 3D convolutions to effectively learn spatial and spectral information simultaneously. The ability of CNNs to capture both local spatial patterns and spectral features has stimulated the development of many innovative unmixing methods [34], [35], [39]–[43]. In particular, convolutional neural network autoencoder unmixing (CNNAEU) [40] exploited the inherent spatial and spectral structures of hyperspectral images to estimate both endmembers and abundances. Unlike traditional CNN architectures that rely on pooling or upsampling layers, CNNAEU processes image patches directly, preserving the spatial structure throughout the network. This allows abundance maps to be generated as feature maps from hidden convolutional layers, preserving detailed spatial relationships during unmixing. The cross-convolution unmixing network (CrossCUN) [34] is a hybrid approach, combining both 3D and 2D convolutions for a more efficient feature extraction. The multi-stage convolutional autoencoder network (MSNet) [35] employs a multi-stage approach to acquire long-range dependencies and high-level contextual information without losing fine spatial details. The network consists of three sub-stages of CNN autoencoders. The first two stages extract broad information and capture long-range dependencies through multi-stage downsampling operations, while the final stage operates at the original resolution to preserve fine spatial details. Although CNN-based unmixing methods have shown significant improvements, the limited receptive field of the traditional CNN limits its ability to capture the global distribution of features across the entire scene.

Very recently, inspired by the remarkable ability of the attention mechanism to capture long-range dependencies in images [44]–[46], several techniques have been proposed that use attention to improve the extraction of spatial and spectral features from hyperspectral data for hyperspectral unmixing [47]–[53]. In [47], a new attention mechanism called multi-head self-patch attention was proposed that employs the long-range dependencies between patches for performing hyperspectral unmixing. In [52], a unidirectional local-attention autoencoder network (ULA-Net) was introduced to effectively capture and utilize discriminative local spatial-spectral information

while addressing spectral variability. ULA-Net successfully addresses the challenges of high computational complexity and slow convergence often encountered when dealing with global information. In [54], the authors proposed a graph attention convolutional autoencoder (GACAE), which employs graph attention convolution to learn the global spatial relationships within hyperspectral data for unsupervised unmixing.

C. Motivations and Contributions

Despite the advances made by autoencoders, CNNs, and attention-based unmixing methods, most decoders estimate the endmembers as weights of a linear layer. To initialize these weights, many methods still rely on techniques such as VCA. Consequently, they face three primary challenges: (1) Existing methods cannot be easily generalized to nonlinear unmixing. Because the dataset is linearly reconstructed, a nonlinear transformation is required to accurately reconstruct the input hyperspectral image, and there is no guarantee that the estimated abundances and endmembers will be correct. (2) The endmembers estimated by VCA are non-unique, as each run produces a different set of endmembers. This randomness is then transferred to networks that initialize decoder weights with VCA's output, impacting the final unmixing performance. (3) The previous unmixing methods do not consider the noise contained in the original hyperspectral images, which will affect the performance of the subsequent unmixing. Although some mature denoising algorithms [55], [56] have been proposed, using them as a priori algorithms will constrain the performance of the unmixing algorithm. To accurately estimate both endmembers and abundances while overcoming these challenges, we propose an automatic spectral-spatial attention unmixing network (ASSAUN) for hyperspectral unmixing. The key innovative contributions of this work can be summarized as follows:

- We propose a novel AUM to directly estimate endmembers instead of weights using an inversion strategy. This not only estimates endmembers from the network but also avoids introducing the randomness of other methods into the network.
- We propose a DDM to filter out noise from hyperspectral images, allowing for the generation of clean, reconstructed images. To the best of our knowledge, this not only provides a promising direction for addressing nonlinear unmixing challenges but also represents the first attempt in the literature to include a separate module for denoising, thereby significantly improving the unmixing performance.
- We design a SSAM into AUM to enhance the performance of unmixing. The SSAM is designed to learn the long-distance vertical and horizontal spatial dependencies in the hyperspectral images and capture the important differences between the spectral bands.

The remainder of this article is structured as follows. Section II describes the related work. Section III elaborates the proposed ASSAUN method. Section IV evaluates the proposed method on synthetic and real hyperspectral datasets. Section V provides relevant discussions, evaluating the effect of the

proposed strategy. Finally, the conclusion is given in Section VI.

II. RELATED WORK

A. Linear Mixture Model (LMM)

In linear hyperspectral unmixing, the observed spectral reflectance at each pixel of a hyperspectral image is assumed to be a linear combination of pure spectral signatures, known as endmembers, and their corresponding proportions, referred to as abundances. This relationship can be formulated as:

$$\mathbf{X} = \mathbf{M}\mathbf{A} + \mathbf{N}, \quad (1)$$

where $\mathbf{X} \in \mathbb{R}^{Nb \times Np}$ represents the hyperspectral image with Nb bands and Np pixels, $\mathbf{M} \in \mathbb{R}^{Nb \times c}$ is the endmember matrix, in which each column corresponds to the spectral signature of an endmember, and c is the number of endmembers. $\mathbf{A} \in \mathbb{R}^{c \times Np}$ denotes the abundance matrix, in which each element a_{ij} represents the proportion (or abundance) of the i -th endmember in the j -th pixel. \mathbf{N} is additive noise. Generally, the abundance matrix satisfies two physical constraints, i.e., the abundance nonnegative constraint (ANC) and the abundance sum-to-one constraint (ASC), which can be expressed as:

$$\text{ANC} : a_{ij} \geq 0; \forall i, j, \quad (2)$$

and

$$\text{ASC} : \sum_{i=1}^c a_{ij} = 1; \forall j. \quad (3)$$

B. Autoencoder

An autoencoder is a type of unsupervised neural network that aims to learn compact, low-dimensional representations of input data and that is commonly applied to tasks such as dimensionality reduction, feature extraction, and data reconstruction. The fundamental architecture of an autoencoder consists of two primary components: an encoder and a decoder.

The encoder compresses the input data \mathbf{X} into a latent space representation \mathbf{Y} , effectively reducing the dimensionality while preserving the most salient information. This process can be mathematically represented as:

$$\mathbf{Y} = f(\mathbf{X}; \mathbf{W}, \mathbf{b}), \quad (4)$$

where f is the activation function of the encoder, typically a non-linear function such as rectified linear unit (ReLU) or sigmoid, and \mathbf{W} and \mathbf{b} represent the learnable weights and biases of the encoder, respectively. The decoder is used to reconstruct the input from the latent representation:

$$\hat{\mathbf{X}} = g(\mathbf{Y}; \tilde{\mathbf{W}}, \tilde{\mathbf{b}}), \quad (5)$$

where g is the activation function of the decoder, and $\tilde{\mathbf{W}}$ and $\tilde{\mathbf{b}}$ are its weights and biases. The objective of the decoder is to generate a reconstruction $\hat{\mathbf{X}}$ that closely approximates the original input \mathbf{X} , capturing the underlying structure of the data. The overall learning process of the autoencoder is driven by the minimization of the reconstruction loss, which measures the difference between the input \mathbf{X} and its reconstruction $\hat{\mathbf{X}}$. The loss is typically formulated by the mean squared error

(MSE) or by other loss functions such as binary cross-entropy and spectral angle distance, depending on the nature of the data. In summary, the autoencoder learns to map the input data to a compressed representation and to reconstruct it effectively, thus capturing key patterns and dependencies in the data.

C. Self-Attention Mechanism

The self-attention mechanism has emerged as a crucial concept in DL, especially in tasks involving sequential or structured data, such as natural language processing and image analysis. This attention mechanism allows models to focus on specific parts of the input data, effectively capturing both local and global dependencies.

Typically, the input to the self-attention mechanism consists of three main components, i.e., query Q , key K , and value V . These components are derived from the same input sequence, allowing the model to dynamically assess the relationships between different parts of the data. The attention scores are calculated by taking the matrix multiplication of the query and the transpose of the key:

$$\mathbf{Att} = \mathbf{QK}^T, \quad (6)$$

This operation produces a scoring matrix that quantifies how much attention each element of the input data should receive relative to others. To ensure that the attention scores are interpretable and stable, they are typically normalized using the *Softmax* function. This step converts the raw scores into a probability distribution, effectively emphasizing the most relevant parts of the input:

$$\begin{aligned} \mathbf{Att}_{\text{norm}} &= \text{Softmax}\left(\frac{\mathbf{Att}}{\sqrt{d}}\right) \\ &= \text{Softmax}\left(\frac{\mathbf{QK}^T}{\sqrt{d}}\right), \end{aligned} \quad (7)$$

where d is the dimension of \mathbf{Q} and \mathbf{K} . The final output of the self-attention mechanism is obtained by weighting the value vectors \mathbf{V} with the normalized attention scores:

$$\mathbf{Z} = \mathbf{Att}_{\text{norm}} \mathbf{V} = \text{Softmax}\left(\frac{\mathbf{QK}^T}{\sqrt{d}}\right) \mathbf{V}, \quad (8)$$

where \mathbf{Z} represents the final output of the attention layer, capturing the important features of the input while filtering out irrelevant information.

III. PROPOSED METHOD

The proposed approach (ASSAUN) includes a novel DDM to filter the noise in the hyperspectral images, followed by an AUM that automatically estimates the abundances and endmembers and simultaneously completes the image reconstruction. To improve performance, a novel SSAM is embedded in the AUM. Fig. 1 shows the architecture of the proposed ASSAUN. The three modules are further elaborated below.

A. Deep Denoising Module

In general, most existing unmixing methods consider the autoencoder (subsection II-B) as the main backbone of the networks to perform abundance estimation and endmember extraction. Noise seriously hinders network robustness and unmixing accuracy, but is usually not taken into account. To this end, we design a DDM to pre-filter noise in hyperspectral images, ensuring cleaner data for further analysis and improving overall unmixing performance.

The proposed DDM uses autoencoder as the core framework, including several encoder-decoder layers that gradually compress and reconstruct the input image while skip connections combine the different encoders and decoders to preserve high-level spatial and spectral features across different network stages.

The input of DDM is a 3D hyperspectral image $\mathbb{X} \in \mathbb{R}^{Nb \times Nx \times Ny}$ with spatial dimensions Nx and Ny (width and height), and the number of spectral bands Nb . A first encoder block transforms the input image to $\mathbb{E}_1 \in \mathbb{R}^{dim \times Nx \times Ny}$:

$$\mathbb{E}_1 = \text{ReLU}(\text{BN}(\text{Conv}(\mathbb{X}))), \quad (9)$$

where Conv denotes the 2D convolutional operation with dim kernels of size 3×3 (in our experiment, $dim = 32$), BN stands for batch normalization, and ReLU is the activation function.

Then, a two-times iteration of a combination of a downsampling and an encoder block follow. For $i = 1, 2$:

$$\begin{aligned} \mathbb{F}_i^{(E)} &= \text{Downsampling}(\text{Conv}(\mathbb{E}_i)) \\ \mathbb{E}_{i+1} &= \text{ReLU}(\text{BN}(\text{Conv}(\mathbb{F}_i^{(E)}))) \end{aligned} \quad (10)$$

where downsampling by max-pooling is performed, hereby reducing the spatial dimensions by a factor of 2, and doubling the number of channels (i.e., $2 * i * dim$ filters are applied).

The decoder reverses the operations performed by the encoder, gradually reconstructing the denoised image while restoring the original spatial dimensions. Starting from the deepest encoder output $\mathbb{E}_3 = \mathbb{D}_3$, a combination of an upsampling and a decoder block is performed twice. For $i = 2, 1$:

$$\begin{aligned} \mathbb{F}_i^{(D)} &= \text{Upsampling}(\text{Conv}(\mathbb{D}_{i+1})) \\ \mathbb{D}_i &= \text{ReLU}(\text{BN}(\text{Conv}(\mathbb{E}_i + \mathbb{F}_i^{(D)}))). \end{aligned} \quad (11)$$

In this case, upsampling restores the spatial dimensions, each time enlarging the spatial dimensions by a factor of 2, and halving the number of channels (i.e., $i * dim$ filters are applied). To ensure that fine-grained features from the encoder are preserved during reconstruction, skip connections are applied between the corresponding encoder and decoder layers to obtain $\mathbb{E}_i + \mathbb{F}_i^{(D)}$.

After the decoding process, a final 2D convolutional layer is applied to map the features back to the original number of spectral bands Nb , and the output is combined with the input \mathbb{X} to produce the final denoised hyperspectral image:

$$\hat{\mathbb{X}}_1 = \text{Conv}(\mathbb{D}_1) + \mathbb{X}, \quad (12)$$

where $\hat{\mathbb{X}}_1 \in \mathbb{R}^{Nb \times Nx \times Ny}$. This additive operation ensures noise removal while preserving both the spectral and spatial details from the input hyperspectral data.

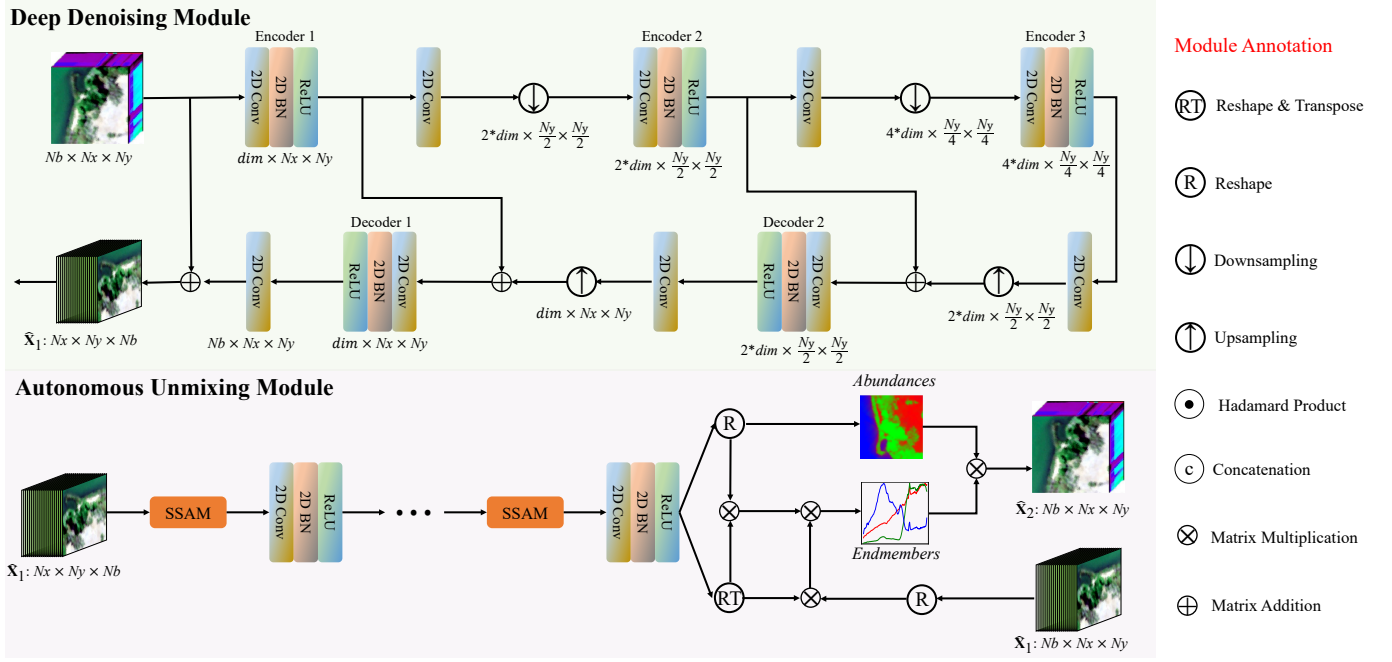


Fig. 1. Architecture of the proposed automatic spectral-spatial attention unmixing network (ASSAUN), containing a deep denoising module (DDM) and an automatic unmixing module (AUM). The designed spectral-spatial attention module (SSAM) is embedded into AUM to enhance vital spectral-spatial features.

B. Automatic Unmixing Module

The denoised image $\hat{\mathbf{A}}_0 = \hat{\mathbf{X}}_1$ is the input of the AUM. AUM performs a sequence of blocks, each of them containing our newly developed spectral-spatial attention module SSAM (see subsection III-C) along with a convolutional layer with a decreasing number of kernels. In this work, 4 blocks are applied with respectively 128, 64, 32, and c kernels. The convolution layers also contain batch normalization and ReLU. The output $\hat{\mathbf{A}}_l$ of the l -th block is given by:

$$\hat{\mathbf{A}}_l = \text{ReLU}(\text{BN}(\text{Conv}(\text{SSAM}(\hat{\mathbf{A}}_{l-1})))), \quad (13)$$

The final estimated abundance maps $\hat{\mathbf{A}}$ is given by the output $\hat{\mathbf{A}}_4 \in \mathbb{R}^{c \times N_x \times N_y}$ of layer 4 (with c nodes).

The abundance maps are then reshaped into matrices of size $(c \times (N_x \times N_y))$:

$$\hat{\mathbf{A}} = \text{Reshape}(\hat{\mathbf{A}}) \quad (14)$$

where $\hat{\mathbf{A}} \in \mathbb{R}^{c \times N_p}$, with $N_p = N_x \times N_y$. Similarly, $\hat{\mathbf{X}}_1$ is reshaped:

$$\hat{\mathbf{X}}_1 = \text{Reshape}(\hat{\mathbf{X}}_1), \quad (15)$$

where $\hat{\mathbf{X}}_1 \in \mathbb{R}^{N_b \times N_p}$.

Under the assumption that the reconstructed image $\hat{\mathbf{X}}_1$ is clean, Eq. (1) becomes:

$$\hat{\mathbf{X}}_1 = \hat{\mathbf{M}}\hat{\mathbf{A}}, \quad (16)$$

where $\hat{\mathbf{M}} \in \mathbb{R}^{N_b \times c}$ is the endmember matrix that needs to be estimated. A direct estimation is obtained by inverting Eq. (16):

$$\hat{\mathbf{M}} = \hat{\mathbf{X}}_1 \hat{\mathbf{A}}^T (\hat{\mathbf{A}} \hat{\mathbf{A}}^T)^{-1}, \quad (17)$$

where the symbol ' $^{-1}$ ' denotes a matrix inversion. From the estimated $\hat{\mathbf{A}}$ and $\hat{\mathbf{M}}$, a final reconstructed image $\hat{\mathbf{X}}_2$ can be obtained as:

$$\begin{aligned} \hat{\mathbf{X}}_2 &= \hat{\mathbf{M}}\hat{\mathbf{A}} \\ &= \hat{\mathbf{X}}_1 \hat{\mathbf{A}}^T (\hat{\mathbf{A}} \hat{\mathbf{A}}^T)^{-1} \hat{\mathbf{A}}. \end{aligned} \quad (18)$$

C. Spectral-Spatial Attention Module

The performance of the unmixing process can be enhanced by improving on the spectral-spatial feature extraction. For this, a spectral-spatial attention module is designed and embedded in the AUM. The module contains a spectral attention module, a spatial attention module and a fusion of both. The architecture of the proposed SSAM is presented in Fig. 2.

1) *Spectral Attention Module*: The spectral attention focuses on capturing the dependencies between different feature channels. This attention mechanism re-calibrates the input feature maps by focusing on the most relevant channels. Assuming that the feature map of one hidden layer is $\mathbb{F} \in \mathbb{R}^{B \times W \times H}$ with B channels, where W is the width and H is the height. Query, key and value matrices are initially identical and computed as follows:

$$\begin{aligned} \mathbf{Q} &= \text{Reshape}(\mathbb{F}) \in \mathbb{R}^{B \times WH}; \\ \mathbf{K} &= \text{Reshape}(\mathbb{F}) \in \mathbb{R}^{B \times WH}; \\ \mathbf{V} &= \text{Reshape}(\mathbb{F}) \in \mathbb{R}^{B \times WH}, \end{aligned} \quad (19)$$

The matrices \mathbf{Q} and \mathbf{K} are used to compute an attention map $\mathbf{A}_{\text{Spe}} \in \mathbb{R}^{B \times B}$ as follows:

$$\mathbf{A}_{\text{Spe}} = \text{Softmax}(\mathbf{Q}\mathbf{K}^T), \quad (20)$$

where T denotes the transpose operation. \mathbf{A}_{Spe} represents the attention weights across channels, capturing the relationships

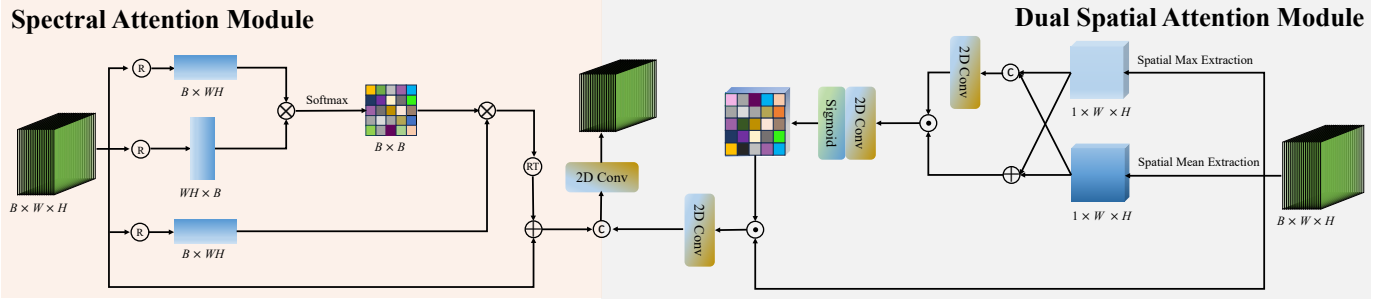


Fig. 2. Architecture of the SSAM, containing a spectral attention module and an dual spatial attention module.

between different feature channels in the input. Next, channel attention is applied to the attention map \mathbf{A}_{Spe} by multiplying it with the value matrix \mathbf{V} to produce the feature map $\mathbf{F}_{Spe} \in \mathbb{R}^{B \times WH}$:

$$\mathbf{F}_{Spe} = \mathbf{A}_{Spe} \mathbf{V}, \quad (21)$$

Finally, the output of the spectral attention module is obtained by reshaping \mathbf{F}_{Spe} back to its original spatial dimensions and adding it to the original input feature map:

$$\mathbb{F}_{Spe} = \alpha \text{Reshape}(\mathbf{F}_{Spe}) + \mathbb{F}, \quad (22)$$

where $\mathbb{F}_{Spe} \in \mathbb{R}^{B \times W \times H}$ and α is a learnable scaling parameter, initialized to zero.

2) *Dual Spatial Attention Module*: Spatial attention mechanisms play a crucial role in enhancing the performance of neural networks by focusing on the most informative parts of an input feature map. In this work, we introduce a dual spatial attention module that effectively utilizes both maxpooling and meanpooling to capture a comprehensive representation of the input features, identifying the most salient features and the average contextual information, respectively across the spatial domain.

Let $\mathbb{F} \in \mathbb{R}^{B \times W \times H}$ be the input feature map from a hidden layer. Maxpooling and meanpooling are performed along the channel dimension to distill the feature map into two distinct forms: \mathbb{F}_{max} , capturing the most pronounced features by computing the maximum value across the channels and \mathbb{F}_{mean} , providing an average overview of the channels, thereby preserving the contextual information:

$$\begin{aligned} \mathbb{F}_{max}(1, W, H) &= \text{Maxpooling}(\mathbb{F}(B, W, H)); \\ \mathbb{F}_{mean}(1, W, H) &= \text{Meanpooling}(\mathbb{F}(B, W, H)); \end{aligned} \quad (23)$$

The module then synthesizes $\mathbb{F}_{max} \in \mathbb{R}^{1 \times W \times H}$ and $\mathbb{F}_{mean} \in \mathbb{R}^{1 \times W \times H}$, using both concatenation and summation. This dual approach forms robust spatial attention signals that integrate the distinct characteristics of the max and mean pooled features:

$$\begin{aligned} \mathbf{A}_{cat} &= \text{Conv}(\text{Concatenate}(\mathbb{F}_{max}, \mathbb{F}_{mean})); \\ \mathbf{A}_{sum} &= \text{Sum}(\mathbb{F}_{max}, \mathbb{F}_{mean}), \end{aligned} \quad (24)$$

with $\mathbf{A}_{cat} \in \mathbb{R}^{1 \times W \times H}$ (a 1×1 convolution was applied to retain the dimensionality) and $\mathbf{A}_{sum} \in \mathbb{R}^{1 \times W \times H}$. These maps are then multiplied in element-wise fashion, and a 1×1

convolution followed by a sigmoid function is applied to bound the attention weights between 0 and 1:

$$\mathbf{A}_{Spa} = \text{Sigmoid}(\text{Conv}(\mathbf{A}_{cat} \odot \mathbf{A}_{sum})), \quad (25)$$

where \odot denotes the Hadamard Product. The refined attention map $\mathbf{A}_{Spa} \in \mathbb{R}^{1 \times W \times H}$ is then used to modulate the input feature map, enhancing crucial areas while subduing less relevant regions:

$$\mathbb{F}_{Spa} = \mathbf{A}_{Spa} \odot \mathbb{F}. \quad (26)$$

where $\mathbb{F}_{Spa} \in \mathbb{R}^{B \times W \times H}$ has the same dimensions as the input. This representation not only highlights significant features but also maintains a balance with the contextual background.

3) *Attention Fusion*: Since both spectral and spatial information play vital roles in capturing the characteristics of a scene, the spectral-attention feature map $\mathbb{F}_{Spe} \in \mathbb{R}^{B \times W \times H}$ and the spatial-attention feature map $\mathbb{F}_{Spa} \in \mathbb{R}^{B \times W \times H}$ are concatenated along the channel dimension. To reduce the number of channels back to B , a 1×1 convolution is applied to the concatenated feature map:

$$\mathbb{F}_{SSAM} = \text{Conv}(\text{Concatenate}(\mathbb{F}_{Spe}, \mathbb{F}_{Spa})), \quad (27)$$

where $\mathbb{F}_{SSAM} \in \mathbb{R}^{B \times W \times H}$ is the final feature map, enriched with information from both spectral and spatial attention mechanisms. This SSAM module is embedded in each of the layers of the AUM to enhance the spectral-spatial feature representation.

D. Loss Function

The proposed ASSAUN is an end-to-end unmixing network that combines a DDM for noise reduction and an AUM for unmixing and reconstruction of the hyperspectral image. To optimize the network, a loss function is designed that combines a reconstruction loss, a denoising loss, and an abundance loss. These losses guide the network in the tasks of learning to denoise the input data, accurately unmixing the spectral signatures, and reconstructing the hyperspectral images with improved precision. The reconstruction loss is computed by:

$$L_R = \frac{1}{N_p} \sum_{j=1}^{N_p} \arccos \frac{\mathbf{x}_j \cdot \hat{\mathbf{x}}_{2j}}{\|\mathbf{x}_j\|_2 \|\hat{\mathbf{x}}_{2j}\|_2}, \quad (28)$$

where $\mathbf{x}_j \in \mathbb{R}^{Nb \times 1}$ denotes the original hyperspectral pixel, $\hat{\mathbf{x}}_{2j} \in \mathbb{R}^{Nb \times 1}$ is the reconstructed pixel from the AUM, and

$\|\cdot\|_2$ denotes the L_2 norm. To guide the denoising module DDM, the denoising loss is defined as:

$$L_D = \frac{1}{Np} \sum_{j=1}^{Np} \arccos \frac{\mathbf{x}_j \cdot \hat{\mathbf{x}}_{1j}}{\|\mathbf{x}_j\|_2 \|\hat{\mathbf{x}}_{1j}\|_2}, \quad (29)$$

where $\hat{\mathbf{x}}_{1j} \in \mathbb{R}^{Nb \times 1}$ represents the denoising pixel in the denoised image $\hat{\mathbf{X}}_1$ from the DDM. The abundance loss includes the ASC and ANC constraints:

$$\begin{aligned} L_{ASC} &= \frac{1}{Np} \sum_{j=1}^{Np} \left[\left(\sum_{m=1}^c \hat{a}_{mj} \right) - 1 \right]^2, \\ L_{ANC} &= \frac{1}{c \times Np} \sum_{i=1}^c \sum_{j=1}^{Np} \max(0, -\hat{a}_{mj}), \\ L_A &= L_{ASC} + L_{ANC}. \end{aligned} \quad (30)$$

where \hat{a}_{mj} is the abundance of the m -th endmember at the j -th pixel, and c is the number of endmembers.

Finally, the total loss function is defined as:

$$L = L_R + \beta L_D + \gamma L_A, \quad (31)$$

where β and γ are regularization parameters, introduced to balance the contributions of the different loss components in the optimization process. These parameters adjust the relative importance of each of the terms, allowing the network to find an optimal trade-off between accurately reconstructing the hyperspectral image and estimating the endmember signatures and the abundances.

IV. EXPERIMENTS

To evaluate the performance of the proposed ASSAUN, experiments were performed on a synthetic dataset (with different noise levels) and three real hyperspectral datasets. Three classical and four state-of-the-art DL-based unmixing methods were chosen for comparison: VCA followed by fully constrained least squares (VCA-FCLS) [57], [58], robust collaborative nonnegative matrix factorization (R-CoNMF) [59], MVSA [20], deep autoencoder unmixing (DAEU) [60], multitask autoencoder unmixing (MTAEU) [61], spectral information divergence autoencoder unmixing (SIDAEU) [62], and MSNet [35].

A. Data Descriptions

1) *Synthetic Dataset*: The proposed method assumes that the observed spectra are linear combinations of pure material spectra. To demonstrate its effectiveness, a synthetic dataset is generated that fully complies with the LMM. This dataset consists of 60×60 pixels and is created by linearly combining five randomly selected endmembers from the United States Geological Survey (USGS) spectral library. The spectral data contains 188 bands with a resolution of 10 nm, covering a wavelength range from $0.38 \mu\text{m}$ to $2.5 \mu\text{m}$. A 64×64 pixel image is divided into 8×8 blocks, with each block filled with one of the five randomly chosen endmembers. The abundance maps are created by applying a 5×5 mean low-pass filter to ensure smooth transitions between adjacent endmembers. The

outer 2×2 rows and columns of pixels are removed, resulting in a final image of 60×60 pixels. To test the robustness of the method under noisy conditions, Gaussian noise with different signal-to-noise ratios (SNRs) is added to the spectral data. For each noise level, different sets of endmembers are used.

2) *Samson Dataset*: The Samson dataset consists of 952×952 pixels with 156 spectral bands, covering a wavelength range from 401 nm to 889 nm. To reduce the computational cost for the analysis, a 95×95 pixel area is extracted, starting from the pixel at coordinates (252, 332). This subset of the dataset contains three endmembers: soil, tree, and water.

3) *Jasper Ridge Dataset*: The Jasper Ridge dataset contains 224 spectral bands with wavelengths from 380 to 2500 nm and consists of 512×614 pixels. For computational efficiency, a subset of 100×100 pixels is extracted, starting from pixel coordinates (105, 269). Due to atmospheric interference and dense water vapor, spectral bands 1–3, 108–112, 154–166, and 220–224 are removed, leaving 198 bands for further analysis. The final Jasper Ridge dataset includes four endmembers: water, soil, tree, and road.

4) *Urban Dataset*: The Urban dataset contains 307×307 pixels with 210 spectral bands covering wavelengths from 400 to 2500 nm. To minimize the impact of atmospheric interference and dense water vapor, bands 1–4, 76, 87, 101–111, 136–153, and 198–210 are removed, leaving 162 bands for further analysis. The final Urban dataset includes four endmembers: asphalt, grass, tree, and roof. The three real datasets and ground-truth for endmembers and abundances can be found in remote sensing lab¹.

B. Evaluation Metrics

In our experiments, we employ three widely-used evaluation metrics to assess the performance of the algorithms: spectral angle distance (SAD), root mean square error (RMSE), and reconstruction error (RE) with respect to the ground truth. These metrics are used to evaluate the accuracy of the estimated endmember signatures, the abundances, and the reconstructed hyperspectral images, respectively. SAD is defined as follows:

$$\text{SAD}(\mathbf{m}_k, \hat{\mathbf{m}}_k) = \arccos \frac{\mathbf{m}_k \cdot \hat{\mathbf{m}}_k}{\|\mathbf{m}_k\|_2 \|\hat{\mathbf{m}}_k\|_2}, \quad (32)$$

where $\hat{\mathbf{m}}_k$ and \mathbf{m}_k represent the estimated and the ground truth endmember signatures, respectively. RMSE is computed by:

$$\text{RMSE}(\hat{\mathbf{a}}_j, \mathbf{a}_j) = \sqrt{\frac{1}{Np} \sum_{j=1}^{Np} (\hat{\mathbf{a}}_j - \mathbf{a}_j)^2}, \quad (33)$$

where $\hat{\mathbf{a}}_j$ and \mathbf{a}_j represent the estimated and ground-truth abundances, and Np is the number of pixels. Finally, RE is defined as:

$$\begin{aligned} \text{RE}(\mathbf{X}, \hat{\mathbf{X}}_2) &= \frac{1}{Np} \sum_{j=1}^{Np} \text{RE}(\mathbf{x}_j, \hat{\mathbf{x}}_{2j}) \\ &= \frac{1}{Np} \sum_{j=1}^{Np} \arccos \frac{\mathbf{x}_j \cdot \hat{\mathbf{x}}_{2j}}{\|\mathbf{x}_j\|_2 \|\hat{\mathbf{x}}_{2j}\|_2}, \end{aligned} \quad (34)$$

¹<https://rslab.ut.ac.ir/data>

TABLE I
PERFORMANCE EVALUATION OF DIFFERENT UNMIXING METHODS ON THE SYNTHETIC DATASET. BEST RESULTS ARE SHOWN IN BOLD.

SNR	Metrics	VCA-FCLS	R-CoNMF	MVSA	DAEU	MTAEU	SIDAEU	MSNet	ASSAUN
10dB	Mean SAD	0.0741	0.0602	0.1620	0.1277	0.1332	0.1179	0.0654	0.0499
	Mean RMSE	0.1154	0.1284	0.2367	0.2513	0.2154	0.1965	0.1194	0.1129
	RE (Noisy GT)	0.4050	0.3989	0.4137	0.3592	0.3577	0.3956	0.3577	0.3571
	RE (Clean GT)	0.1901	0.1770	0.2144	0.0743	0.0579	0.1745	0.0578	0.0543
20dB	Mean SAD	0.1379	0.1457	0.1870	0.1430	0.1094	0.2630	0.1579	0.0364
	Mean RMSE	0.0662	0.1067	0.1765	0.2174	0.1372	0.2211	0.1020	0.0603
	RE (Noisy GT)	0.2118	0.1897	0.1617	0.1286	0.1219	0.1276	0.1200	0.1204
	RE (Clean GT)	0.1628	0.1398	0.1044	0.0462	0.0289	0.0478	0.0217	0.0239
30dB	Mean SAD	0.0141	0.0265	0.0469	0.0796	0.0938	0.1223	0.0264	0.0033
	Mean RMSE	0.0397	0.0697	0.1070	0.2170	0.2320	0.2340	0.1154	0.0394
	RE (Noisy GT)	0.1585	0.1686	0.1785	0.0419	0.0412	0.0470	0.0377	0.0343
	RE (Clean GT)	0.1530	0.1637	0.1741	0.0230	0.0216	0.0311	0.0149	0.0051

where $\hat{\mathbf{x}}_{2j}$ and \mathbf{x}_j are the reconstructed and ground truth spectra of pixel j .

TABLE II
PERFORMANCE EVALUATION OF DIFFERENT UNMIXING METHODS ON THE SAMSON DATASET. BEST RESULTS ARE SHOWN IN BOLD.

Methods	VCA-FCLS	R-CoNMF	MVSA	DAEU	MTAEU	SIDAEU	MSNet	ASSAUN
SAD	Soil	0.0232	0.0534	0.0455	0.0271	0.0393	0.0236	0.0163
	Tree	0.0206	0.0290	0.0247	0.0322	0.0430	0.0243	0.0218
	Water	0.1058	0.1861	0.3724	0.0467	0.0439	0.0542	0.0377
Mean SAD		0.0499	0.0895	0.1475	0.0353	0.0421	0.0340	0.0253
Mean RMSE		0.2748	0.3145	0.2747	0.0700	0.0786	0.0614	0.0269
RE		0.4009	0.4791	0.4578	0.0501	0.0544	0.0590	0.0362

C. Experiments on the Synthetic Dataset

Table I presents the mean SAD and mean RMSE obtained by the different unmixing methods on the synthetic dataset with different noise levels. The proposed ASSAUN consistently outperformed the other methods in terms of both SAD and RMSE. This indicates that ASSAUN is highly effective in extracting endmembers and estimating their abundances, even when noise is introduced into the synthetic datasets. To further assess the noise robustness of the proposed ASSUN, RE values are shown with the original noisy and clean image as ground truth, respectively (note that the noisy image was always the input for all unmixing methods). It can be observed that DL-based unmixing methods, such as DAEU, MTAEU, SIDAEU, and MSNet, exhibited superior performance in terms of image reconstruction compared to traditional techniques like VCA-FCLS, R-CoNMF, and MVSA. Notably, the reconstruction results of ASSAUN were closer to the original clean image compared to other techniques, demonstrating that it is immune to noise, highlighting its capability to effectively deal with noise, leading to more accurate unmixing results (even in challenging conditions). Moreover, we can observe that the accuracy of ASSAUN decreases as the SNR decreases, which

is consistent with the behavior of all methods due to the increasing difficulty of unmixing under noisy conditions.

D. Experiments on the Samson Dataset

Table II shows a quantitative performance assessment of all algorithms on the Samson dataset. The results show that VCA-FCLS, MSNet, and ASSAUN achieved the best performance in extracting the tree, water, and soil endmembers, respectively. However, ASSAUN stood out overall, providing the best results in terms of mean SAD, mean RMSE, and RE, demonstrating that ASSAUN is highly effective for endmember extraction, abundance estimation, and image reconstruction. Fig. 3 provides a visual comparison of the endmembers estimated by different unmixing methods. Clearly, the DL-based methods outperformed traditional methods such as R-CoNMF and MVSA, which struggle to effectively extract the endmembers. The abundance maps estimated by different unmixing methods are presented in Fig. 4. It can be observed that DAEU, MTAEU, SIDAEU, and ASSAUN successfully separated the three endmembers more clearly compared to VCA-FCLS, R-CoNMF, and MVSA, demonstrating the superiority of the DL-based approaches for this task.

E. Experiments on the Jasper Ridge Dataset

Table III provides a quantitative comparison of the different algorithms. The table indicates that DAEU accurately estimated the endmembers for trees and water, while MSNet and ASSAUN were the most successful in estimating soil and road, respectively. Overall, ASSAUN stood out in terms of mean SAD, as well as in RMSE and RE. Fig. 5 presents the endmember signatures estimated by different unmixing methods on the Jasper Ridge dataset. The results show that the endmember signatures from ASSAUN aligned closely with the ground truth. Fig. 6 displays the visual results of abundance maps estimated by different unmixing methods.

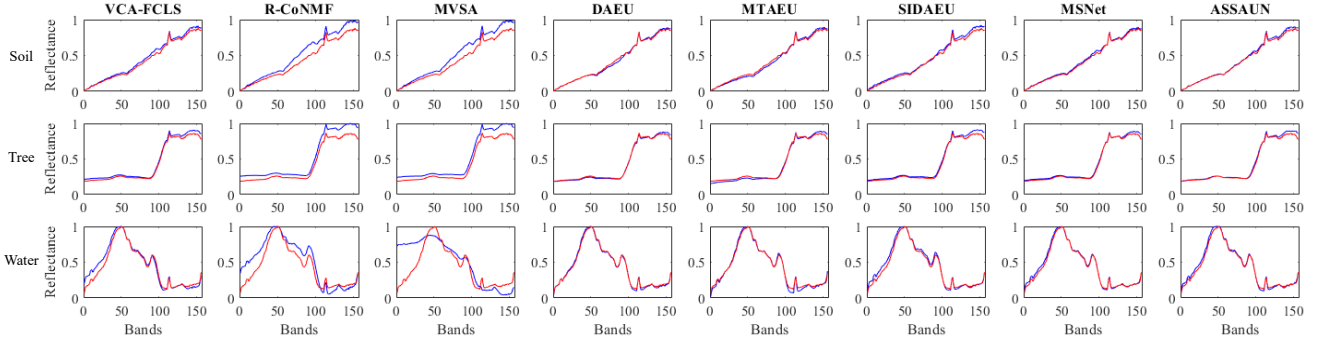


Fig. 3. Reference (red) and endmember signatures (blue) estimated by the different unmixing methods on the Samson dataset.

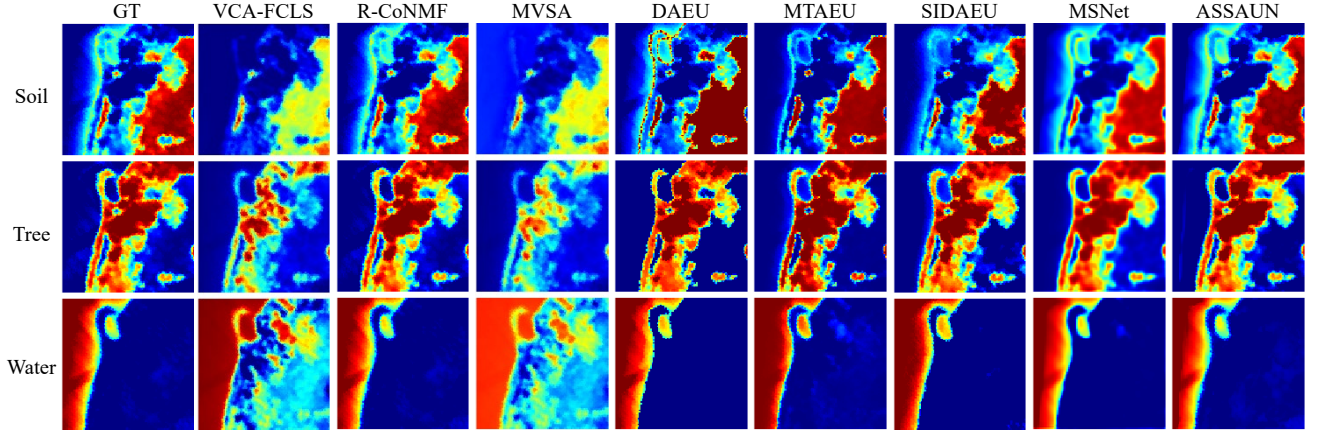


Fig. 4. Abundance maps estimated by the different unmixing methods on the Samson dataset. The GT column shows the ground truth abundance maps.

It has been noted that traditional unmixing methods, such as VCA-FCLS, R-CoNMF, and MVSA, did not accurately estimate the abundances of endmembers. In contrast, our proposed ASSAUN effectively estimated the abundances of trees, water, and roads, whereas MSNet excelled in generating abundance maps for soil.

F. Experiments on the Urban Dataset

Table IV quantitatively assesses the performance of the different methods on the Urban dataset. ASSAUN was not only superior in estimating each of the endmembers but also achieved the best results in terms of mean mean SAD and RMSE. Although SIDAUE obtained the best RE values, ASSAUN was competitive, showing only a small gap. Overall, the results underline ASSAUN's effectiveness in hyperspectral unmixing and image reconstruction, confirming its effectiveness across multiple performance metrics. Fig. 7 provides a visual comparison of the reference signatures and the endmembers estimated by different methods. The figure highlights that ASSAUN exhibited high accuracy and consistency compared to other approaches, indicating its stable ability in extracting precise endmembers. Fig. 8 shows the estimated abundance maps for the Urban dataset, generated by different methods. Clearly, MSNet had the best result in estimating abundances of roof, and ASSAUN had clearer abundance maps in estimating asphalt, grass, and tree than other methods.

TABLE III
PERFORMANCE EVALUATION OF DIFFERENT UNMIXING METHODS ON THE JASPER RIDGE DATASET. BEST RESULTS ARE SHOWN IN BOLD.

Methods		VCA-FCLS	R-CoNMF	MVSA	DAEU	MTAEU	SIDAUE	MSNet	ASSAUN
SAD	Tree	0.3176	0.0330	0.0490	0.0185	0.0961	0.0300	0.0442	0.0310
	Water	0.2956	0.0253	0.1227	0.0098	0.0955	0.0261	0.0427	0.0146
	Soil	0.6569	0.0786	0.1137	0.0506	0.1048	0.0796	0.0479	0.0606
	Road	0.5195	0.0473	0.0550	0.2056	0.2172	0.2433	0.1014	0.0240
Mean SAD		0.4474	0.0460	0.0851	0.0711	0.1284	0.0948	0.0591	0.0326
Mean RMSE		0.3545	0.1641	0.2007	0.1319	0.2700	0.1309	0.0977	0.0913
RE		0.3276	0.3951	0.4380	0.0768	0.0888	0.0718	0.0728	0.0627

G. Computational Cost

We conducted all experiments on a computer equipped with a 2.6 GHz Intel Core i7 CPU, 16 GB of memory, and an NVIDIA GeForce RTX 2060 GPU. The efficiency of different unmixing methods across all datasets is documented in Table V. This table shows that traditional methods such as VCA-FCLS, R-CoNMF, and MVSA achieved higher efficiency compared to DL-based unmixing methods. Nevertheless, when considering a comprehensive evaluation, the efficiency of the proposed ASSAUN method remained acceptable. This balance between performance and computational efficiency highlights the practical utility of ASSAUN in hyperspectral unmixing applications.

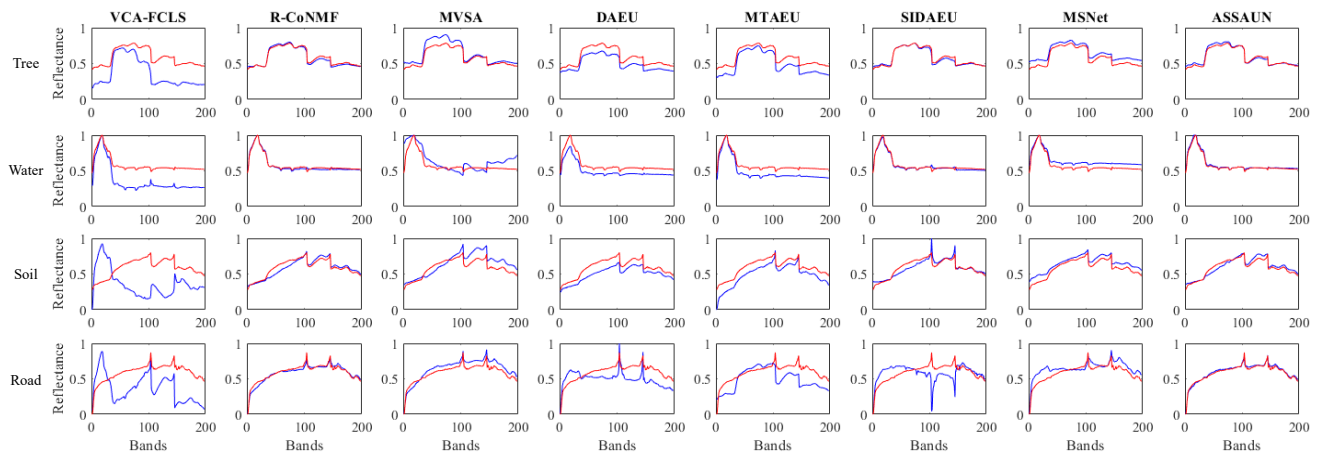


Fig. 5. Reference (red) and endmember signatures (blue) estimated by different unmixing methods on the Jasper Ridge dataset.

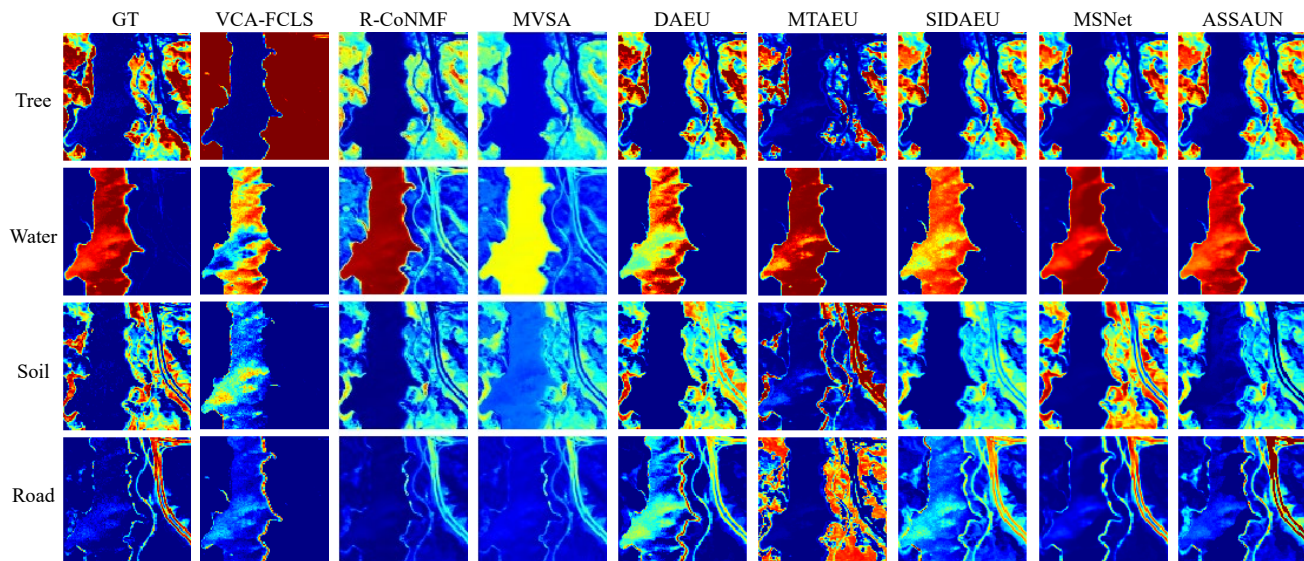


Fig. 6. Abundance maps estimated by different unmixing methods on the Jasper Ridge dataset. The GT column shows the ground truth abundance maps.

TABLE IV
PERFORMANCE EVALUATION OF DIFFERENT UNMIXING METHODS ON THE URBAN DATASET. BEST RESULTS ARE SHOWN IN BOLD.

Methods		VCA-FCLS	R-CoNMF	MVSA	DAEU	MTAEU	SIDAUE	MSNet	ASSAUN
SAD	Asphalt	0.3459	0.2091	0.1923	0.2106	0.1411	0.2901	0.1511	0.0773
	Grass	0.1170	1.0611	1.0430	0.2171	0.3427	0.3471	0.1022	0.0659
	Tree	0.2314	0.0728	0.0825	0.0806	0.0773	0.1338	0.0948	0.0222
	Roof	0.3608	0.1341	0.1314	0.2436	0.1473	0.2555	0.1736	0.1235
Mean SAD		0.2638	0.3693	0.3623	0.1880	0.1771	0.2566	0.1304	0.0722
Mean RMSE		0.3184	0.3080	0.2887	0.1454	0.1560	0.1670	0.1259	0.1103
RE		0.2835	0.4925	0.4454	0.0548	0.0713	0.0509	0.0837	0.0521

H. Hyperparameter Settings

We employ an Adam optimizer alongside Eq. (31) as the loss function to guide the optimization process. The regularization parameters β and γ in Eq. (31) play a crucial role in balancing the trade-off between the image reconstruction, denoising, and abundance estimation tasks. The size of the applied convolution kernel across the different layers of the

network is another hyperparameter. Fig. 9 provides a detailed analysis of the impact of these hyperparameters. The analysis shows that setting the regularization parameter β to 0.01 and keeping the kernel size at 3×3 consistently yielded the best performance for all datasets. The optimal settings for the regularization parameter γ varied per dataset: 0.02 for the Samson dataset, 0.015 for the Jasper Ridge dataset, and 0.1 for the Urban dataset. These specific settings significantly improve performance in terms of mean SAD and mean RMSE, thereby confirming their effectiveness in hyperspectral unmixing tasks.

V. DISCUSSION

A. Ablation Study for the Spectral-Spatial Attention Module

In the proposed approach, we embedded a novel SSAM into the AUM to enhance the performance of hyperspectral unmixing. SSAM contains a spatial attention module and a spectral attention module that are fused together. We performed an ablation study, in which either or both of the attention modules

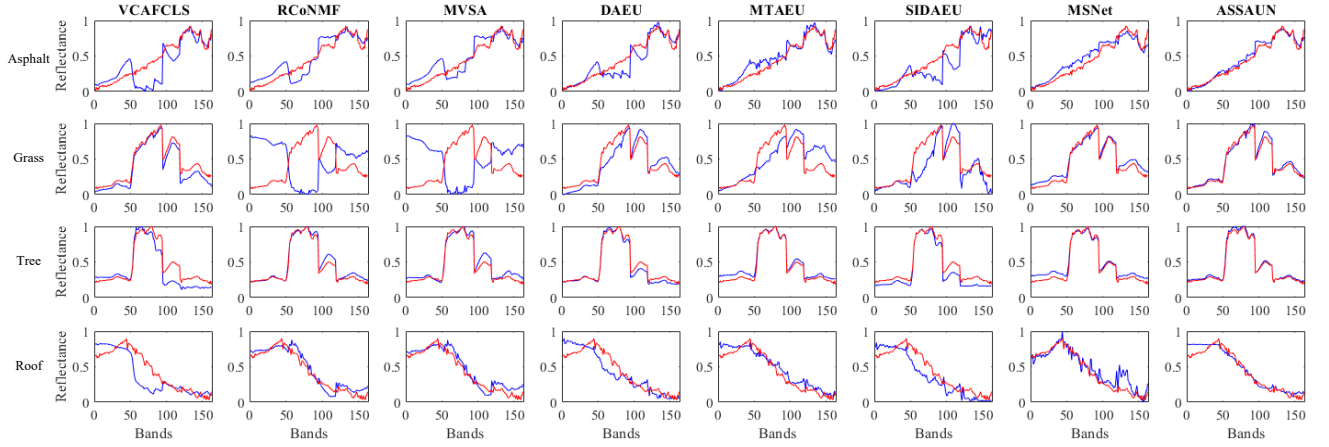


Fig. 7. Reference (red) and endmember signatures (blue) estimated by different unmixing methods on the Urban dataset.

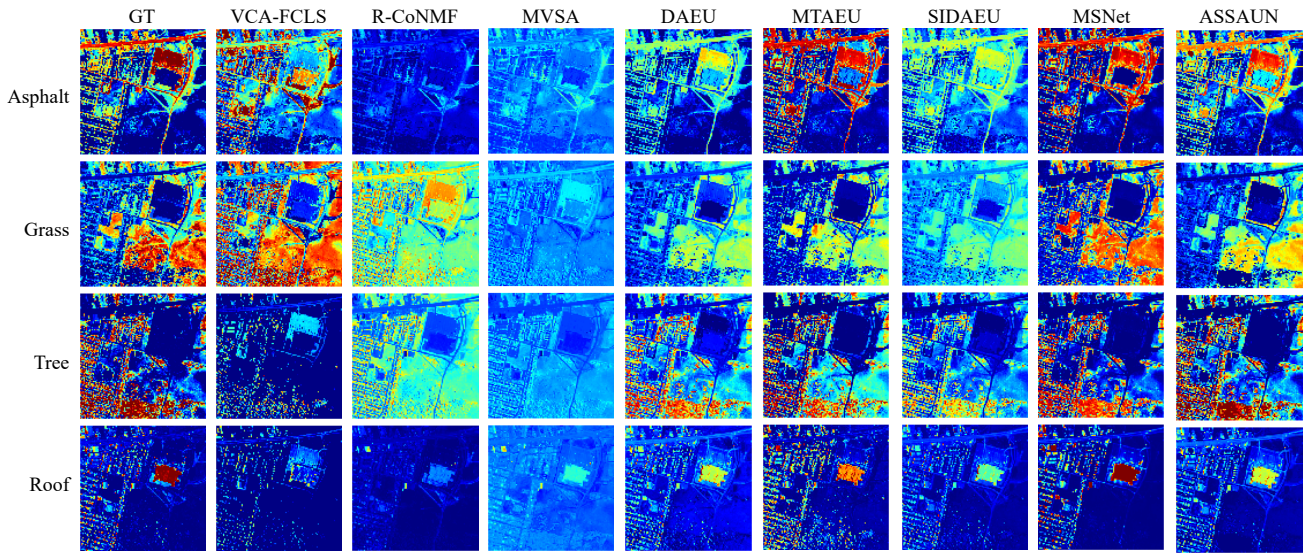


Fig. 8. Abundance maps estimated by different unmixing methods on the Urban dataset. The GT column shows the ground truth abundance maps.

TABLE V
COMPUTATIONAL COST OF ALL METHODS ON DIFFERENT DATASETS (IN SECONDS).

Methods	Synthetic (20dB)	Samson	Jasper Ridge	Urban
VCA-FCLS	0.2909	0.4276	0.4401	4.2662
R-CoNMF	2.2753	1.1273	1.2587	20.9045
MVSA	0.7224	0.8615	0.4283	3.3006
DAEU	18.4865	43.8835	47.9196	52.8121
MTAEU	35.5518	85.9920	99.3320	107.5883
SIDAUEU	4.9552	41.2642	10.7187	48.4249
MSNet	10.7441	11.2745	11.6601	49.6279
ASSAUN	16.8025	23.3912	25.1283	172.1192

TABLE VI
ABLATION STUDY FOR OUR PROPOSED ASSAUN WITH VARYING ATTENTION MODULES ON DIFFERENT DATASETS. BEST RESULTS ARE SHOWN IN BOLD.

Datasets	Spectral attention	Spatial attention	Mean SAD	Mean RMSE
Synthetic data (20dB)	✓	✗	0.1671	0.1563
	✗	✓	0.1759	0.0854
	✓	✓	0.0364	0.0603
Samson	✓	✗	0.0385	0.0506
	✗	✓	0.0556	0.0489
	✓	✓	0.0245	0.0269
Jasper Ridge	✓	✗	0.0332	0.1023
	✗	✓	0.0364	0.0974
	✓	✓	0.0326	0.0913
Urban	✓	✗	0.0849	0.1168
	✗	✓	0.0726	0.1140
	✓	✓	0.0722	0.1103

are applied, and the obtained results are compared. Table VI presents the results. The combination of both spectral and spatial attention led to the best results. In some cases, only applying the spatial or the spectral module matches the results of applying both. In other cases, the combination is

significantly superior, underlining the advantage of attentively focusing on both spectral and spatial information.

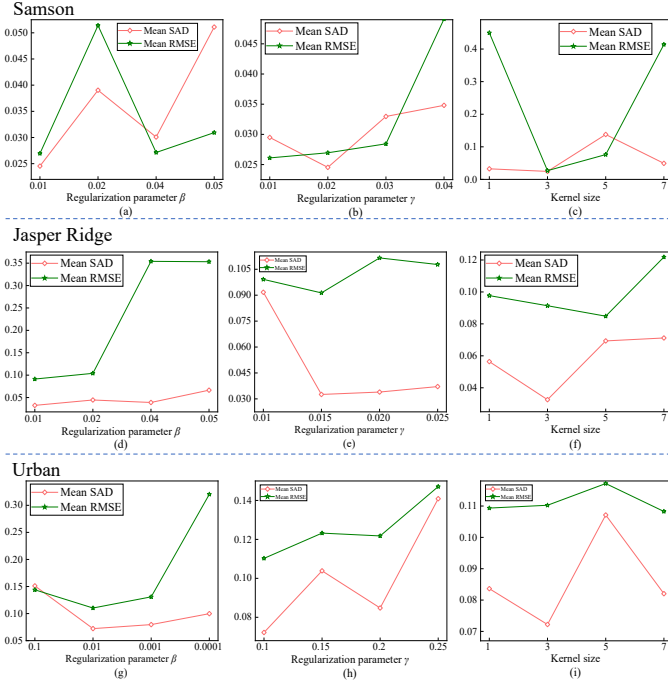


Fig. 9. Hyperparameter analysis conducted by varying: regularization parameter β , regularization parameter γ , and kernel size for different datasets: (a)-(c) Samson dataset, (d)-(f) Jasper Ridge dataset, and (g)-(i) Urban dataset.

TABLE VII

ABLATION STUDIES FOR OUR PROPOSED DUAL SPATIAL ATTENTION MODULE USING DIFFERENT COMBINATIONS FOR DIFFERENT KINDS OF SPATIAL EXTRACTION ON DIFFERENT DATASETS. BEST RESULTS ARE SHOWN IN BOLD.

Datasets	Concatenation	Summation	Mean SAD	Mean RMSE
Synthetic data (20dB)	✓	✗	0.1514	0.1229
	✗	✓	0.3097	0.3491
	✓	✓	0.0364	0.0603
Samson	✓	✗	0.0460	0.0361
	✗	✓	0.0537	0.0409
	✓	✓	0.0245	0.0269
Jasper Ridge	✓	✗	0.0468	0.1476
	✗	✓	0.0928	0.1156
	✓	✓	0.0326	0.0913
Urban	✓	✗	0.0985	0.3279
	✗	✓	0.0989	0.1429
	✓	✓	0.0722	0.1103

B. Ablation Study for the Spatial Attention Module

In the dual spatial attention module, both concatenation and summation steps are applied to merge the feature maps \mathbb{F}_{max} and \mathbb{F}_{min} , as detailed in Eq. (23). We performed an ablation study in which either or both of the steps are applied, and the results are compared. Results, presented in Table VII, indicate that the combined use of concatenation and summation for designing the attention module yielded superior results.

VI. CONCLUSION

In this work, we proposed an automatic spectral-spatial attention unmixing network (ASSUN) for effective hyperspectral

unmixing and image reconstruction. We addressed the challenges common to conventional DL-based unmixing methods and improved performance through several key innovations. ASSAUN includes a DDM that preemptively filters out noise, strengthening the robustness and accuracy of the network. The core unmixing tasks are handled by AUM, which directly estimates the abundance maps from the output. Furthermore, instead of using weights to estimate the endmembers, an innovative inversion strategy is used. Image reconstruction can be performed using the multiplication of estimated endmembers and abundances. A SSAM is carefully designed to identify and highlight critical features across spectral channels while capturing extensive vertical and horizontal spatial dependencies. This dual attention to spectral and spatial details allows our newly developed ASSUN to distinguish and enhance relevant features, significantly improving unmixing accuracy. Extensive evaluations on both synthetic and real-world datasets have validated the effectiveness and robustness of ASSUN, confirming its superior performance in hyperspectral unmixing and image reconstruction tasks. Our future efforts will focus on expanding ASSUN's capabilities to address nonlinear unmixing problems. This initiative aims to adapt the network to more complex scenarios, increasing its applicability and its effectiveness in various hyperspectral unmixing applications.

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