

HIDFlowNet: A Flow-Based Deep Network for Hyperspectral Image Denoising

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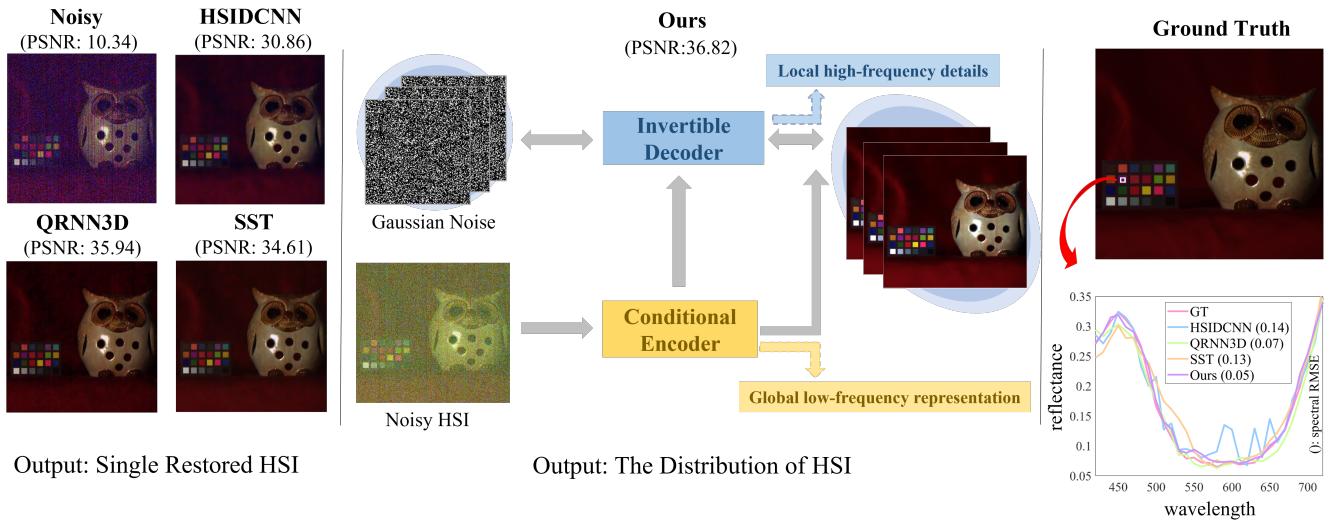


Figure 1: Instead of performing HSI denoising with a deterministic mapping, our HIDFlowNet learns the conditional distribution of clean HSI given corresponding noisy counterpart, which explicitly alleviates the ill-posed nature of HSI denoising and enables us to sample diverse clean HSIs. The charts on the right demonstrate that the reconstructed spectral reflectance of our HIDFlowNet is more consistent with the ground truth than that of other approaches, verifying the superiority of our proposed method.

ABSTRACT

Hyperspectral image (HSI) denoising is essentially ill-posed since a noisy HSI can be degraded from multiple clean HSIs. However, current deep learning-based approaches ignore this fact and restore the clean image with deterministic mapping (i.e., the network receives a noisy HSI and outputs a clean HSI). To alleviate this issue, this paper proposes a flow-based HSI denoising network (HIDFlowNet) to directly learn the conditional distribution of the clean HSI given

the noisy HSI and thus diverse clean HSIs can be sampled from the conditional distribution. Overall, our HIDFlowNet is induced from the flow methodology and contains an invertible decoder and a conditional encoder, which can fully decouple the learning of low-frequency and high-frequency information of HSI. Specifically, the invertible decoder is built by stacking a succession of invertible conditional blocks (ICBs) to capture the local high-frequency details since the invertible network is information-lossless. The conditional encoder utilizes down-sampling operations to obtain

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low-resolution images and uses transformers to capture correlations over a long distance so that global low-frequency information can be effectively extracted. Extensive experimental results on simulated and real HSI datasets verify the superiority of our proposed HIDFlowNet compared with other state-of-the-art methods both quantitatively and visually.

CCS CONCEPTS

- Computing methodologies → Reconstruction;

KEYWORDS

Hyperspectral image denoising, Flow, Deep network

1 INTRODUCTION

Hyperspectral image (HSI) depicts an object in numerous narrow and contiguous spectral bands across the electromagnetic spectrum. Compared with RGB images, HSIs enable a more comprehensive depiction of captured scenes due to more spectral bands and have been widely applied in various fields including remote sensing [33, 44, 53], medical diagnosis [3, 37, 39], agriculture [14, 29, 38] and so on. However, owing to multiple factors such as instrument instability, circuit malfunction and light disturbance, HSIs are often subjected to various noises during the data acquisition stage, which can negatively impact the performance of the downstream applications aforementioned. Therefore, noise reduction is an essential step in HSI analysis and processing. However, HSI denoising is an ill-posed problem since a given noisy HSI can be degraded from multiple clean HSIs, which presents significant challenges when designing HSI denoising approaches.

In the last decade, numerous HSI denoising techniques have been proposed and these methods can be categorized into two classes, i.e., model-based approaches and deep learning-based methods. Model-based approaches rely on human handcrafted prior and conduct HSI denoising in an iterative optimization manner. However, since the characteristics of HSIs are complex, the hand-crafted priors only partially reflect the features of HSIs, making these approaches incapable of handling unknown real-world noise. Moreover, the iterative optimization process consumes a substantial amount of time to denoise a single image. In contrast, by utilizing the impressive nonlinearity capability of neural networks, deep learning-based approaches model the intrinsic characteristics of HSIs in a data-driven manner. These methods learn the underlying image features statistically with abundant clean and noisy image pairs. Although these approaches can achieve desirable denoising performance, they can only predict a single clean HSI with a deterministic mapping (see Figure 1) and ignore the ill-posed nature of HSI denoising. Compared with distribution learning-based denoising approaches, these deterministic methods overemphasize pixel similarity and tend to predict the average of all possible clean images, resulting in over-smoothed areas and loss of image details. Additionally, most of the existing deep learning-based methods focus on directly learning the network mapping from numerous training pairs and always neglect the fact that noise is part of the high-frequency component. Thus the existing network architectures often fail to decouple the learning of low-frequency and high-frequency and thus lack specific physical meaning.

To alleviate these issues, this paper proposes a flow-based hyperspectral image denoising network (i.e., HIDFlowNet). HIDFlowNet aims to directly learn the conditional distribution of the clean HSIs by transforming the unknown conditional distribution of clean HSIs into a known Gaussian distribution (see Figure 1). Concretely, the HIDFlowNet decouples the learning of low-frequency and high-frequency information of HSI and contains two main components: a conditional encoder network and an invertible decoder network. The encoder network composed of a series of transformer blocks and down-sampling operations, is utilized to extract global low-frequency information in an unsupervised manner. To be specific, the down-sampling operations employed in the encoder enable the network to obtain low-resolution images so that low-frequency information is extracted efficiently. Transformers which are able to capture long-distance correlations are also adopted to extract global information effectively. Additionally, the invertible decoder is built by stacking a successive of invertible conditional blocks (ICBs) to preserve local high-frequency details since invertible networks are information-lossless [35]. Finally, HIDFlowNet is trained by minimizing the negative log-likelihood of the conditional distribution given the training data and a reconstruction loss to obtain high-quality HSIs. Once the training is finished, diverse clean HSIs corresponding to one noisy HSI can be generated by first sampling in the latent space and then performing inverse transforms.

In summary, our contributions are shown as follows:

- A flow-based network namely HIDFlowNet is proposed to learn the conditional distribution of a clean HSI given its corresponding noisy counterpart. The model is able to generate diverse restored images by sampling random Gaussian noise and performing inverse transforms. To our knowledge, this is the first attempt to employ a flow-based model for HSI denoising.
- The architecture of HIDFlowNet induced from the flow methodology contains two main components and has an explicit physical interpretation since it decouples the learning of low-frequency and high-frequency information of HSI. The invertible decoder preserves the local high-frequency details and the conditional encoder network extracts global low-frequency representation.
- Extensive experiments on the simulated and real HSI datasets verify the superiority of our proposed method compared with other state-of-the-art methods.

2 RELATED WORK

In this section, we give a brief review of several research fields related to our work, including two major HSI denoising directions and flow-based generative models.

Model-based methods utilize priori information about the underlying statistical properties of the hyperspectral data to perform denoising. Handcrafted priors such as low-rank [5, 7, 11, 18, 30, 47, 61, 68], sparse representation [41, 60, 62, 69], total variation [22, 23, 64] and nonlocal similarity [21, 43, 48] are proposed and corresponding model regularization terms are designed to obtain promising denoising results. For example, in [68], low-rank matrix recovery (LRMR) is proposed to simultaneously remove various

noises by utilizing the low-rank property of HSIs and the sparsity nature of non-Gaussian noise. Cao *et al.* [5] proposed a mixture of exponential power distribution in the low-rank matrix factorization framework to capture the complex noise of HSIs. Xue *et al.* [62] proposed a structured sparse low-rank representation (SSLRR) model to induce sparse property. Spatial-spectral total variation regularized local low-rank matrix recovery (LLRSSTV) [22] employed a global reconstruction strategy to fully utilize both low-rank property and smoothness properties of HSIs. He *et al.* [21] proposed NG-Meet which unified spatial and spectral low-rank properties. While these methods effectively preserve the spectral and spatial characteristics of HSIs, the optimization of the model is typically complex and thus these methods can be considerably time-consuming. In addition, the denoising performance is highly dependent on the consistency between the priors and HSIs. However, manually designed priors only reflect the intrinsic characteristics of HSIs partially, limiting their ability for HSI denoising.

Recently, deep learning-based methods for HSI denoising gain increasing attention and popularity owing to the powerful nonlinear fitting ability of neural networks. These methods capture the statistical characteristics of HSIs in a data-driven manner with a large number of training pairs. For instance, HSI-DeNet [6] employs a 2-D convolutional neural network to learn multiple image filters for HSI denoising. HSID-CNN [65] employs convolution kernels of multiple sizes to extract multilevel features, which are then fused to restore the HSIs. QRNN3D [59] introduces 3-D convolution blocks and quasi-recurrent mechanisms to extract spatial and spectral simultaneously without damaging the image structure. GRN [4] used two reasoning modules based on the graph neural network (GNN) to carefully extract both global and local spatial-spectral features. TRQ3DNet [45] first introduces a vision Transformer in HSI denoising, modelling the spatial long-range dependencies of HSIs and achieving desirable denoising performance. SST [31] conducts attention mechanisms in both spatial and spectral dimensions to fully explore the similarity characteristics of HSIs. HWnet [51] is proposed to improve the generalization ability of model-based methods in a data-driven manner. While demonstrating promising denoising performance, these approaches learn a deterministic mapping and neglect the fundamental ill-posed nature of HSI denoising.

Flow-based generative models have shown promising results in a variety of applications, including image generation [20, 50, 63], speech synthesis [13, 49, 55], and physics simulations [15, 19]. These models transform a complex distribution into a known simple distribution (e.g., Gaussian Distribution) with an invertible network so that diverse samples can be obtained by sampling in the known latent space and performing inverse transforms. For example, NICE [16] stacks several additive coupling layers and a rescaling layer to learn manifolds. Based on NICE, RealNVP [17] further proposes affine coupling layers with masked convolution to improve fitting ability. Glow [27] employs invertible 1×1 convolutions to perform channel permutations and actnorm layers to accelerate training. Recently, flow-based models which model complex conditional distribution have been increasingly proposed to tackle various tasks [1, 52]. SRFlow [40] models the conditional distribution of high-resolution images given corresponding low-resolution images, enabling the trained model to predict diverse high-resolution images. VideoFlow [28] predicts high-quality stochastic multi-frame videos

based on past observations using a normalizing flow. In this paper, we follow this research line and further exploit the application of flow-based methods in HSI denoising task.

3 THE PROPOSED METHOD

In this section, we provide a detailed description of our proposed HIDFlowNet. Firstly, we present the problem of the ill-posed nature of HSI denoising and then introduce conditional flow models. Next, we illustrate the network structure of HIDFlowNet in detail.

3.1 Conditional Generative Flows

The task of HSI denoising is to restore clean HSIs from given noisy HSIs. Generally, a degraded HSI can be mathematically modeled as

$$\mathbf{Y} = \mathbf{X} + \boldsymbol{\epsilon}. \quad (1)$$

where $\mathbf{Y} \in \mathbb{R}^{H \times W \times B}$ denotes the degraded HSI, $\mathbf{X} \in \mathbb{R}^{H \times W \times B}$ is the corresponding clean HSI and $\boldsymbol{\epsilon} \in \mathbb{R}^{H \times W \times B}$ stands for the additive noise. H, W, B denote the height, width and spectral band number of the HSI, respectively.

As previously mentioned, HSI denoising is an ill-posed problem since a noisy HSI can be degraded from multiple clean HSIs that are equally reasonable. Therefore, instead of learning a deterministic mapping $\mathbf{Y} \rightarrow \mathbf{X}$ as existing deep learning-based methods do, we propose to employ a flow-based network f_θ to learn the conditional distribution $P_{\mathbf{X}|\mathbf{Y}}(\mathbf{X}|\mathbf{Y}, \theta)$ of clean HSI \mathbf{X} given corresponding noisy counterpart \mathbf{Y} . Specifically, the network is designed to be invertible to guarantee one-to-one mapping. To put it another way, the invertible network transforms a clean and noisy HSI pair (\mathbf{X}, \mathbf{Y}) into a latent variable $\mathbf{z} = f_\theta(\mathbf{X}; \mathbf{Y})$, and the clean HSI \mathbf{X} can be reconstructed exactly by performing inverse transforms as $\mathbf{X} = f_\theta^{-1}(\mathbf{z}; \mathbf{Y})$. In this context, by applying the change-of-variables formula, the probability density of $p_{\mathbf{X}|\mathbf{Y}}$ can be explicitly defined as

$$p_{\mathbf{X}|\mathbf{Y}}(\mathbf{X}|\mathbf{Y}, \theta) = p_{\mathbf{z}}(f_\theta(\mathbf{X}; \mathbf{Y})) \left| \det \frac{\partial f_\theta}{\partial \mathbf{X}}(\mathbf{X}; \mathbf{Y}) \right|. \quad (2)$$

where the $\det(\cdot)$ term is the determinant of the Jacobian matrix $\frac{\partial f_\theta}{\partial \mathbf{X}}(\mathbf{X}; \mathbf{Y})$. Therefore, the conditional distribution of the clean HSI can be directly learned by minimizing the negative log-likelihood (NLL) as

$$\begin{aligned} \mathcal{L}_{nll}(\theta; \mathbf{X}, \mathbf{Y}) &= -\log p_{\mathbf{X}|\mathbf{Y}}(\mathbf{X}|\mathbf{Y}, \theta) \\ &= -\log p_{\mathbf{z}}(f_\theta(\mathbf{X}; \mathbf{Y})) - \log \left| \det \frac{\partial f_\theta}{\partial \mathbf{X}}(\mathbf{X}; \mathbf{Y}) \right|. \end{aligned} \quad (3)$$

In addition, the flow-based network is decomposed into a succession of invertible layers so that the determinant term in Eq.(3) can be readily calculated. Specifically, the flow-based network consists of N invertible layers, i.e., $f_\theta = f_\theta^N f_\theta^{N-1} \cdots f_\theta^1$, where f_θ^n denotes the n_{th} layer. The n_{th} layer takes the outputs of the previous layer as inputs, i.e., $\mathbf{h}^{n+1} = f_\theta^n(\mathbf{h}^n; \mathbf{X})$, where $\mathbf{h}^1 = \mathbf{X}$ and $\mathbf{h}^{N+1} = \mathbf{z}$. Then, by employing the chain rule and the multiplicative property of the determinant, the NLL objective in Eq.(3) can be defined as

$$\mathcal{L}_{nll}(\theta; \mathbf{X}, \mathbf{Y}) = -\log p_{\mathbf{z}}(\mathbf{z}) - \sum_{n=1}^N \log \left| \det \frac{\partial f_\theta^n}{\partial \mathbf{h}^n}(\mathbf{h}^n; \mathbf{X}, \mathbf{Y}) \right|. \quad (4)$$

As a consequence, we only need to ensure that each layer is invertible and corresponding log-determinant of the Jacobian matrix can

be efficiently computed, which will be detailed in the following section. Then clean HSIs can be sampled from $p_{X|Y}(X|Y, \theta_*)$ by drawing samples from a simple distribution (e.g. Gaussian) p_z and performing inverse transforms, i.e., $X = f_{\theta_*}^{-1}(\hat{z}; Y), \hat{z} \sim p_z$, where θ_* is the learnt parameters of the proposed network.

3.2 Network Architecture

In this section, we illustrate the network architecture and implementation details of our proposed method.

3.2.1 Overall Network Architecture. While the invertibility of flow-based networks ensures one-to-one mapping, this constraint also imposes limitations on the network design and decreases the fitting ability. Furthermore, the dimensionality of HSIs is significantly larger than RGB images, resulting in the learning of HSI distribution more challenging. Therefore, we propose to decouple the learning of global low-frequency representation and local high-frequency details. Specifically, we propose a flow-based framework namely HIDFlowNet, which is composed of a transformer-based encoder and an invertible decoder as shown in Figure 2. The framework employs a conditional encoder without the constraint of invertibility to learn global low-frequency information. Then the flow-based decoder consisting of invertible conditional blocks (ICBs) takes the features maps of the conditional encoder’s hidden layers as conditional inputs and transforms samples drawn from Gaussian distribution into local high-frequency information. Since invertible networks are information-lossless and can preserve details [35], the flow-based decoder is ideal for learning the distribution of the high-frequency part of HSIs. Finally, we apply a bilinear upsampling operation to the outputs of the encoder to expand the spatial size. Then the restored HSI is obtained by adding up the outputs of the encoding network and the flow-based decoder so that the global low-frequency and local high-frequency details are restored simultaneously. Next, we will introduce the conditional encoder network and the invertible decoder network in detail.

3.2.2 Conditional Encoder. Previous works [1, 17, 34, 36] perform either checkerboard pattern squeeze operation or Haar wavelets to reshape image to lower resolutions and capture information in a larger distance when designing invertible networks. However, each time the squeeze operation is performed, the number of channels becomes four times the original number as the size of the image needs to remain unchanged to ensure reversibility. Such operations are not suitable for HSIs which contain tens and even hundreds of spectral bands, as the exponential growth of the number of channels could lead to intolerable computational cost and model complexity. Therefore, inspired by previous work [42], we compress the high-dimensional image data by applying down-sampling operations in the encoder which is not necessarily invertible to capture low-frequency information while reducing model complexity in an unsupervised manner. Recently, vision transformers have gained great popularity in various tasks such as classification [2, 8, 24], segmentation [9, 54] and image restoration [32, 67]. The self-attention mechanism in transformers enables networks to capture global dependencies and has demonstrated powerful representation capabilities. Therefore, in this work, the encoding network is built by

staking a succession of transformers with down-sampling operations to obtain global low-resolution representations as shown in Figure 2. Specifically, the locally-enhanced window (LeWin) transformer block proposed in [58] is employed in the HIDFlowNet as the block is considerably efficient and captures both local and global features. Since the LeWin transformer is not the main point of our proposed method, readers could refer to [58] for further details. The downsampling is implemented by a 2-D convolution block with stride=2.

3.2.3 Invertible Decoder. The architecture of the invertible decoder which learns the distribution of high-frequency information requires careful design to ensure that the network is invertible and the Jacobian determinant term in Eq.(3) is tractable. Based on previous works [27, 40], a novel invertible conditional block (ICB) is proposed in this work. As shown in Figure 3, each ICB consists of a conditional affine layer and a residual invertible 1×1 convolution.

The conditional affine layer utilizes an information transfer layer to perform element-wise scaling and addition. Concretely, the conditional affine layer takes the low-resolution feature map t^n of the encoder layer as conditional inputs and generates scale and bias, which can be illustrated as

$$\begin{aligned} \mathbf{s}, \mathbf{b} &= \text{split}(g_\theta(\text{BU}(t^n))) \\ \mathbf{h}^{n+1} &= \exp(\mathbf{s}) \odot \mathbf{h}^n + \mathbf{b} \end{aligned} \quad (5)$$

where g_θ denotes the information transfer layer, BU denotes bilinear upsampling and \odot is Hadamard product. Half instance normalization block [10] with channel attention [25] (HinCaBlock) is employed as the information transfer layer in our work, which is shown in Figure 4.

The Jacobian matrix of this affine transformation is diagonal and the log-determinant can be efficiently computed by adding up the elements of scale \mathbf{s} . The inverse of this transformation is given by

$$\mathbf{h}^n = (\mathbf{h}^{n+1} - \mathbf{b}) \oslash \exp(\mathbf{s}) \quad (6)$$

where \oslash is element-wise division. [27] proposed an invertible 1×1 convolution as a permutation operation. However, the determinant of the convolution weight matrix is likely to be a large value and change drastically during the training process as the magnitude of the matrix elements is equivalent. In our work, we further propose a residual invertible 1×1 convolution to improve the stability of the training process. Specifically, the residual convolution can be defined as

$$\mathbf{h}_{ij}^{n+1} = \mathbf{W}\mathbf{h}_{ij}^n + \mathbf{h}_{ij}^n = (\mathbf{W} + \mathbf{I})\mathbf{h}_{ij}^n \quad (7)$$

where \mathbf{h}_{ij}^n is the feature vector on spatial coordinate (i, j) . The log-determinant is computed in a straightforward way as

$$\log \left| \det \left(\frac{d \text{ResidualConv}(\mathbf{h}; \mathbf{W})}{d\mathbf{h}} \right) \right| = h \cdot w \cdot \log |\det(\mathbf{W} + \mathbf{I})| \quad (8)$$

where h and w are the height and width of the feature map \mathbf{h} , and ResidualConv is the residual invertible convolution. Since the channel number remains unchanged in the invertible decoder, the log-determinant can be trivially calculated. In addition, the Jacobian determinant term in Eq.(3) prevents the coefficient matrix $\mathbf{W} + \mathbf{I}$ from being singular. We initialize the parameters \mathbf{W} with small values, such that the residual convolution performs as an identity

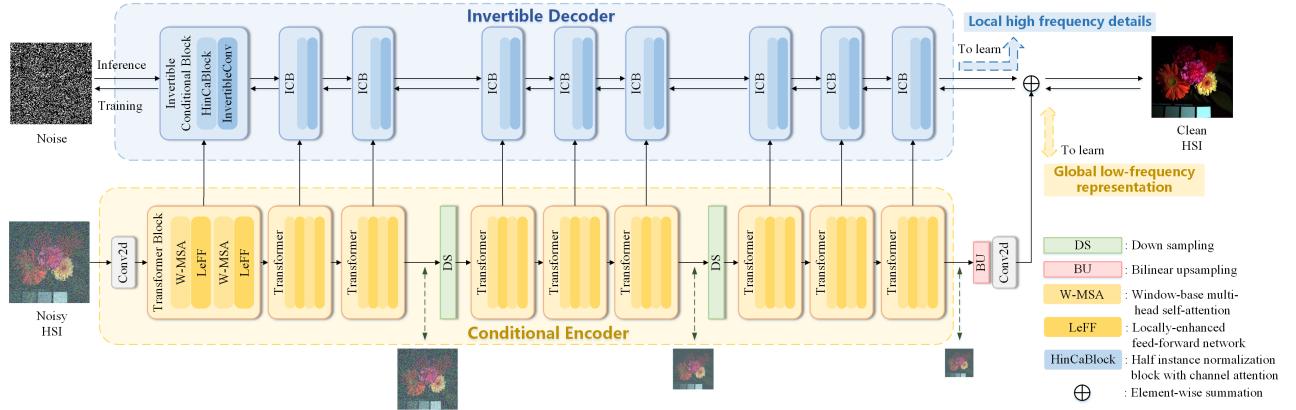


Figure 2: The network architecture of HIDFlowNet includes a conditional encoder (yellow) and an invertible decoder (blue). The encoder takes the noisy HSI as input and generates multiple-scale feature maps with a series of transformer blocks and down-sampling operations. The invertible decoder transforms a latent representation which conforms to a simple distribution (e.g., a Gaussian distribution) into high-frequency information utilizing a succession of invertible conditional blocks with the guidance of the encoder. Finally, the low and high-frequency parts are merged to restore clean HSI. The whole framework is trained by minimizing the negative log-likelihood and reconstruction loss, and then can predict diverse clean HSIs during the inference stage.

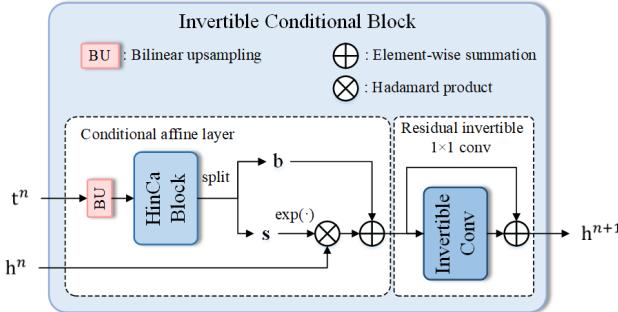


Figure 3: The invertible conditional block is composed of an invertible conditional affine layer and a residual invertible convolution layer. The feature map of the encoder t^n is processed through an upsampling layer and a HinCa Block to generate the scale and bias terms of the affine transform. And then the output h^{n+1} is generated by performing an invertible convolution.

function approximately, which is helpful for training deep networks [27].

3.2.4 Objective Function. As mentioned earlier, we propose a negative log-likelihood loss $\mathcal{L}_{nll}(\theta; \mathbf{X}, \mathbf{Y})$ to learn the distribution of HSIs. To restore high-quality HSI and accelerate training, we further define reconstruction loss as

$$\mathcal{L}_{rec}(\theta; \mathbf{X}, \mathbf{Y}, \hat{\mathbf{z}}) = \|\mathbf{f}_\theta^{-1}(\hat{\mathbf{z}}; \mathbf{Y}) - \mathbf{X}\|_1. \quad (9)$$

Finally, the total objective function is defined as

$$\mathcal{L}_{total}(\theta; \mathbf{X}, \mathbf{Y}, \hat{\mathbf{z}}) = \lambda_1 \mathcal{L}_{nll}(\theta; \mathbf{X}, \mathbf{Y}) + \lambda_2 \mathcal{L}_{rec}(\theta; \mathbf{X}, \hat{\mathbf{z}}) \quad (10)$$

where λ_1 and λ_2 are hyperparameters. In our experiments, λ_1 and λ_2 is set as 0.001 and 1, respectively.

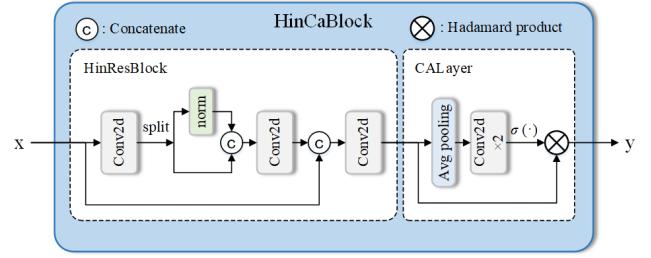


Figure 4: The details of HinCaBlock which consists of a half instance normalization block and a channel attention layer.

4 RESULTS

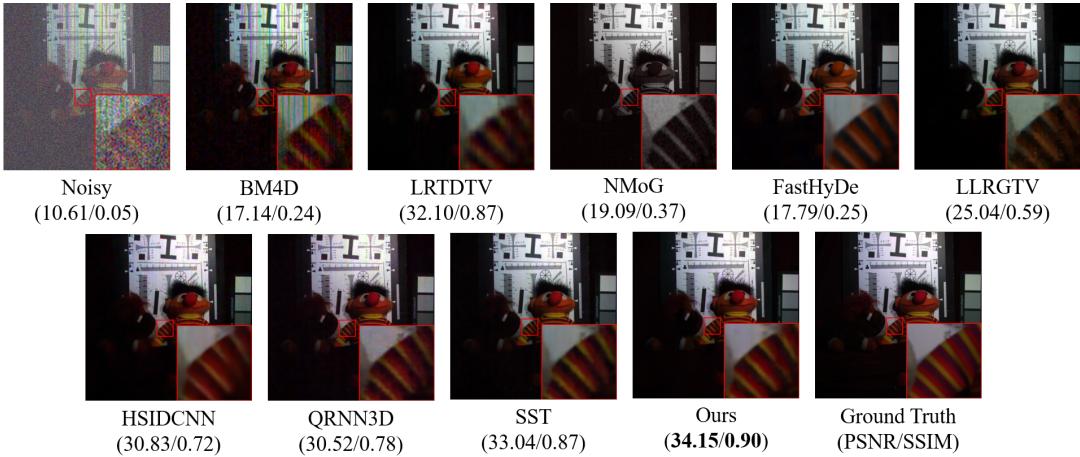
4.1 Experimental Settings

In this section, we provide a detailed description of the datasets and training settings in our experiment.

4.1.1 Synthetic Datasets. Two datasets, i.e., CAVE [46] and KAIST [12], are used in our experiments. CAVE dataset consists of 32 HSIs with a spatial resolution of 512×512 over 31 spectral bands. KAIST dataset contains 30 HSIs with a spatial resolution of 2704×3376 over 31 spectral bands. For the CAVE dataset, we use 20 images for training, 2 images for validation and 10 images for testing. For the KAIST dataset, 20 images are used for training and the rest are used for testing, 2 images selected from the CAVE dataset are used for validation. We crop the training set with a spatial size of 64×64 and stride 16 to enlarge training sets, resulting in 16824 training patches in total. Various transformations, i.e., random flipping and multi-angle image rotation (angles of $0^\circ, 90^\circ, 180^\circ, 270^\circ$) are employed for data augmentation.

Table 1: The quantitative denoising results on the CAVE dataset in Gaussian and complex noise cases.

σ	Index	Noisy	Model based methods					Deep Learning based methods			
			BM4D [43]	LRTDTV [56]	NMoG [11]	FastHyDe [70]	LLRGTV [22]	HSIDCNN [65]	QRNN3D [59]	SST [31]	Ours
50	PSNR	14.152	35.790	33.002	26.796	34.464	32.532	36.595	33.934	35.714	36.510
	SSIM	0.068	0.891	0.860	0.534	0.896	0.819	0.928	0.876	0.934	0.951
	SAM	1.137	0.192	0.209	0.415	0.172	0.274	0.177	0.238	0.177	0.125
70	PSNR	11.229	33.930	32.353	24.993	33.841	30.750	35.019	31.508	34.446	35.597
	SSIM	0.041	0.846	0.842	0.455	0.879	0.755	0.904	0.762	0.915	0.940
	SAM	1.222	0.232	0.226	0.480	0.191	0.332	0.209	0.351	0.201	0.135
90	PSNR	9.047	32.554	31.675	23.700	32.372	29.358	33.562	27.687	33.298	34.769
	SSIM	0.027	0.806	0.826	0.404	0.846	0.700	0.868	0.535	0.893	0.929
	SAM	1.279	0.264	0.244	0.535	0.224	0.383	0.257	0.514	0.230	0.145
Mixture	PSNR	13.948	18.229	32.256	19.340	18.217	24.800	34.022	32.494	32.894	33.964
	SSIM	0.114	0.234	0.865	0.309	0.206	0.617	0.858	0.828	0.858	0.907
	SAM	1.086	0.376	0.202	0.421	0.342	0.324	0.387	0.268	0.269	0.190
Parameters (M)		N/A	N/A	N/A	N/A	N/A	N/A	0.399	0.860	4.096	2.808
Time (s)		N/A	186.810	225.869	92.731	2.968	248.932	0.512	0.125	1.598	0.467

**Figure 5: Visual result comparison of simulated complex noise removal on two HSIs selected from CAVE dataset.**

4.1.2 Real HSI Data. We evaluate all competing approaches on one real-world noisy HSI, i.e., Indian Pines dataset, which consists of 145×145 pixels with 220 bands. For computational convenience, we crop the centre area with a spatial size of 128×128 for comparison.

4.1.3 Noise Setting. We consider two types of noises (i.e., Gaussian noise and mixture noise) which are consistent with real-world situations [11, 68]. In the Gaussian noise case, HSIs are contaminated by noises with variance set as {50, 70, 90}. In the mixture noise case, HSIs are contaminated by non-i.i.d. Gaussian noise, impulse noise, deadlines and strips. Specifically, each band of the clean HSIs is firstly corrupted by Gaussian noise with random intensities which range from 10 to 70. Next, the spectral bands are randomly divided into three parts, each part is respectively added with impulse noise, stripe noise and deadline noise.

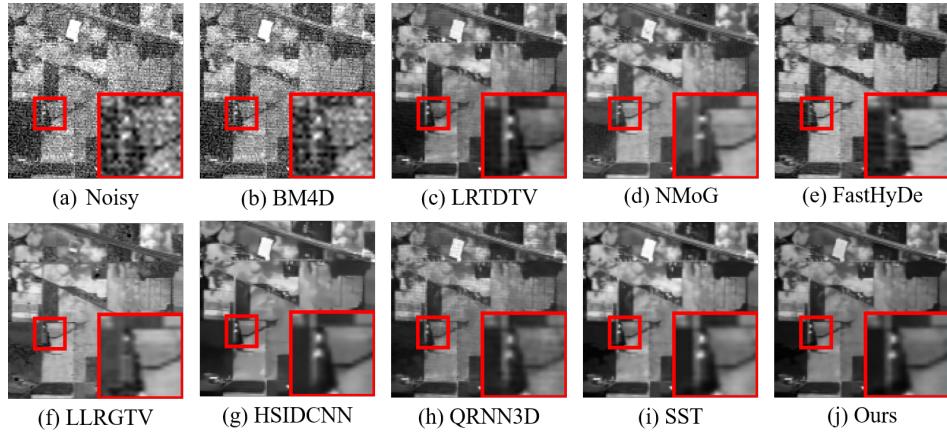
4.1.4 Competing Methods and Evaluation Metrics. Eight HSI reconstruction methods are adopted for comparison, including five model-based methods, i.e., BM4D [43], LRTDTV [56], NMoG [11],

FastHyDe [70], LLRGTV [22], and three learning based methods, i.e., HSIDCNN [65], QRNN3D [59], SST [31]. Three commonly used image quality evaluation metrics, including peak signal-to-noise ratio (PSNR), structural similarity (SSIM) [57] and spectral angle mapper (SAM) [66], are employed to evaluate the denoising performance of different approaches. Larger values of PSNR and SSIM and smaller values of SAM indicate better image quality.

4.1.5 Implementation Details. We implement the proposed framework HIDFlowNet in Pytorch. Adam [26] optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$ is employed to update model parameters and the learning rate is set to 2×10^{-4} . All models are trained in an easy-to-difficult way which has been proven helpful for network training [59]. Concretely, the networks are trained with Gaussian noise for 50 epochs and then trained with mixture noise for another 50 epochs. The training batch size is set as 8. For fair comparisons, all deep learning-based methods are trained and tested in the same way. The models trained for 50 and 100 epochs are employed to remove Gaussian noise and mixture noise respectively. All deep

Table 2: Quantitative comparison of denoising performance on the KAIST dataset in Gaussian and complex noise cases.

σ	Index	Noisy	Model based methods					Deep Learning based methods			
			BM4D [43]	LRTDTV [56]	NMoG [11]	FastHyDe [70]	LLRGTv [22]	HSIDCNN [65]	QRNN3D [59]	SST [31]	Ours
50	PSNR	14.151	35.775	32.999	26.422	34.312	32.361	37.960	34.974	35.997	38.067
	SSIM	0.060	0.893	0.875	0.550	0.870	0.866	0.917	0.853	0.923	0.942
	SAM	1.094	0.192	0.194	0.409	0.192	0.234	0.130	0.199	0.149	0.101
70	PSNR	11.228	33.854	32.021	24.849	32.772	30.498	36.366	31.712	34.820	37.224
	SSIM	0.036	0.850	0.856	0.474	0.823	0.808	0.890	0.719	0.906	0.933
	SAM	1.186	0.232	0.211	0.475	0.221	0.288	0.158	0.299	0.166	0.106
90	PSNR	9.047	32.373	31.227	23.674	32.193	29.006	34.819	27.432	33.708	36.288
	SSIM	0.024	0.810	0.838	0.425	0.809	0.758	0.852	0.480	0.885	0.921
	SAM	1.249	0.266	0.226	0.528	0.235	0.335	0.198	0.463	0.188	0.112
Mixture	PSNR	13.748	17.856	32.178	18.192	17.877	24.980	34.661	34.964	33.929	34.774
	SSIM	0.103	0.189	0.882	0.221	0.161	0.604	0.835	0.864	0.845	0.901
	SAM	1.089	0.382	0.192	0.403	0.350	0.305	0.329	0.224	0.232	0.146

**Figure 6: Visual comparison of denoising results on the real HSI dataset Indian Pines.**

learning-based models are trained on an NVIDIA Geforce RTX 3090 GPU.

4.2 Experimental Results

4.2.1 Experiment on Synthetic Data. The denoising results on the CAVE dataset are shown in Table 1 and Figure 5. It can be seen that our proposed HIDFlowNet demonstrates better performance in most cases. While achieving desirable results in Gaussian noise cases, most model-based methods fail to tackle complex noise as manually designed priors cannot fully describe complex situations. In addition, although HSIDCNN achieves the best PSNR in several cases by performing multiscale feature extraction, HIDFlowNet also achieves promising PSNR and performs significantly better in other evaluate indexes. The visualization results of reconstructed HSIs are provided in Figure 5. As shown in the figure, model-based approaches yield either still noisy images or over-smooth results. Deep learning-based methods obtain promising denoising results but are also prone to provide over-smooth predictions since these methods overemphasize the pixel similarity and ignore the underlying distribution of clean HSIs. In contrast, HIDFlowNet is more capable of preserving fine-grained details while restoring spatial

smoothness without introducing undesirable artefacts. The excellent performance of HIDFlowNet is primarily owing to the fact that the compressive encoding component suppresses noise and enhances the low-frequency part of HSIs, and the flow-based decoder enjoys the information-less property and preserves textural details. Moreover, HIDFlowNet also exhibits desirable denoising performance on the KAIST dataset as shown in Table 2, which further verifies the superiority of our proposed method.

4.2.2 Experiment on Real-World Data. We further employ all models trained on the Indian Pines dataset for real-world HSI denoising to verify the effectiveness of our proposed approach. Since there is no ground truth for real-world data, we provide visualization results shown in Figure 6 for comparison. It can be observed that the original image is seriously degraded owing to environmental factors such as terrible atmosphere or sensor failure. Compared with other approaches, our HIDFlowNet effectively handles the unknown noise and outputs sharper and more realistic results, convincing the robustness and superiority of HIDFlowNet.

4.2.3 Effectiveness of Flow Model. We present visualization results of the generated HSIs derived from different Gaussian noises in Figure 7 to verify the effectiveness of our proposed flow-based model. It can be observed that while generated HSIs are highly similar which verifies the stability of the trained model, there still exist differences in local details owing to different noises, confirming the effectiveness of our proposed flow-based model.

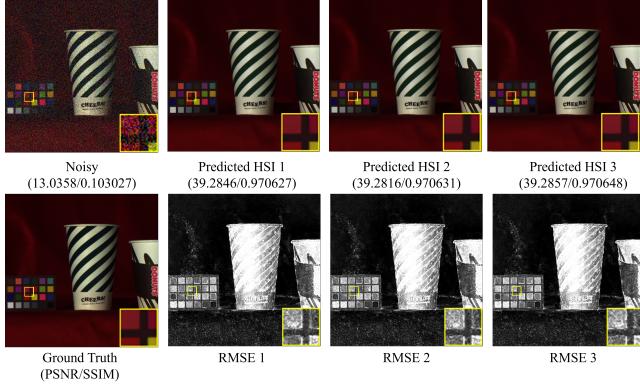


Figure 7: Diverse predictions of clean HSI given one noisy HSI in the KAIST dataset by our method.

4.3 Ablation Study

In this section, we provide an ablation study on the components of HIDFlowNet and model complexity.

4.3.1 Feature Decoupling Analysis. In addition to quantitative results, we provide visual analysis to further prove the effectiveness of the proposed encoding network and the flow-based decoder. Specifically, the inputs and the feature maps of the 3th, 6th and 9th layers of the encoder and decoder are depicted in Figure 8. It can be seen that with the increase of layers, the outputs of the encoder tend to ignore local details (e.g., the joint of the blocks) and gradually capture global low-frequency information. Since attention is calculated in local windows as elaborated in [58], the feature map of the last layer exhibits a relatively obvious reticular structure. The outputs of the decoder demonstrate that with the guidance of the encoder, random Gaussian noise is transformed into local high-frequency information progressively, convincing the feasibility of the invertible network.

4.3.2 Component Analysis. There are two components in an invertible conditional block, including an affine conditional layer and a residual invertible convolution. In this section, to verify the effectiveness and rationality of the two components adopted in our work, we conduct denoising on the KAIST dataset in Gaussian noise case with $\sigma = 50$ for comparison and the effectiveness of the two components is explored as illustrated in Table 3. As can be seen, the model without affine conditional layers demonstrates the worst performance since the decoder is a pure generative network without conditional information in this case, and the quality of the denoising result is highly reliant on the performance of the encoder.

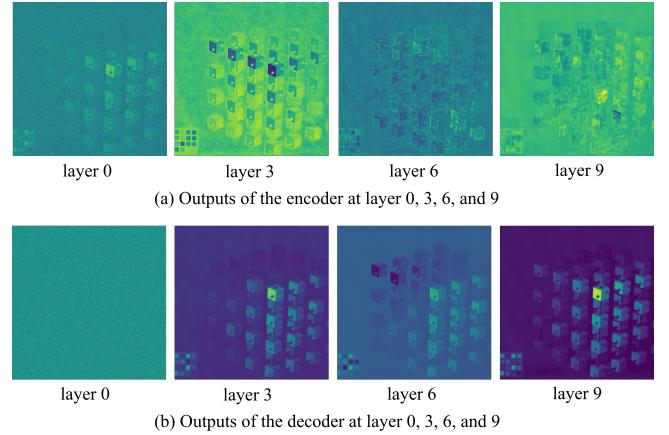


Figure 8: The visual results of the feature maps of the conditional encoder and the invertible decoder.

HIDFlowNet adopted in our work outperforms other configurations, verifying the rationality of the proposed approach.

Table 3: Ablation study of the two components in the invertible conditional block.

Configuration	PSNR	SSIM	SAM
No Invertible Conditional Affine Layer	32.145	0.896	0.150
No Residual Invertible Convolution	37.837	0.940	0.108
Ours	38.067	0.942	0.101

4.3.3 Model Complexity. We further investigate the influence of the depth of HIDFlowNet by testing models on the KAIST test set in Gaussian noise case with $\sigma = 50$. As shown in Table 4, the denoising performance improves with the increasing number of ICBs. HIDFlowNet with 9 ICBs is adopted in our work for a tradeoff between complexity and performance.

Table 4: Ablation study of different network depth.

Depth	PSNR	SSIM	SAM	Parameters (M)	Time (s)
6	37.779	0.940	0.102	1.937	0.374
9	38.067	0.942	0.101	2.808	0.467
12	38.315	0.944	0.101	3.679	0.628

5 LIMITATIONS AND FUTURE WORK

While our proposed HIDFlowNet exhibits plausible denoising performance, there are still several limitations. Specifically, the invertible requirement of flow-based models puts limitations on the use of various operations such as convolution with larger kernels, attention mechanisms and dimension reduction, reducing the fitting ability of the network. Moreover, the proposed method lacks control over the generative process and is unable to explicitly generate

HSIs with expected specific properties such as higher SSIM. In the future, novel invertible frameworks and controllable generative models are worth further exploration to alleviate these problems.

6 CONCLUSION

To alleviate the ill-posed nature of HSI denoising (i.e., multiple predictions are reasonable for a given noisy HSI) which is ignored by most existing deep learning-based approaches, this paper proposes a novel flow-based network namely HIDFlowNet. The network directly learns the distribution of clean HSIs conditioned on noisy counterparts and is capable of generating diverse clean HSIs. Specifically, the proposed HIDFlowNet is composed of a conditional encoder and an invertible decoder to decouple the learning of low-frequency and high-frequency information. The encoder utilizes transformers and down-sampling operations to obtain low-resolution images so that global representation is effectively extracted, while the decoder employs a series of invertible conditional blocks to preserve local details. Extensive experiments on two synthetic datasets and one real-world dataset demonstrate the superiority of our proposed model both quantitatively and qualitatively.

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