Improved Quasi-Recurrent Neural Network for Hyperspectral Image Denoising

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Abstract. Hyperspectral image is unique and useful for its abundant spectral bands, but it subsequently requires extra elaborated treatments of the spatial-spectral correlation as well as the global correlation along the spectrum for building a robust and powerful HSI restoration algorithm. By considering such HSI characteristics, 3D Quasi-Recurrent Neural Network (QRNN3D) is one of the HSI denoising networks that has been shown to achieve excellent performance and flexibility. In this paper, we show that with a few simple modifications, the performance of QRNN3D could be substantially improved further. Our modifications are based on the finding that through QRNN3D is powerful for modeling spectral correlation, it neglects the proper treatment between features from different sources and its training strategy is suboptimal. We, therefore, introduce an adaptive fusion module to replace its vanilla additive skip connection to better fuse the features of the encoder and decoder. We additionally identify several important techniques to further enhance the performance, which includes removing batch normalization, use of extra frequency loss, and learning rate warm-up. Experimental results on various noise settings demonstrate the effectiveness and superior performance of our method.

Keywords: Hyperspectral Image Denoising · Quasi-Recurrent Neural Network · Adaptive Skip Connection. Frequency Loss.

1 Introduction

Hyperspectral Image (HSI) is made up of numerous bands across a wide range of the spectrum. Different from common RGB images, HSI divides images into much more bands than three, whose wavelengths can be extended beyond the visible. In comparison with multispectral images, HSI measures continuous spectral bands instead of spaced ones. Such properties make HSI especially attractive and useful for the applications of remote sensing [2], face recognition [32], classification [1], etc. However, due to the limitation of existing hyperspectral imaging techniques, the captured HSIs often suffer from severe corruption, which makes the development of robust post-processing algorithms for HSI denoising an urgent need.

Traditionally, optimization algorithms are often adopted to solve HSI denoising with different hand-crafted priors exploring the domain knowledge of the HSI,
i.e., global correlation along the spectrum and spatio-spectral correlation. Typical priors that are extensively studied includes, total variation [27], wavelet [20], and low-rank [31]. By considering the spectral and spatial redundancy, non-local patch-similarity [19] is also widely used in conjunction with variable splitting algorithms [10] and tensor-based dictionary learning [22]. These methods generally have no requirement for a large amount of training data or even be training-free, which makes them attractive in some data-insufficient scenarios, e.g., remotely sensed image processing. However, their performance is strongly correlated with the matching degree of handcrafted priors with the underlying characteristics of HSIs, which weaken their robustness.

Recent works on HSI denoising shift their attention to the deep-learning for its capability to model complex intrinsic characteristics of HSI using a data-driven manner with neural networks. Following this direction, researchers have explored various network architectures, including extension [4] of 2D image denoising network DnCNN [29], introduction of residual connection [28], U-net [8], recurrent network [26], etc. These networks embed the domain knowledge of HSI, i.e., the spatial-spectral correlation and the global correlation along the spectrum, to varying degrees. Among these methods, the 3D quasi recurrent neural network (QRNN3D) [26] receives great attention for its powerfulness, simplicity, as well as flexibility for handling HSI with a diverse number of bands using a single model. It achieves these engaging properties mainly with a 3D convolutional quasi-recurrent unit, which uses 3D convolution for spatial-spectral correlated feature extractions and a quasi-recurrent network for information aggregation along the global spectrum.

Despite the superior performance of QRNN3D [26] achieved, we show that it can be substantially improved further by elucidating the network design and training pipeline with only a few simple modifications. The intuition behind this is that even though QRNN3D is powerful at modeling spectral dependency and correlation, it lacks proper attention on the inter-relationship of different features from encoder and decoder, which is shown to be considerably important for boosting performance in various computer vision tasks [25].

In this paper, we propose a simple yet effective network component, i.e., adaptive skip connection fusion, to further improve the performance of QRNN3D. This block is plug-and-play so that it can be easily integrated into the existing architecture of QRNN3D and beyond. Specifically, we replace the vanilla skip connection in QRNN3D, which is implemented with naive addition, with an adaptive one that dynamically fuses the shallow features from the encoder and the high-level features from the decoder. With this simple network change, we then propose several techniques, including removing batch normalization, fine-tuning the model with frequency loss, and the use of learning rate warm-up, to push the performance even higher. We perform experiments on Gaussian noise with various noise strengths. The quantitative and visual results demonstrate the effectiveness and superior performance of the proposed method.

Our contributions are summarized as follows:
1. We propose a simple yet effective network component, i.e., adaptive fusion, to remedy the deficiencies of QRNN3D [26] in modeling inter-relationship of features from encoder and decoder.

2. We introduce several techniques to further improve the performance, consisting of removing batch normalization, fine-tuning the model with frequency loss, and the use of learning rate warm-up.

3. We achieve substantial improvement over the original QRNN3D and obtain advanced performance for HSI denoising under various noise settings.

2 Related Works

As one of the central topics in HSI processing systems, HSI denoising has been extensively studied in recent years. There has diverse range of directions for solving this task, including traditional optimization-based methods, deep-learning ones, and hybrid ones as well. In this section, we provide an overview of the recent major methods for HSI denoising. Besides, several important techniques that are proposed for RGB image restoration are also included for completeness.

2.1 Traditional Methods

Traditional methods solve the problem of HSI denoising by treating it as an optimization problem, where they attempt to find unknown clean HSI by minimizing an optimization objective that incorporates the intrinsic properties of spectrum and images. Such incorporation is generally achieved by designing different hand-crafted priors, e.g., total variation priors [27], wavelet priors [20], and low-rank priors [31]. By considering the non-local self-similarity in the spectral and spatial dimensions, many works such as block-matching and 4-D filtering (BM4D) [19] and the tensor dictionary learning [22] are proposed.

These optimization-based HSI denoising methods are flexible to remove different types of noise [11] and can be even extended to task beyond denoising [5]. However, their performance is significantly restricted by the matching degree of handcrafted prior and the underlying properties of HSI, which is difficult to ensure for complex real scenes. To address this problem, Plug-and-Play methods [3] are introduced by integrating the optimization-based method with a learning-based prior, i.e., a plug-and-play Gaussian denoiser [30]. Specifically, Liu et al [17] propose a fibered rank constrained tensor restoration framework and adopt BM3D [7] as an extra plug-and-play regularization. In [18], FFDNet [30] is used for local regularity, alongside the Kronecker-basis-representation-based tensor low-rankness for global structures regularity. Lai et al [16] propose a more powerful denoiser prior for HSI restoration, by regularizing the global spatial-spectral correlation.

2.2 Deep Learning Methods

Deep-learning-based methods have gained superior popularity in recent years. Inspired by 2D image denoising network DnCNN [29], Chang et al [4] proposed
HSI-DeNet that learns multi-channel 2-D filters to model spectral correlation. Yuan et al [28] introduce residual network structure with a sliding window strategy for remote sensed HSI. To further exploit the spatial-spectral correlation, Dong et al [8] designed a 3D U-net architecture. These methods have been successfully applied to different HSIs, but all of them lack the flexibility to handle HSIs with different number of bands using one model. To address such issues, Wei et al proposed a 3D convolutional quasi recurrent neural network (QRNN3D), which uses 3D convolution to extract spatial-spectral correlated features, and then adopts a quasi recurrent network to integrate information from different bands in a global perspective.

In parallel with the applications of deep learning for HSI denoising [4,8], there are much more networks [29,6] that were introduced to handle RGB or gray scale image restoration [29]. People have shown the effectiveness the various useful network components, such as residual connection [9], channel attention [6], layer normalization [6], as well as GELU activation [6]. Our work is greatly inspired by these preceding works, and we show that the original QRNN3D [26] can be greatly enhanced with only a few network modifications and the improvement of training strategy.

3 Improved Quasi Recurrent Neural Network

The original Quasi Recurrent Neural Network for HSI denoising was proposed in QRNN3D [26]. In this section, we provide a detailed illustration of our improved version.

3.1 Overall Architecture

The original QRNN3D [26] is basically a U-net [24] where each block is a quasi recurrent unit (QRU). To be more specific, The input noisy HSI will be feed into a feature extractor, i.e., a Bi-directional QRU, to obtain shallow features. These features are then passed to a series of plain and downsampling QRU blocks, and reversed set of upsampling blocks. Finally, the output clean HSI will be produced by a Bi-QRU reconstructor.

Our improved architecture is shown in Figure 1. The overall U-net architecture remains unchanged, but we replace the original additive skip connection with an pixel-wise fusion module to further enhance the feature integration adaptively. We also remove the batch normalization for the entire network, as we found it normalize the features using global statistics of HSI that ignore the bandwise discrepancy, which is undesirable for HSI denoising.

3.2 Adaptive Fusion

Skip connection is the most essential part that distinguishes the U-net [24] from other network architectures. It provides a direct but effective way to recover
Fig. 1. Overall architectures of the proposed improved quasi recurrent neural network.

the low-level information that is lost during the downsampling of the commonly used bottleneck convolutional neural network.

The original QRNN3D uses the vanilla additive skip connection, which is implemented as an addition between encoder and decoder features at the same depth. Suppose features of encoder and decoder at the $i^{th}$ depth level are $F^i_e$ and $F^i_d$, respectively, the addition skip connection can be precisely described as follow,

$$F^{i+1}_d = F^i_d + F^i_e.$$ (1)

The major problem of the addition skip connection is that it put the same weight on the shallow features from the encoder and highly processed features from the decoder. This could be problematic due to the imbalanced information density of features from the encoder and decoder. Hence, we propose an adaptive skip connection to explicitly fuse the features from different sources. By denoting the weight of $i^{th}$ depth level as $w_i$, the detailed formulation is

$$F^{i+1}_d = \text{Conv3D}([F^i_d, F^i_e]).$$ (2)

An visualization of our adaptive skip connection and the additive one is shown in Figure 2.

3.3 Training Techniques

In this section, we identify several important training techniques to further improve the performance and stabilize the training.

Normalization Batch normalization [13] is empirically known as an important technique to stabilize the training of the deep neural network. It works by normalizing the activation to approach zero mean and unit variance, which
is generally favorable for different neurons. However, the batch normalization normalizes the HSI input with the statistics of all bands that ignores the band discrepancy along the spectrum. As a result, the use of batch normalization might not be as useful as its applications in other domains [9,12] than it is for HSI [26]. We, therefore, propose to remove it and we empirically found it brings nonnegligible improvement.

**Learning Rate Warm Up** In [26], a multi-stage training strategy is used for training a single model to handle different noise settings. Specifically, the original strategy first trains the network on a fixed noise strength for a number of epochs using a set of learning rates, and then further fine-tuned on a larger set of noise strengths for another number of epochs. The used learning rate scheduler is shown in Table 1.

It can be observed that there is a sudden change in learning rate when it switches from the first training stage to the second one. We observe that it is suboptimal and could lead to training instability and deteriorated performance after removing the batch normalization. Instead of reducing the initial learning rate for the second stage of training, which reduces the possibility to escape the local optimal, we propose to use learning rate warm-up to gradually increase the learning rate from 0 to $1 \times 10^{-3}$ for the first epoch.

| Stage | 1            | 2            |
|-------|--------------|--------------|
| Noise | Fixed noise strength | Random noise strength |
| Epoch | 0-20 | 20-30 | 30-35 | 35-45 | 45-50 |
| Learning Rate | $10^{-4}$ | $10^{-4}$ | $10^{-3}$ | $10^{-3}$ | $10^{-3}$ |

**Frequency Loss** The mean square error or least absolute deviations in the spatial domain is a reasonable optimization objective for most image reconstruction tasks, like HSI denoising. Combining with the recent advanced neural network, the reconstruction quality has been lifted to a relatively high altitude. This makes
the difference in the spatial domain less distinguishable, and the use of previous optimization objectives might not be able to provide sufficient supervision for the difficult part during the reconstruction. Fortunately, it is shown that there are some unobservable reconstruction errors that could be easily observed at the frequency domain [14]. Hence, we propose to use focal frequency loss [14], in comparison with spatial losses, to further fine-tune our model to alleviate the bias of neural networks and obtain better performance.

4 Experiments

In this section, we provide the quantitative results as well as visualization results of the proposed method against the competing ones for both Gaussian denoising and complex denoising. An ablation study is also included to demonstrate the effectiveness of each component.

4.1 Datasets

All the experiments are conducted with the ICVL hyperspectral dataset, which contains 201 clean HSI in the resolution of $1392 \times 1300$ that divides the spectrum into 31 spectral bands. The dataset covers several different outdoor natural scenes and manually designed indoor scenes. An overview of the example images of the dataset is shown in Figure 3. Following [26], we split the dataset into three parts, i.e., 100 images for training, 51 for validation, and 50 for testing. For training, we process the original HSIs into multiple overlapped smaller data cubes via even-stride cropping. The spatial resolution of each cube is $64 \times 64$ and the spectral resolution remains unchanged. Random rotation and scaling are also employed to further augment the dataset. For testing, the main region of each HSI with the size of $512 \times 512 \times 31$ is used.

4.2 Implementation Details

We implement the proposed network using PyTorch [21]. Adam [15] optimizer is used to minimize the hybrid loss described in Section. We follow the same training strategy as [26], with slight modifications on the setup of the learning rate. The strategy is briefly described here and we refer interested readers to [26] for more details. In short, the network is first trained on a fixed Gaussian noise level of 50 for 20 epochs and then finetuned with random Gaussian noise from a given set for 30 epochs to produce the first-stage Gaussian denoising model. In the second stage, the complex denoising model is obtained via another 50 epochs of fine-tuning using the trained Gaussian denoising model. The learning rate is set to $1 \times 10^{-3}$ at first, but decayed by 0.1 once the number of epochs reaches one of the milestones, and finally reduced to $1 \times 10^{-5}$ for each stage. The batch size is set to 16 or 64 based on the training stages.
4.3 Evaluation Metrics

We evaluate the performance of the proposed method, using three quantitative quality indices including PSNR, SSIM, and SAM. Both PSNR and SSIM measure the spatial quality, but SSIM focuses more on the reconstruction quality of structural details. SAM focuses more on spectral quality. The larger PSNR and SSIM values the better the restored images are, while the smaller values of SAM imply better spectral reconstruction quality. PSNR and SSIM are calculated as the average of the bandwise results for each HSI.

4.4 Results on Gaussian Noise

For the experiments with Gaussian noise, we evaluate our model with different noise strengths, including 30, 50, and random strengths (Blind) ranging from 30 to 70. The simulated noisy input is generated by adding zero-mean additive white Gaussian noise with a given variance. We use a single model from the first training stage to tackle different noise levels.

For systematical evaluation, we compare our method with three traditional HSI denoising methods as well as two deep-learning ones. The traditional methods include BM4D [19], KBR, and WLRTR [5]. The deep-learning-based methods include HSID [28] and QRNN3D [26]. In the spirit of fairness, the hyperparameters in traditional methods are carefully tuned, and the deep-learning-based models are retrained if needed.

The quantitative results are shown in Table 2. It can be easily observed that our method achieves the best performance in all different settings with a large margin over the competing methods. Specifically, our method achieves over 0.7 dB PSNR improvement on noise strength of 30 and over 0.4 PSNR improvement on average. The visual comparison is provided in Figure 4. It can be seen that our
Table 2. Quantitative denoising results of different methods under several noise levels on ICVL dataset.

| Sigma Metric Method | Noisy BM4D [19] | KBR [23] | WLRTR [5] | HSID [28] | QRNN3D [26] | Ours |
|---------------------|------------------|----------|----------|----------|-------------|------|
| 30                  | PSNR 18.59       | 38.45    | 41.48    | 42.62    | 38.70       | 42.22 | **42.96** |
|                     | SSIM 0.110       | 0.934    | 0.984    | 0.988    | 0.949       | 0.988 | 0.990 |
|                     | SAM 0.807        | 0.126    | 0.088    | 0.056    | 0.103       | 0.062 | 0.053 |
| 50                  | PSNR 14.15       | 35.60    | 39.16    | 39.72    | 36.17       | 40.15 | **40.54** |
|                     | SSIM 0.046       | 0.889    | 0.974    | 0.978    | 0.919       | 0.982 | **0.983** |
|                     | SAM 0.991        | 0.169    | 0.100    | 0.073    | 0.134       | 0.074 | **0.073** |
| Blind               | PSNR 17.34       | 37.66    | 40.68    | 41.66    | 37.80       | 41.37 | **41.93** |
|                     | SSIM 0.114       | 0.914    | 0.979    | 0.983    | 0.935       | 0.985 | **0.986** |
|                     | SAM 0.859        | 0.143    | 0.087    | 0.064    | 0.116       | 0.068 | **0.054** |

method perverse more structural details while other methods tend to produce over-smoothed results.

4.5 Ablation Study

To verify the effectiveness of each proposed component, an ablation study is performed. We evaluate the PSNR improvement each component brings by adding them one by one, starting from the baseline model, i.e., QRNN3D [26].

Table 3. Evaluation of the effectiveness of the proposed network components and training techniques.

| Baseline | w/o BN | Adaptive Fusion | Frequency Loss | PSNR   |
|----------|--------|-----------------|----------------|--------|
| ✓        | ✓      | ✓               |                | 42.28  |
| ✓        | ✓      | ✓               | ✓              | 42.45  |
| ✓        | ✓      | ✓               | ✓              | 42.91  |
| ✓        | ✓      | ✓               | ✓              | 41.54  |
| ✓        | ✓      | ✓               | ✓              | 42.96  |

We train all the model variants for the Gaussian denoising task and evaluate them on 30 noise strengths. The experimental results is shown in Table 3. As we can observe, removing batch normalization improves the PSNR of the baseline model by 0.17. Our adaptive fusion brings substantial improvement further with over 0.4 increase on PSNR, which demonstrates its effectiveness and simplicity. Our frequency loss also brings improvements.
Fig. 4. Simulated Gaussian noise removal results at 20th band of image under noise level $\sigma = 50$ on ICVL dataset.

5 Conclusion

In this paper, we have introduced several simple modifications that push the performance of QRNN3D even further, while maintaining the simplicity of the overall network architecture. We find that the original QRNN3D [26] pays much attention to the spectral correlation of HSI, but lacks effective network components to explore the inter-channel relationships, which are shown to be important in many RGB restorations works [6]. Intending to address these issues, we propose two simple yet effective plug-and-play components, i.e., adaptive skip connection and simplified channel attention, which strengthen the network’s ability for modeling channel interaction. We also find that by removing batch normalization, using frequency similarity loss, and scaling up the model by increasing depth, our improved QRNN3D could obtain substantial improvement over the old one, and achieve the state-of-the-art performance for various HSI denoising tasks.
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