Coupled Convolutional Neural Network with Adaptive Response Function Learning for Unsupervised Hyperspectral Super-Resolution

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Abstract—Due to the limitations of hyperspectral imaging systems, hyperspectral imagery (HSI) often suffers from poor spatial resolution, thus hampering many applications of the imagery. Hyperspectral super-resolution refers to fusing HSI and MSI to generate an image with both high spatial and high spectral resolutions. Recently, several new methods have been proposed to solve this fusion problem, and most of these methods assume that the prior information of the Point Spread Function (PSF) and Spectral Response Function (SRF) are known. However, in practice, this information is often limited or unavailable. In this work, an unsupervised deep learning based fusion method HyCoNet that can solve the problems in HSI-MSI fusion without the prior PSF and SRF information is proposed. HyCoNet consists of three coupled autoencoder nets in which the HSI and MSI are unmixed into endmembers and abundances based on the linear unmixing model. Two special convolutional layers are designed to act as a bridge that coordinates with the three autoencoder nets, and the PSF and SRF parameters are learned adaptively in the two convolution layers during the training process. Furthermore, driven by the joint loss function, the proposed method is straightforward and easily implemented in an end-to-end training manner. The experiments performed in the study demonstrate that the proposed method performs well and produces robust results for different datasets and arbitrary PSFs and SRFs.

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Index Terms—Hyperspectral Image, Super-Resolution, Coupled Convolutional Neural Network, Autoencoder, Adaptive Learning

I. INTRODUCTION

A Hyperspectral image (HSI) is a data cube containing hundreds of contiguous narrow-bandwidth images covering a large wavelength range [1]. Because of its high spectral resolution, HSI is very important in many applications such as land cover classification [2]–[5], target detection [6]–[9], feature extraction and dimensionality reduction [10]–[13], data fusion [14]–[16], and spectral unmixing [17]–[19]. However, the hyperspectral imaging system often has a trade-off between spectral resolution and spatial resolution, due to hardware restrictions. This causes the spatial resolution of HSI to usually be coarser than that of multispectral imagery (MSI). The limited spatial resolution restricts further applications of HSI. To enhance the spatial resolution of HSI, a natural solution is to fuse it with higher-resolution MSI. This approach is called hyperspectral and multispectral image fusion (HSI-MSI Fusion).

HSI-MSI Fusion is similar to the MSI pansharpening process in which a low spatial resolution MSI is fused with a high-resolution panchromatic (PAN) image. However, applying these pansharpening methods to directly fuse HSI and PAN imagery remains challenging as PAN images contain limited spectral information, and, as a result, spectral distortion can easily occur [20]. Recently, HSI-MSI Fusion has attracted a lot of attention because the result preserves more accurate spectral information with a high-spatial resolution. The existing fusion methods can be categorized as: (1) extensions of pansharpening methods; (2) Bayesian-based approaches; and (3) matrix factorization-based methods [21].

In the first category, Richard et al. first attempted to use a pansharpening-based method to fuse HSI and MSI using a wavelet technique [22]. However, the results were highly dependent on spectral resampling, which made it difficult to enhance the spatial resolution. Zhang et al. proposed a pansharpening-based fusion method that used a 3-D wavelet transform [23]. Chen et al. proposed a framework for fusing HSI and MSI by dividing the HSI into several regions and fusing the HSI and MSI in each region using the pansharpening method [24]. Aiazzi et al. proposed a component substitution fusion method that took the spectral response function (SRF) as part of the model [25]. Liu et al. proposed a spectral...
preservation fusion method that was based on a simplified solar radiation and land-surface reflection model [26].

In the second category, Eismann et al. proposed a Bayesian-based fusion method that used a stochastic mixing model of the underlying spectral content to achieve resolution enhancement [27]. Qi et al. proposed a variational-based fusion method that assumed the target image in a low-dimensional subspace and that solved the fusion problem by alternating optimization with respect to the coding coefficients and the target image [28]. Simes et al. formulated the fusion problem as a minimization of a convex objective containing two quadratic terms and an edge-preserving term [29]. Akhtar et al. proposed a non-parametric Bayesian sparse coding strategy which first inferred the probability distributions of the material spectra and then computed the sparse codes of the high-resolution image [30].

Methods in the third category the matrix factorization methods usually assume that the HSI is composed of a series of pure spectral vectors and that the matrix HSI can be decomposed into abundances and endmembers. The fusion problem becomes an estimation problem for the endmembers of the low-resolution HSI and abundances of the high-resolution MSI. Kawakami et al. proposed an unmixing approach to fusing a low-resolution HSI with a high-resolution RGB image. Firstly, the unmixing algorithm was employed to estimate the basis endmembers of the low-resolution HSI; this was then combined with a high-resolution RGB image to produce the final result [31]. Instead of keeping the estimated endmembers of the low-resolution HSI fixed, Yokoya and Lanaras presented a coupled NMF (CNMF) to estimate endmembers and abundances using an alternating unmixing approach [32], [33]. Wycoff et al. restricted sparse regularization to abundances which assume that each pixel is composed of only a small number of endmembers [34]. Akhtar et al. proposed a sparse representation-based approach with a local spatial structure constraint whose main feature was the exploitation of the local patch prior knowledge using a greedy pursuit algorithm [35]. Yi et al. proposed an interactive feedback strategy fusion method with spectral unmixing and spatial constraints [36]. Tensor-based fusion methods utilizing tensor factorization with sparse constraint or subspace projection have also been proposed [14], [37].

In recent years, deep learning has been successfully applied in many spectral tasks [38]–[41]. To deal with the HSIMSI fusion problem with deep learning, Wang et al. proposed a convolutional neural network to fuse HSI and MSI using a residual network and a preserved spectral loss function [42]. Han et al. proposed a partially densely connected network to fuse MSI and HSI spatial and spectral information [43]. Palsson et al. proposed a 3-D convolutional neural network together with reducing the dimensionality of the HSI to make the fusion more computationally efficient [44]. Dian et al. initialized the HSI by solving a Sylvester equation and then implementing a neural network to learn the mapping between the initialized HSI and target HSI [45]. Xie et al. proposed a fusion network that took the observation models of low-resolution images and the low-rank knowledge into consideration [46]. Wang et al. proposed a deep learning-based blind hyperspectral image fusion method with iterative and alternating optimization strategy [47]. Han et al. presented a multi-scale spatial and spectral fusion convolutional neural network (CNN) for HSI-MSI Fusion [48]. However, all of the deep learning-based methods mentioned above are supervised learning methods that are difficult to apply in practice because the high-resolution HSI needed for training is unavailable. Qu et al. proposed an unsupervised deep learning-based fusion method with a sparse Dirichlet network [49]. Zhou et al. proposed a registration algorithm and a fusion algorithm to handle HSI and MSI image with significant scale difference and nonrigid distortion [50]. Fu et al. proposed a camera spectral response (CSR) optimization layer to learn the spectral response with an unsupervised way [51].

Some of fusion methods assume that the prior information of the SRF or point spread function (PSF) is known. However, in practice, this information is often difficult to obtain [29]. In this paper, an unsupervised deep learning-based fusion network that can handle situations where the PSF and SRF are unknown is proposed. The only information our proposed method requires is the spectral coverage of the MSI and HSI, which is easy to obtain from the data provider. To our knowledge, this is the first time which the unsupervised coupled CNN was developed with learnable PSFs for the HSI-MSI Fusion task. The main contributions of this study can be summarized as follows:

- A novel unsupervised network called HyCoNet is proposed to solve the HSIMSI fusion problem for an unknown SRF and PSF. The results show that the proposed method can deal well with arbitrary SRFs and PSFs in comparison with nine state-of-the-art HSIMSI fusion methods, as applied to four remote sensing datasets;
- Based on the linear unmixing theory, three autoencoder networks are jointly coupled in the proposed method. Within these networks, the endmembers comprise the parameters of one convolution layer, which is shared between two autoencoder networks. Also, in order to improve the consistency of these networks, a learned PSF layer acts as a bridge connecting the low- and high-resolution abundances;
- A joint-loss function that drives the model using unsupervised learning and an end-to-end training manner, thus providing a simple and direct training strategy for obtaining the final result, is introduced.

This paper is organized as follows. Section II describes the basic formulation of the HSI and MSI fusion problem. Section III introduces the proposed fusion model, including the network architecture and the joint-loss function. Section IV presents the experimental results and discussion; Section V is the conclusion.

## II. Problem Formulation

The HSI-MSI fusion problem requires the estimation of the HSI, which has both high spectral and high spatial resolution and is denoted as $X \in \mathbb{R}^{M \times N \times L}$, where $M$, $N$ and $L$ are the width, height, and number of spectral bands. The input images include a high spatial resolution MSI denoted as $Y \in \mathbb{R}^{M \times N \times l}$ and a low spatial resolution HSI denoted as $Z \in \mathbb{R}^{M \times N \times l}$. The core of the fusion problem is to estimate the HSI from the MSI and HSI, which is denoted as $\hat{X} \in \mathbb{R}^{M \times N \times L}$.
where the matrix $R \in \mathbb{R}^{m \times n \times l}$ describes the spatial degradation function, and $A \ast$ denotes the convolution operator.

Consider the spectral degraded version of $X$.

$X = AE$ \hspace{1cm} (1)

where the matrix $A \in \mathbb{R}^{MN \times p}$ is formed from the abundances, the matrix $E \in \mathbb{R}^{p \times l}$ is made up of the endmembers, and $p$ is the number of pure spectral bases. This equation describes the degree of mixing for each pixel in the image $X$.

Similarly, the input $Z$ can also be expressed as a linear combination of the same endmembers $E$:

$Z = A_h E = S \ast X = S \ast AE$ \hspace{1cm} (2)

where the matrix $A_h \in \mathbb{R}^{mn \times p}$ represents the abundances, the matrix $S \in \mathbb{R}^{L_m \times L_n}$ is the point spread function (PSF), which describes the spatial degradation function, and $\ast$ denotes the convolution operator. $L_m$ and $L_n$ are the spatial size of the convolution filter. $Z$ also denotes the spatially degraded version of image $X$. The input $Y$ is the spectrally degraded version of $X$:

$Y = XR = AER$ \hspace{1cm} (3)

where the matrix $R \in \mathbb{R}^{L \times l}$ is the spectral response function (SRF), which describes the spectral degradation process.

Moreover, the spectral degraded version of $Z$ should approximate to the spatially degraded version of $Y$:

$Y_{lr} = ZR = S \ast Y$ \hspace{1cm} (4)

where the matrix $Y_{lr} \in \mathbb{R}^{m \times n \times l}$ represents the low spatial resolution multispectral image (LRMSI).

In addition, our goal is to estimate $X$ using the inputs $Y$ and $Z$ with the following constraints also satisfied:

$$\sum_{j=1}^{p} a_{ij} = 1 \quad \forall \ i, j$$

$$a_{ij} \geq 0 \quad \forall \ i, j$$

$$1 \geq e_{ij} \geq 0 \quad \forall \ i, j$$

where $a_{ij}$ is a component unit of $A$ and $e_{ij}$ is a component unit of $E$. These constraints relate to the sum-to-one property of the abundance, the non-negative property of the abundance and the bounded non-negative property of the endmembers, respectively [23]. In addition, the abundances should be sparse, meaning that each HSI pixel is composed of only a few pure spectral bases.

## III. Proposed Method

According to Eqs. (1)-(3), to solve the HSIMSI fusion problem, the key point is to estimate the high spatial resolution abundance matrix $A$ and the spectral bases matrix $E$. The HRMSI provides detailed spatial contextual information that is highly correlated with $A$. Also, the LRHSI preserves the spectral information, which is highly consistent with the target spectral endmembers matrix $E$. The basic idea of the proposed method is based on matrix factorization. The proposed HyCoNet is an unsupervised network that includes three coupled autoencoder networks. The target HRHSI is embedded in one of the networks; this will be elaborated on in the part A of this section, and the Part B introduces the joint objective function used in the training.

### A. Coupled Autoencoder Network for Image Fusion

The proposed network is composed of three autoencoder nets, as shown in Fig. 2. The upper one called LRHSI autoencoder, and the lower one called HRMSI autoencoder. The estimated target HRHSI $X$ is embedded in the HRMSI autoencoder. The LRMSI autoencoder can be seen at the upper right.

Since the 2D convolution layer, which has a kernel size of $1 \times 1$, is equivalent to the fully connected layer when it applied to a spectral vector, all the fully connected layers in the traditional autoencoder network are replaced by the convolution layers, as shown in Fig. 2. In addition, all the convolution kernel sizes are set to be $1 \times 1$, except for the PSF convolution layer. Instead of using the fully connected layer, the convolution layer is used to preserve the spatial structure of the input image cube for easy implementation of the PSF operation. Further details of the PSF operation are discussed below.

In the LRHSI autoencoder, the network tries to learn an approximation to the identity function $f(Z) \approx Z$. Since the input LRHSI contains sufficient spectral information, the
endmembers $E$ and abundances $A_h$ can be extracted during the reconstruction process for this autoencoder.

The module before the latent variable $A_{ah}$ is the encoder:

$$A_{ah} = f_{en}(Z)$$

(6)

where the $f_{en}()$ try to learn a nonlinear mapping which transforms the input LrHSI to its abundances $A_{ah}$; $A_{ah} \in \mathbb{R}^{m \times n \times p}$ represents the abundances of $Z$, and $p$ is the number of endmembers.

The module after the latent variable is the decoder function:

$$\tilde{Z}_a = f_{de}(A_{ah})$$

(7)

where $\tilde{Z}_a$ is the output of this upper autoencoder, which represents the reconstructed input image cube. The decoder function $f_{de}()$ is a convolution layer without bias and is shown as the green convolution layer 1x1 Conv in Fig. 2. This layer is also used in the HrMSI autoencoder, meaning that these two autoencoders share the same parameters as this convolution layer. The parameters of the shared convolution layer are denoted as the endmember matrix $E$, and $SRF()$ is the spectral resampling operation. The HrHSI is the output of the shared convolution layer:

$$\tilde{X} = f_{de}(A)$$

(10)

where $\tilde{X}$ is the estimated target image.

To handle the situation where the SRF parameters are unknown, a convolution layer and a normalization layer are placed after the target $\tilde{X}$ to learn the unknown parameters of the SRF. The SRF consists of spectral resampling from HSI to MSI and the process can be defined as:

$$\varphi_i = \frac{\int_{\lambda_{i,U}}^{\lambda_{i,L}} R(\lambda)\varepsilon(\lambda) d\lambda}{\int_{\lambda_{i,U}}^{\lambda_{i,L}} R(\lambda) d\lambda}$$

(11)

where $\varphi_i$ is the spectral radianse of band $i$ of the HrMSI, $\lambda$ is the wavelength, $\lambda_{i,U}$ and $\lambda_{i,L}$ are the wavelength bounds of band $i$ of the HrMSI, $R(\lambda)$ is the spectral response function, and $\varepsilon$ is the spectral radianse of the HrHSI. To implement the spectral resampling in the neural network, a convolution layer
with kernel size $1 \times 1$ (shown in red and labeled 1x1Conv in Fig. 2) is added after the target image $\tilde{X}$ to simulate the numerator of Eq. (11). A normalization layer (labeled Norm in Fig. 2) follows the convolution layer and simulates the denominator of Eq. (11).

Therefore, the SRF process within our network can be expressed as:

$$\varphi_i = SRF(\varepsilon_{\lambda}) = \frac{\sum_{\lambda=b}^{\lambda=L} w_{i,\lambda} \varepsilon_{\lambda}}{\sum_{\lambda=b}^{\lambda=L} w_{i,\lambda}} \tag{12}$$

where $\varphi_i$ is the band $i$ image in $\tilde{Y}$, $w_{i,\lambda}$ is the weight of the SRF convolution layer, and $\varepsilon_{\lambda}$ is the band with wavelength $\lambda$ in $\tilde{X}$. The use of this function means that the convolution layer and the normalization layer integrate the HrHSI $X$ and the HrMSI autoencoder and forces the reconstructed image to be spectrally consistent and the HrMSI autoencoder and forces the reconstructed image.

The PSF means that a given pixel is a weighted combination of contributions from the pixel and its neighboring pixels [54]. In the fusion problem, this means that a pixel in the HRMSI $Y$ is a weighted combination of the pixel and its neighboring pixels from the LRMSI $X$. Therefore, the PSF means that a given pixel is a weighted combination of the pixel and its neighboring pixels from the LRMSI $X$. Therefore, the PSF is a convolution process and a convolution operation can easily be implemented as part of the convolutional neural network. In our network, to simulate the PSF, a convolution layer with 1 input channel and 1 output channel is implemented for every band of the abundance $A$. According to the definition of the PSF, the relationship between $X$ and $Z$ can be expressed as $Z = PSF(X)$. Also, $X$ and $Z$ are composed of the same linear unmixing endmembers. Therefore, another low-resolution abundance $A^b_h$ can be expressed as:

$$A^b_h = PSF(A) \tag{13}$$

where $PSF()$ is the convolution layer labeled with the blue arrow and 1LayerConv in Fig. 2. The spatial size of this PSF convolution kernel is the same as the ratio of the Ground Sampling Distance (GSD) of the LrHSI to that of the HrMSI, and the stride of the convolution layer equals the kernel size. The PSF process acts as a bridge between the LrHSI autoencoder and the HrMSI autoencoder and forces the reconstructed image to be spectrally consistent $\tilde{X}$. Therefore, another LrHSI $\tilde{Z}_b$ can be reconstructed using $A^b_h$ and $E$:

$$\tilde{Z}_b = f_{de}(A^b_h) \tag{14}$$

In addition, the spatial degraded version of the HrMSI is equivalent to the spectrally degraded version of the LrHSI shown as LrMSI-Autoencoder in Fig. 2. This relation can be expressed as:

$$PSF(Y) = \tilde{Y}_{lr}^b \approx \tilde{Y}_{lr}^b = SRF(Z) \tag{15}$$

where $\tilde{Y}_{lr}$ is the estimated LrMSI.

Fig. 3 shows flow charts for the proposed method, including input images, output images and corresponding target images. The first row of Fig. 3 indicates the inference of the input $Z$ in the LrHSI-Autoencoder and is also represented by the yellow arrows in Fig. 2. The inference of the HrMSI $Y$ includes two parts. The first one is shown as the second row of Fig. 3 which includes the PSF operation to generate the LrHSI and the SRF operation; this process is represented by the blue arrows in Fig. 2. The second part can be seen in the third row of Fig. 3 and consists of the SRF operation; this process is represented by the red arrows in Fig. 2. The last row of Fig. 3 shows the relationship between the two LrMSIs. Therefore, the objective function for reconstruction can be expressed as:

$$L_{base}(Y, Z) = \left\| Z - \tilde{Z}_a \right\|_1 + \alpha \left\| Z - \tilde{Z}_b \right\|_1 + \beta \left\| Y - \tilde{Y}_c \right\|_1 + \gamma \left\| \tilde{Y}_{lr} - \tilde{Y}_{lr}^b \right\|_1 \tag{16}$$

where $\alpha$, $\beta$, and $\gamma$ are trade-off parameters that tune the weights between these reconstruction errors.

The sum-to-one and non-negative properties given in Eq. (5) also need to be satisfied. First, we constrain the sum of the abundances in the channel dimension to meet the sum-to-one property:

$$L_{sum2one}(Y, Z) = \left\| 1 - \sum_{i=1}^{P} A_i \right\|_1 + \left\| 1 - \sum_{i=1}^{P} h_{h,i} A^a_{h,i} \right\|_1 + \left\| 1 - \sum_{i=1}^{P} h_{b,i} A^b_{h,i} \right\|_1 \tag{17}$$

where $i$ indicates the $i$th band of the abundance matrix $A$. Although the softmax function can be used to strictly enforce the sum-to-one property for the abundances, the resulting convergence accuracy is lower than for the proposed method. Part IV-D will explain this in detail.

Secondly, to enforce the non-negative property, several tricks are applied during training. The clamp function is applied to the output of the last convolution layer of both the encoder nets and decoder nets to force all the elements of the abundances and reconstruction images into the range [0,1]. Although we tried to use the sigmoid activation layer for this purpose, we found that it was difficult to make the network converge using this function. In addition, the weights of the shared convolution layer (containing the endmember parameter matrix, $E$), PSF layer and SRF layer should also meet the non-negative property. Since the weights of these
layers may be updated to a negative value after the back-
propagation, we applied the clamp function to these layers
after the weights were updated to force these weights into
the non-negative range. The range of the clamp function was 
[0, 1]. As a result, the weights satisfied the non-negative and
bounding constraints for each forward propagation, except for
the first time.

Since each pixel of the HSI is composed of a small number
of pure spectral bases, the abundance matrix $A$ should be
sparse. To guarantee the sparsity of the abundance, the KL
divergence is used to ensure that most of the elements in the
abundance are close to a small number:

$$L_{sparse}(Y, Z) = \sum_{i=1}^{s} \sum_{j=1}^{p} KL(a \parallel \tilde{a}_{i,j})$$

$$= \sum_{i=1}^{s} \sum_{j=1}^{p} (a \log(\frac{a}{\tilde{a}_{i,j}}) + (1-a) \log(\frac{1-a}{1-\tilde{a}_{i,j}}))$$

(18)

where $s$ is the number of pixels, $p$ is the number of convolution
kernels and also the number of endmembers, $a$ is a sparsity parameter which is set to a small value close to zero (0.0001 in
our network), and $\tilde{a}_{i,j}$ is an element of the abundance matrix
$A$. To satisfy this constraint, the elements of $A$ must mostly
be near zero. The sparsity constraint is also applied to the
abundance matrix $A^a_{\hat{}}$.

Ultimately, our aim is to solve the fusion problem in
accordance with the optimization problem:

$$L(Y, Z) = L_{base}(Y, Z)$$

$$+ \mu L_{sum2one}(Y, Z) + \nu L_{sparse}(Y, Z)$$

(19)

where $\mu$ and $\nu$ are the trade-off parameters used to balance the
errors. This loss function can be directly used in the optimizer,
thus providing a simple and direct solution.

### IV. EXPERIMENTS

To get an accurate assessment of the fusion quality and evaluate
the performances of different fusion methods, simulation
experiments [56] are used in the experiment. The proposed
HyCoNet was implemented using four different simulated data
sets. Firstly, the sensitivity of the trade-off parameters $\alpha$, $\beta$
, $\gamma$, $\mu$ and $\nu$ was evaluated. Secondly, the constraints on the
abundances were investigated. Thirdly, we compared the
effectiveness of the method for different numbers of endmem-
bers. Fourthly, the learned PSF kernels were investigated using
different spatially down-sampled kernels. The character of the
estimated abundances was then explored. Finally, the fused
images obtained using the different methods were evaluated
using both visual and quantitative measures.

#### A. Experimental Dataset

The proposed HyCoNet was evaluated using four widely
used HSI datasets: Pavia University, Indian Pines, Washington
DC, and University of Houston. The Pavia University data
were acquired by the ROSIS-3 optical airborne sensor in 2003.
This image consists of $610 \times 340$ pixels with a GSD of 1.3m
and spectral range of 430 nm-840 nm in 115 bands. Due to
the effects of noise and water vapor absorption, 12 bands have
been removed. An area covering 366 $\times$ 360 pixels in the lower-
left corner of the image and containing 103 bands was selected
for use in this experiment. The Indian Pines data were acquired
by the AVIRIS sensor in 1992. This image consists of 145 $\times$
145 pixels with a 20m GSD; the spectral range is 400 nm-2500
nm covering 224 bands. After removing 33 noisy bands, we
selected a 144 $\times$ 144-pixel area with 191 bands as experimental
data. The Washington DC data were acquired by the HYDICE
sensor in 1995. This image has an area of 1280 $\times$ 307 pixels
and a GSD of 2.5m. The spectral range is 400 nm-2500 nm
consisting of 210 bands. After removing 19 noisy bands, we
selected 191 bands covering 304 $\times$ 304 pixels for use. The
University of Houston data were used in the 2018 IEEE GRSS
Data Fusion Contest [57], and consist of 601 $\times$ 2384 pixels with
a 1-m GSD. The data covers the spectral range 380 nm-1050 nm
with 48 bands. We selected 46 bands consisting of 320 $\times$ 320
pixels from this imagery for use as experimental data.

#### B. Implementation Details

In the experiment, simulated spatial downsampling was used
to generate the LrHSI using a Gaussian filter, as is widely
used in remote sensing [58]. In the experiment, the width
and height of the Gaussian filter was set equal to the ratio
between the high-resolution GSD and the low-resolution GSD.
The standard deviation of all the Gaussian filters was set to
0.5, except as described in part [IV-F] and [IV-H] where different
standard deviations were used to evaluate the robustness of the
fusion model. To simulate the HrMSI, the SRF for the blue
to SWIR2 bands of the Landsat 8 were used [59]. To verify the
stability of the model, different GSD ratios and number
bands were used to simulate the LrHSI and HrMSI. For the
Pavia University and Indian Pines data, the GSD ratio was set

| Number of Bands of HrMSI | Pavia University | Indian Pines | Washington DC | University of Houston |
|-------------------------|-----------------|--------------|---------------|-----------------------|
| Spatial size of HrHSI   | 336 $\times$ 336| 144 $\times$ 144| 304 $\times$ 304| 320 $\times$ 320       |
| Spectral range of HrHSI | 466-834 nm      | 400-2500 nm  | 400-2500 nm   | 403-1047 nm           |
| Number bands of HrMSI   | 103             | 191          | 191           | 46                    |
| GSD ratio               | 4               | 4            | 8             | 8                     |
| Spatial size of LrHSI   | 84 $\times$ 84  | 36 $\times$ 36| 38 $\times$ 38| 40 $\times$ 40        |
| Bands of HrMSI          | Blue-Green-Red  | Blue to SWIR2| Blue to SWIR2 | Blue-Green-Red        |
| Number bands of HrMSI   | 3               | 6            | 6             | 3                     |
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(a) Parameters discussion for $\alpha$ and $\beta$.
(b) PSNR results using different $\gamma$.
(c) Accuracy comparison between $\mu$ and $\nu$.

Fig. 4. Parameters discussion. (a): Fusion accuracy of using different $\alpha$ and $\beta$ in Pavia University data, where $\alpha$ and $\beta$ mean the weights of reconstruction errors for LrLSI and HrMSI, respectively; (b): PSNR results of the different $\gamma$ in Pavia University data, where $\gamma$ represents the weight of LrMSI reconstruction error; (c): Accuracy comparison between $\mu$ and $\nu$ in the Pavia University data. $\mu$ and $\nu$ are the weights of sum-to-one error and sparsity error.

Fig. 5. Ablation study for the proposed network. $\varnothing$ means removing part of the network/losses and studying it’s performances.

(a) Convergence curve using clamp and softmax function.
(b) Function curves of clamp and softmax function.

Fig. 6. Convergence curve when using different constrained functions for abundances. (a) Convergence accuracy for comparing clamp function and softmax function, respectively. (b) Function curves of clamp and softmax function for a vector evenly spaced 0.01 over the range [-5, 5].

Table I summarizes the simulated parameters for all of the datasets used in this experiment.

To evaluate the performances of different fusion methods, simulation experiments are used in this experiment. Simulation experiments refer to that the spatial and spectral down-sampling are implemented on the original HrHSI, and this one is the truth target image to evaluate the performance of the estimated HrHSI. Five different quality measures were used to evaluate the performance of the fusion results: the root mean square error (RMSE), peak SNR (PSNR), spectral angle mapper (SAM), relative global dimension error (ERGAS), and mean relative absolute error (MRAE) [56], [60]. Of these measures, the RMSE, MRAE, and SAM were used in the visual evaluation, and the PSNR, SAM, and ERGAS were used in the quantitative evaluation.

The proposed model was trained using an Adam optimizer [61] with the default parameters $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\varepsilon = 10^{-8}$; the initial learning rate was set to $5 \times 10^{-3}$. Learning rate schedules seek to adjust the learning rate during training by reducing the learning rate according to a linear decay. After a total of 10000 epochs, the learning rate drops to 0. In our experiment, the number of input images was one; therefore, 1 epoch was equal to 1 iteration and the batch size was also 1. The Pytorch deep learning framework was used to train the proposed model [62]. The training environment consisted of an Intel i7-6850K CPU, 128-GB RAM, and 4×NVIDIA TITAN Xp 12G GPU.

C. Parameters Discussion

In the proposed method, the parameters $\alpha$, $\beta$, $\gamma$, $\mu$ and $\nu$ in the loss function Eqs. [16] and [19] need to be set. The parameters $\alpha$, $\beta$ and $\gamma$ are used to balance the weights of the different reconstruction errors. The parameters $\mu$ and $\nu$ are the trade-off parameters for the sum-to-one loss and sparsity loss.

Due to the fact that, in our method, the HSIMSI fusion is driven by the autoencoder network, the reconstruction errors are the main factor that influence this process. Therefore, firstly, we set the parameters $\gamma$, $\mu$ and $\nu$ to a fixed value to 4; it was set to 8 for the Washington DC and University of Houston imagery. The bluegreen-red bands of the Landsat 8 SRF were used for Pavia University and University of Houston data, and the blue to SWIR2 part of the Landsat 8 SRF was used for Indian Pines and Washington DC.

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of 1 to evaluate the effect of using different values of the parameters $\alpha$ and $\beta$. In this part of the experiment, we used the Pavia University data to investigate the performance. Fig. 4(a) shows the PSNR of the target image $X$ for different values of the trade-off parameters $\alpha$ and $\beta$. It can be seen that both parameters have a considerable effect on the fusion quality with the results being more sensitive to $\beta$ than to $\alpha$. This is because $\beta$ controls the weight of the reconstructed HrMSI, and therefore affects the spatial quality of the fused image. $\alpha$ also has an important effect on the quality of the fused target image. It is the weight of the $\tilde{Z}_b$ reconstruction error and the process of reconstructing image $\tilde{Z}_b$ is constrained by both the LrHSI and HrMSI autoencoder networks. Overall, the target image has a high PSNR when the two parameters $\alpha$ and $\beta$ are equal: these PSNR values have been marked in Fig. 4(a). Clearly the PSNR increases as these two parameters increase and tends to be smoother when $\alpha = \beta = 1$. The best result is achieved for $\alpha = \beta = 10$. Therefore, we set $\alpha$ and $\beta$ to 10 in the later experiments.

In the second experiment, we tested the effect of parameter $\gamma$, which controls the weight for the reconstruction of the LrMSI images. Fig. 4(b) shows the experiment results. It can be seen that $\gamma$ has only a slight effect on the fusion quality. Since the reconstruction accuracy is higher and more stable when $\gamma = 100$, we set $\gamma$ to 100 in the later experiments.

In the third experiment, the effects of $\mu$ and $\nu$ were investigated and the results are shown in Fig. 4(c). $\mu$ is the weight of the sum-to-one loss and $\nu$ is the weight of the sparsity loss. It can clearly be seen that the performance is sensitive to $\mu$ as this parameter affects the precision of the fusion reconstruction. In contrast, the performance is not sensitive to $\nu$ since we set the number of endmembers $p$ to 100. This is because the larger the number of endmembers, with the sum-to-one property, the more likely the endmembers are to be sparse. More details about the experiment carried out using different numbers of endmembers will be given in part IV-E. Accordingly, we set $\mu$ and $\nu$ to 0.001 in the subsequent experiments.

To investigate the essentiality of the proposed network, as shown in Fig. 5, ablation study was implemented in the case of the hyperparameters setting mentioned above. In this experiment, we can clearly see the performances when missing certain parts of the network or losses. As shown in Fig. 5, $\mathcal{C}$ means removing certain parts of the network or losses. It can be seen that the performances suddenly drop when removing $\tilde{Z}_b$. Compared to this branch, removing one of the other branches interacts only with less effect. This indicates the branch of $\tilde{Z}_b$ strongly ablation affects the overall fusion performance. Moreover, the branch $\tilde{Z}_b$ means that the core advantage of the learnable PSF layer play an important role in improving the fusion performance.

D. Constraint Function for the Abundance

Eq. (17) indicates that the sum-to-one property is restricted in the loss function; furthermore, a clamp function is used before the abundance to produce non-negative abundances. [63] reported that combing a softmax function before the abundances can also perfectly restrict the property of sum-to-one and nonnegative. However, in contrast to the clamp function, we found that using the softmax function leads to a lower reconstruction accuracy. Fig. 6(a) shows the fusion accuracy obtained when using different constraint functions for the abundances. It can be observed that the fusion accuracy obviously improves when the clamp function is used. Although the softmax function has a smoother curve, the convergence accuracy and convergence speed are slightly lower.

Fig. 6(b) can explain the results of this experiment: the figures shows the curves for the clamp and softmax functions. It can be seen that, due to the characteristics of the softmax function, it does not converge uniformly, meaning that different points converge at different rates and may converge arbitrarily slowly. This causes the gradient to be smaller for points with smaller values, which is equivalent to the gradient vanishing. In contrast, the gradient of the clamp function is updated faster in the range [0, 1].
Fig. 8. The visualization of original and estimated PSF kernel. (a) Pavia University, (b) Washington DC.

Fig. 9. The characters of learned abundances of three estimated abundances (Pavia University as example). (a) histograms, (b) the heatmaps of errors for the sum of abundance.

E. Number of Endmembers

In general, the reconstruction accuracy improves as the number of endmembers, \( p \), increases. Fig. 7 shows the changes in the PSNR and SAM with the number of endmembers for the four experimental datasets. To fully explore the effect of the hyperparameter \( p \), the experiment was repeated three times for each value of \( p \) using the same environment. The average values of the PSNR and SAM are shown in Fig. 7. In our model, the number of endmembers \( p \) represents the number of feature size of abundance and also represents the kernel size of the shared convolution layer. Therefore, a larger number of endmembers allows the model to be more representative. Although the number of endmembers is assumed to be equal to the number of pure spectral bases in the linear unmixing, the number of endmembers can also be larger than the actual number of pure bases because the convolution weight matrix \( E \) can contain mixed material [32]. In addition, the convergence accuracy depends on the image complexity. In the experiments using the Indian Pines and Houston University data, the reconstruction accuracy began to converge at \( p = 30 \), and fast convergence also occurred with the Washington DC data. For the Pavia University data, although the convergence was slow, the results were acceptable for smaller values of \( p \). For convenience, we set \( p = 100 \) in all cases when exploring the performance of the proposed model.

F. Learned PSF Kernel

The LrHSI was simulated using a PSF with a filter corresponding to the Gaussian function equal to the ratio of the GSD resolutions. Using the Pavia University and Washington DC data, we evaluated the learned kernels under different conditions. For each dataset, the standard deviations of the Gaussian kernel were set to 0.5, 1, and 2. The original PSF kernels and the estimated ones are shown in Fig. 8. Since the GSD ratios for the Pavia University and Washington DC data were 4 and 8, respectively, the kernel sizes for the two datasets were also 4 and 8, respectively. For Fig. 8, it can be seen that the estimated kernels are similar to the original ones. A large standard deviation produces a smoother kernel and a large weighted combination of contributions from the local pixel. From the above experimental results, it can be seen that the proposed method is highly suitable for estimating arbitrary PSFs for different datasets.

G. Estimated Abundances

In our network, the abundance is constrained by the sparse and sum-to-one characteristics of the loss function. Therefore, we next used the Pavia University data to explore the three
Fig. 10. The visualization of Pavia University fusion results. The first column is the color-composite of fusion results; the second column is RMSE error of color-composite image; the third column is the MARE error of HSI cube; the fourth column is the SAM error of HSI cube.

estimated abundances corresponding to \( A_h^a \), \( A_h^b \), and \( A_h \). The histograms of these abundances are shown in Fig. 9(a). The figure clearly shows that the estimated abundances are sparse. Fig. 9(b) shows heatmaps of the errors relative to the sum of the abundances. The heatmap for \( A_h^a \) shows that some of the areas at the edges did not completely satisfy the sum-to-one constraint. The reason for this is that although the sum-to-one character is constrained by the loss function, it is possible that errors remain for some pixels. In contrast, the results for \( A_h^b \) and \( A_h \) are much better because they are constrained simultaneously by the LrHSI and HrMSI autoencoders. The abundances in our network, therefore, mostly do have sparse

Fig. 11. The visualization of Indian Pines fusion results. The first column is the color-composite of fusion results; the second column is RMSE error of color-composite image; the third column is the MARE error of HSI cube; the fourth column is the SAM error of HSI cube.
Fig. 12. The visualization of Washington DC fusion results. The first column is the color-composite of fusion results; the second column is RMSE error of color-composite image; the third column is the MARE error of HSI cube; the fourth column is the SAM error of HSI cube.

and sum-to-one characteristics.

H. Comparison with the State of the Art

1) Visual Performance: Following the work of Yokoya [56], in this study, a set of baseline methods were used for comparison. These included CNMF [32], GSOMP [35], FUSE [64], GLPHS [65], GSA [25], HySure [29], Lanarass method (for convenience, we called it ICCV15 because it was published in proceedings of the 2015 International Convention on Computer Vision) [33], MAPSMM [27], SFIM-HS [26], and uSDN [49]. Because of the proposed fusion model is unsupervised algorithm and there is shortage of training sam-
TABLE II
Quantitative performance comparison with the different algorithms on the Pavia University data. The best one is shown in bold.

| CNMF | GSOMP | FUSE | GLPHS | GSA | HySure | ICCV15 | MAPSMM | SFIMHS | uSDN | HyCoNet |
|-----|-------|------|-------|-----|--------|--------|--------|--------|------|---------|
| σ = 0.5 |
| mSAM | 4.8715 | 10.5319 | 4.7626 | 5.4793 | 4.1585 | 4.0756 | 4.4325 | 5.1705 | 5.4588 | 5.5644 | 3.4107 |
| Ergas | 4.3905 | 8.5799 | 6.4135 | 4.6189 | 3.179 | 3.3403 | 3.2346 | 4.4652 | 25.2178 | 4.2374 | 2.8285 |
| σ = 1 |
| mSAM | 4.4029 | 9.0941 | 4.4667 | 4.7169 | 3.4810 | 3.5015 | 4.0694 | 4.0270 | 4.8534 | 5.3427 | 3.4002 |
| Ergas | 34.8032 | 31.0354 | 28.1708 | 32.9595 | 37.5222 | 36.9652 | 36.2953 | 34.9411 | 24.9070 | 33.1369 | 38.9132 |
| σ = 2 |
| mSAM | 3.7239 | 8.4744 | 4.4371 | 4.3608 | 3.4896 | 3.6169 | 4.0755 | 4.0317 | 4.5768 | 5.8754 | 3.4266 |
| Ergas | 36.0128 | 32.0090 | 28.2257 | 34.6688 | 38.4199 | 37.5251 | 36.7325 | 37.4392 | 27.5338 | 32.9005 | 38.5464 |

TABLE III
Quantitative performance comparison with the different algorithms on the Indian Pines data. The best one is shown in bold.

| CNMF | GSOMP | FUSE | GLPHS | GSA | HySure | ICCV15 | MAPSMM | SFIMHS | uSDN | HyCoNet |
|-----|-------|------|-------|-----|--------|--------|--------|--------|------|---------|
| σ = 0.5 |
| mSAM | 2.4152 | 2.9762 | 3.4716 | 2.7551 | 2.4707 | 2.4194 | 2.4718 | 2.5734 | 2.9597 | 3.0225 | 2.3211 |
| Ergas | 1.4630 | 1.5615 | 2.6297 | 1.737 | 1.3428 | 1.3927 | 1.6685 | 1.6691 | 20.515 | 1.5496 | 1.3236 |
| σ = 1 |
| mSAM | 2.2617 | 2.8014 | 3.3703 | 2.3955 | 2.2692 | 2.2854 | 2.3812 | 2.3034 | 2.5387 | 2.9288 | 2.2477 |
| Ergas | 1.3687 | 1.5447 | 2.5078 | 1.837 | 1.2040 | 1.3392 | 1.5949 | 1.3654 | 1.5670 | 1.6710 | 1.1946 |
| σ = 2 |
| mSAM | 2.2378 | 2.6955 | 3.3703 | 2.2745 | 2.3766 | 2.2390 | 2.2395 | 2.2378 | 2.6423 | 2.2022 | 2.3075 |
| Ergas | 1.3535 | 1.4978 | 2.4895 | 1.2376 | 1.1560 | 1.3785 | 1.5928 | 1.2865 | 1.3548 | 1.6187 | 1.1203 |

TABLE IV
Quantitative performance comparison with the different algorithms on the Washington DC data. The best one is shown in bold.

| CNMF | GSOMP | FUSE | GLPHS | GSA | HySure | ICCV15 | MAPSMM | SFIMHS | uSDN | HyCoNet |
|-----|-------|------|-------|-----|--------|--------|--------|--------|------|---------|
| σ = 0.5 |
| mSAM | 8.8273 | 13.1330 | 8.6505 | 6.9509 | 7.1772 | 9.8828 | 8.8196 | 7.3361 | 7.2102 | 7.0720 | 3.1984 |
| Ergas | 2.8031 | 3.4564 | 3.0064 | 2.2598 | 2.2679 | 2.7298 | 2.6514 | 2.4260 | 3.4973 | 1.6220 | 1.4334 |
| σ = 1 |
| mSAM | 7.2022 | 10.9944 | 8.2811 | 5.8102 | 5.8450 | 7.7087 | 8.0205 | 5.9814 | 6.0686 | 7.5995 | 3.2828 |
| Ergas | 27.8536 | 27.9343 | 25.7046 | 29.3968 | 30.0665 | 28.7836 | 29.9389 | 28.8842 | 26.9397 | 31.1618 | 34.9646 |
| σ = 2 |
| mSAM | 5.8034 | 9.6210 | 7.9871 | 4.1380 | 4.8277 | 6.5962 | 7.3153 | 3.7289 | 4.4360 | 4.8462 | 3.4581 |
| Ergas | 32.6577 | 28.9048 | 27.2447 | 34.4368 | 35.6293 | 29.8371 | 31.1686 | 33.7772 | 30.8051 | 32.8157 | 35.8561 |

TABLE V
Quantitative performance comparison with the different algorithms on the University of Houston data. The best one is shown in bold.

| CNMF | GSOMP | FUSE | GLPHS | GSA | HySure | ICCV15 | MAPSMM | SFIMHS | uSDN | HyCoNet |
|-----|-------|------|-------|-----|--------|--------|--------|--------|------|---------|
| σ = 0.5 |
| mSAM | 4.1054 | 7.8904 | 4.5623 | 5.3563 | 5.0434 | 3.2919 | 4.7705 | 5.5041 | 5.3316 | 5.7001 | 2.6070 |
| Ergas | 27.0969 | 28.5365 | 24.0123 | 25.7426 | 27.7226 | 33.0650 | 31.3685 | 25.2709 | 22.5418 | 29.1871 | 35.2361 |
| σ = 1 |
| mSAM | 3.2652 | 7.9230 | 4.3228 | 4.7508 | 4.3542 | 3.2576 | 4.7106 | 4.3736 | 4.8702 | 4.9899 | 2.6670 |
| Ergas | 29.5757 | 28.9063 | 24.4412 | 26.9179 | 29.1212 | 34.0103 | 31.8105 | 26.9350 | 23.7143 | 29.0370 | 35.1123 |
| σ = 2 |
| mSAM | 3.2239 | 7.6917 | 4.1386 | 3.6522 | 3.5930 | 3.0419 | 4.1594 | 3.0458 | 4.0967 | 5.0680 | 2.6976 |
| Ergas | 31.0872 | 30.0214 | 24.9240 | 29.6952 | 32.8512 | 35.4746 | 32.7251 | 31.2549 | 26.2060 | 29.4944 | 35.5182 |

Due to the fact that the proposed network is a fusion model where the SRF and PSF are unknown and the only assumption is that prior information about the spectral coverage of the MSI...
is known, to conduct a fair comparison, the estimated SRFs obtained by the HySure SRF estimation method [29] were used for the compared methods that require a SRF as input. These included CNMF, GSOMP, ICCV15, FUSE, MAPSMM and uSDN. The HySure SRF estimation method also only requires to know the spectral coverage of the HrMSI bands. Based on the GSD ratio of the simulated input image, a Gaussian kernel with a kernel size equal to the GSD ratio was used for all the methods which required a PSF kernel [56]; otherwise, the default source code settings were used.

Firstly, we used color-composite and heatmap images to visually evaluate the performance of the fusion results when \( \sigma = 0.5 \). In Figs. [10-13] the first column is the color-composite image (RGB image), the second column is the RMSE heatmap of the color-composite image, the third column is the MRAE heatmap, which can be considered to show the pixel-wise error for the reconstructed image cube, and the fourth column is the SAM error, which represents the spectral consistency of each pixel in the reconstructed image. For most of the methods, the results for the color-composite images in the first column are good. However, for the heatmap in the second column, there are big differences between these methods. The RGB images for GSOMP, HySure, ICCV15 and uSDN produce good results, indicating that these methods fully utilize the input HrMSI and the results retain more information about the HrMSI. Although the GSOMP method produces a good result for the RGB image, the heatmaps for MRAE and SAM are the poorest of those shown in Fig. [10][12] and [13] A similar result was also reported by Yokoya et al [56], who explained that the reason for this is that, in GSOMP, the high-resolution abundance is only estimated by the HrMSI and the sparsity prior. The errors for MAPSMM and FUSE show a block error distribution, which indicates that estimation of the results using patch-by-patch processing is unstable. For GSA and GLPHS, the errors have an inhomogeneous plaque block distribution. This is because the high-resolution image is obtained by sharpening the low-resolution image by adding spatial detail information and the cumulative error in the sharpened image can induce local irregular errors.

In the MRAE and SAM images, edge errors for objects are unavoidable for all the methods and this situation is particularly obvious in Figs. [10][12] and [13] This can be explained by the fact that the mixing effect of low-resolution images makes it difficult to achieve better results in heterogeneous regions. Nonetheless, the results of our proposed method achieve the best visual results.

2) Quantitative Performance: We investigated the quantitative performance of all the compared methods, and the quality measures obtained are shown in Tables [III-V] The mSAM is the mean of the SAM for all pixels and is used to evaluate the spectral consistency of the reconstructed HSI. The mPSNR is the mean PSNR of all the bands and is a measure of the spatial quality. The ERGAS is a global statistical measure used to evaluate the dimensionless global error for fused data.

From Tables [III-V] it can be seen that our proposed method produces stable results for different datasets and different PSF deviations. However, the performance is unstable for all of the compared methods, especially for the Washington DC dataset. Due to the complexity of the objects in this imagery, most methods cannot handle the local relationship between the LrHSI and HSI when \( \sigma = 0.5 \), this happened even to the methods that do not need prior knowledge of the PSF, e.g. GSA, SFIM-HS, GSOMP, HySure and MAP-SMM. For most methods, the performance improves as the standard deviation of the PSF increases. The results for the Indian Pines data are stable because the GSD for these data is the largest and the land objects are the simplest. The results for HySure, ICCV15 and uSDN are stable except for the Washington DC data. Although an adaptive PSF is also implemented in the HySure model, the performance varies depending on the dataset used. Compared with the other methods, CNMF, FUSE, GSA, HySure and ICCV15 have a better spectral consistency.

Fig. [14] shows the PSNR for the different bands of the HSI when \( \sigma = 0.5 \), showing the reconstructed spatial quality for each band. It is clear that our proposed method significantly outperforms the other methods that were tested. For the Pavia University and University of Houston data, the results for HySure, ICCV15 and GSOMP are good; however, again, all of the compared methods produce poor results for the Washington DC data. The results for the proposed method are not greatly affected by which dataset is used.

V. Conclusion

In this paper, we proposed a novel unsupervised deep learning method called HyCoNet to solve the HSI and MSI fusion problem for arbitrary PSFs and SRFs. Three coupled autoencoder nets were designed to extract spectral information from the LrHSI and spatial-contextual information from the HrMSI. Based on these autoencoder nets, the PSF was learned adaptively according to the correlation between the high- and low-resolution abundances, and the SRF was also learned by reconstruction of the autoencoder. Using the joint loss
function, the proposed method can easily be implemented in an end-to-end training manner and provide a straightforward training strategy. The experiments that were performed indicated that the proposed method solved the HSI and MSI fusion problem without knowing the prior information of the PSF and SRF; and produced stable and robust fusion results for arbitrary PSFs and SRFs.

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