Spectral Super-resolution for RGB Images
Using Class-based BP Neural Networks

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Abstract—Hyperspectral images are of high spectral resolution and have been widely used in many applications, but the imaging process to achieve high spectral resolution is at the expense of spatial resolution. This paper aims to construct a high-spatial-resolution hyperspectral (HHS) image from a high-spatial-resolution RGB image, by proposing a novel class-based spectral super-resolution method. With the help of a set of RGB and HHS image-pairs, our proposed method learns nonlinear spectral mappings between RGB and HHS image-pairs using class-based back propagation neural networks (BPNNs). In the training stage, unsupervised clustering is used to divide an RGB image into several classes according to spectral correlation, and the spectrum-pairs from the classified RGB images and the corresponding HHS images are used to train the BPNNs, to establish the nonlinear spectral mapping for each class. In the spectral super-resolution stage, a supervised classification is used to classify the given RGB image into the classes determined during the training stage, and the final HHS image is reconstructed from the classified given RGB image using the trained BPNNs. Comparisons on three standard datasets, ICVL, CAVE and NUS, demonstrate that, our proposed method achieves a better spectral super-resolution quality than related state-of-the-art methods.

Keywords—spectral super-resolution, BP neural network, spectral classification, spectral mapping

I. INTRODUCTION

Hyperspectral (HS) images with tens or hundreds of spectral bands can provide abundant spectral information, and have been widely used in environment monitoring [1][2], image classification [3][4], target detection [5][6] and so on. However, the imaging process to achieve high spectral resolution is at the expense of spatial resolution [7]. Compared with HS images, RGB images usually have much higher spatial resolution, but only have three spectral bands, and this greatly limits its effectiveness in the above-mentioned applications. Fortunately, the spectral information lost in RGB image may be recovered using the relationship between RGB and high-spatial-resolution hyperspectral (HHS) image-pairs provided by some generalized image databases. In other words, spectral super-resolution of RGB image is an alternative way to obtain the HHS image, if we can establish the spectral mapping from RGB to the hyperspectral spectral bands, using a large number of RGB and HHS image-pair samples.

Spectral super-resolution methods can be mainly divided into two groups: dictionary learning based and neural network based methods. Among the dictionary learning based methods, Arad et al. [8] have proposed a sparse representation method to obtain hyperspectral images from RGB images. Specifically, a spectral dictionary for hyperspectral and the corresponding RGB image-pairs is learned, using the hyperspectral image priors provided by the K-singular value decomposition (K-SVD) algorithm [9]. The sparse coefficients are estimated by the greedy orthogonal matching pursuit (OMP) algorithm [10] for the spectral dictionary learned above. To further improve the quality of reconstructed HHS image, Aeschbacher et al. [11] have re-implemented the above method [8] for better accuracy and runtime, and also proposed a shallow learned spectral reconstruction method based on the A+ method proposed for fast spatial super-resolution [12]. The comparable performance of [11] indicates its feasibility in the spectral super-resolution.

In order to further accurately establish the spectral mapping under a large number of RGB and HHS image-pair samples, neural network based methods have been developed very recently. Nguyen et al. [13] have proposed a radial basis function network based method to reconstruct a hyperspectral response from a single RGB image, with known spectral response function. It is a nonlinear mapping with a white-balancing process to reduce the effect of different illumination conditions. Galliani et al. [14] have proposed a deep convolutional neural network (CNN) method to learn an end-to-end mapping from RGB images to hyperspectral images. It has 56 layers, and can bring a better performance than that of the dictionary learning based methods. Inspired by the above methods, Can et al. [15] have proposed a rather shallow CNN method with residual blocks to learn the spectral mapping from RGB to HHS images. In addition, in order to increasing the number of image-pair samples for a better learning result, data augmentation [16] is also utilized, such as image rotating, flipping and downsampling. The common thread of the above CNN based methods is to establish the spectral mapping using image patches, such as a patch size of 36×36 used in [15] and a patch size of 64×64 used in [14], which means that the index space for spectral mapping is the texture provided by the
image patches, and the possible combination of such a large size image patches may lead to a huge requirements for the number of image-pair samples. That is one of the main reasons why data augmentation technique is also utilized in [16].

Considering it is more direct and efficient to use spectral domain as the index space, and the intrinsic characteristics that spectrum-pairs are more similar within each class of material than between classes and so do the corresponding spectral mapping. Hence in this paper, a novel spectral super-resolution method in the spectral domain is proposed to construct the HHS image from an RGB image, using class-based back propagation neural networks (BPNNs) [17]. In the training stage, unsupervised clustering is used to divide an RGB image into several classes according to spectral correlation, and the nonlinear spectral mappings for different classes are established using the spectrum-pairs from the classified RGB images and the corresponding HHS images by different BPNNs, respectively. In the spectral super-resolution stage, a supervised classification is used for the given RGB image to classify it into the classes determined during the training stage, and the final HHS image is reconstructed from the classified given RGB image using the trained BPNNs directly.

The main contributions of this paper are listed as follows.
1) To the best of our knowledge, this new framework for spectral super-resolution in the spectral domain based on the BPNNs is firstly given here.
2) A class-based BPNN learning method is proposed, to guarantee the similarity of spectral mappings from RGB to HHS images in each class.
3) An associative spectral classification is proposed, to ensure that the classes in the training and spectral super-resolution stages are consistent.

The rest of this paper is organized as follows. The proposed spectral super-resolution method is presented in Section II. Section III provides experimental results and discussions on different methods and datasets, followed by the conclusions in Section IV.

II. PROPOSED METHOD

An RGB image $Y \in \mathbb{R}^{3 \times N}$ with three spectral bands can be seen as a spectral degradation of an HHS image $X \in \mathbb{R}^{3 \times 3 \times N}$ by the spectral response function $L \in \mathbb{R}^{3 \times 3 \times 3}$:

$$Y = LX + N_Y$$  \hspace{1cm} (1) 

where $N$ represents the number of pixels per band, $\lambda_X$ ($\lambda_X \gg 3$) represents the number of spectral bands in $X$, and $N_Y$ denotes the zero-mean Gaussian noise in the degradation model which is a popular assumption in the imaging process modeling [20][21].

According to the intrinsic characteristics that the similar spectrum-pairs in a single class are more similar than that in the total spectral domain and similar spectrum-pairs should have similar spectral mappings, the RGB image $Y$ is divided into $K$ classes. Besides, Fig.1 shows the spectral mappings of different classes using typical spectrum-pairs on the CAVE dataset [24], which will describe in more detail in Section III. As can be seen in Fig.1, the spectral mappings are much similar in each class, while they are much different among different classes. In this case, the spectral mapping of class $i$ ($i = 1, ..., K$) from RGB to HHS can be described as

$$Y^{c(i)} = LX^{c(i)} + N_Y^{c(i)}$$  \hspace{1cm} (2) 

where $Y^{c(i)}$ and $X^{c(i)}$ denote the spectrums in class $i$ of RGB image $Y$ and HHS image $X$, respectively. According to
Eq.(2), for each class, if the spectral mapping of spectrum-pairs from RGB to HHS can be learned by our proposed method, the spectrums of HHS image can be reconstructed from the corresponding ones of RGB image. The details of our proposed method are described as follows.

A. Associative Spectral classification for RGB image

The classification of RGB image \( Y \) can be described as the following minimization problem, using the minimum intra-class distance criterion:

\[
\arg\min_{c, \mu_c} \sum_{i=1}^{K} \sum_{j=1}^{N} d(y_j, \mu_{c(i)})
\]

where \( y_j \in \mathbb{R}^2 \) denotes the \( j \)th column (i.e., spectrum) of \( Y \), \( \mu_{c(i)} \in \mathbb{R}^3 \) denotes the clustering center of class \( i \), and \( d(\cdot, \cdot) \) denotes the distance between the spectrums \( y_j \) and \( \mu_{c(i)} \). In this paper, spectral correlation is employed as the measure of distance, defined as

\[
d(y_j, \mu_{c(i)}) = 1 - \cos\left(\frac{\langle y_j, \mu_{c(i)} \rangle}{\|y_j\|_2 \|\mu_{c(i)}\|_2}\right).
\]

In the training stage, given the number of classes \( K \), the above spectral classification problem in an RGB image can be viewed as an unsupervised clustering problem which can be solved by the k-means clustering algorithm [22].

In the spectral super-resolution stage, using the clustering center \( \mu_{c(i)} \) determined during the training stage, each spectrum \( y_j \) of the input RGB image \( Y \) can be classified into the \( K \) clusters, by the following optimization problem:

\[
\arg\min_{c} \sum_{i=1}^{K} d(y_j, \mu_{c(i)}).
\]

The above unsupervised clustering and supervised classification in the training and spectral super-resolution stage respectively, can be seen as an associative classification method carried out before the spectral mapping.

B. Class-based BP Neural Networks and Spectral Mapping

The spectral mapping from the classified RGB image to the corresponding HHS image in Eq.(2) is a challenging underdetermined inverse problem. To solve this problem, we treat it as a nonlinear spectral mapping to be represented by a BP neural network, which has a strong nonlinear mapping capability with a few hidden layers. A basic three-layer BP neural network used in this paper, including one hidden layer, is shown in Fig.2. The output of the BP neural network is

\[
a_2 = l(w_2g(w_1a_0 + b_1) + b_2),
\]

where \( a_0 \) and \( a_2 \) denote the inputs and outputs of BPNN respectively, \( g(\cdot) \) denotes the nonlinear active function in the hidden layer, \( l(\cdot) \) denotes the linear active function in the output layer, and \( (w_1, w_2, b_1, b_2) \) are the weights and offsets respectively.

We can see from the above that our proposed method first learns the nonlinear spectral mappings of spectrum-pairs of RGB and HHS images, and then can reconstruct the HHS image from only an RGB image. The two stages of overall framework of our proposed method are shown in Fig.3 and Fig.4, respectively. In the training stage shown in Fig.3, an unsupervised clustering is performed on the spectrums of RGB images. Then the classified spectrums of an RGB image and those of its corresponding HHS image form the spectrum-pairs for training different BPNNs for different classes, thereby establishing a nonlinear mapping between RGB and HHS for each class. In the spectral super-resolution stage shown in Fig.4, after an associative spectral classification on the given RGB image, each spectrum in its corresponding HHS image is reconstructed by using the
established nonlinear spectral mapping of this corresponding class.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

To evaluate the super-resolution performance of our proposed method, the relative state-of-the-art methods from Nguyen et al. [13], Galliani et al. [14], Arad et al. [8], Aeschbacher et al. [11] and Can et al. [15] are used for comparison on the ICVL [8], CAVE [24] and NUS [13] datasets. Additionally, seven full-reference quality metrics are used to evaluate the performance of each method, including spectral angle mapper (SAM) [20]; absolute RMSE, RMSE\textsubscript{G} and RMSE\textsuperscript{e}; relative rRMSE, rRMSE\textsubscript{G} and rRMSE\textsuperscript{e} defined in [8], [14] and [15].

A. Datasets

The CAVE database [24] captured by a cooled CCD camera (Apogee Alta U260) has 32 images with a dimension of 512×512×31, ranging from 400 to 700 nm with 10 nm increments. Following the experiments of Galliani et al. [14], Aeschbacher et al. [11] and Can et al. [15], we use the CIE 1964 spectral response functions to simulate corresponding RGB images of the hyperspectral images.

The ICVL dataset [8] captured by a line scanner camera (Specim PS Kappa DX4 hyperspectral) includes 201 hyperspectral images with a dimension of 1392×1300 over 519 spectral bands (400-1000nm). To facilitate comparison and reduce computational costs [8], they are downsampled in the spectral domain with 31 bands from 400nm to 700nm with 10nm increments. We also use the CIE 1964 spectral response functions to simulate corresponding RGB images of the hyperspectral images, like in the original paper.

The NUS dataset [13] captured by a Specims PFDCL-65-V10E spectral camera contains 66 spectral images, ranging from 400 to 700nm, with 10nm increments. Following the experiments of Galliani et al. [14] and Aeschbacher et al. [11], Canon 1D Mark III spectral response functions are used to obtain the RGB images from the corresponding hyperspectral images.

B. Experimental Results

Since our proposed method learns the spectral mapping based on the classified spectrum-pairs, a different selection of training and test spectrums is used in this experiment. For the CAVE and ICVL datasets, instead of dividing the images into two sets [11], we divide the classified spectrums into two sets as 2-fold cross-validation. Similarly, for the NUS dataset, the classified spectrums are divided into a training set and a test set with the training/test split ratio provided in [13]. In the training set, the spectrum-pairs are selected randomly from each class to training different BPNNs. For the fairness of the comparisons, the numbers of training and test spectrums used in our proposed method are the same with those of the method proposed by Aeschbacher et al. [11]. Additionally, in the training process, 85% of the training spectrum-pairs are used to train the BPNNs, and 15% of them are used as the validation data, to mitigate overfitting. Besides, the loss function in the training process is the mean squared error between the target spectrums and the mapped spectrums; the sigmoid function is used as the active function in the hidden layer, and a linear function is used in the output layer; the maximum training epochs is set to 100. According to different datasets and different numbers of training data, Table 1 shows the number of classes and the number of nodes in each layer of BPNNs for the three different datasets.

Table 1 Parameters in our proposed method on different datasets.

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<tr>
<td>Number of training data</td>
<td>10000×16</td>
<td>2000×100</td>
<td>400×41</td>
</tr>
<tr>
<td>Number of classes</td>
<td>160</td>
<td>100</td>
<td>10</td>
</tr>
<tr>
<td>Number of nodes in BPNNs</td>
<td>3-10-31</td>
<td>3-20-31</td>
<td>3-6-31</td>
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on the results. The spectral super-resolution results performs best with the lowest rRMSE and the smallest variance of rRMSE at different wavelengths, and the spectral spectral super-resolution results in rRMSE with the results provided by [8] and [11], Fig.6 shows the average and best results (underlined). The spectral super-resolution results performs best with the lowest rRMSE and the smallest variance compared with that of the methods [8] and [11], even in the wavelength ranges such as 400-420 nm, which are not well covered by the spectral response functions of the RGB image. Additionally, the training time and the testing time of different methods are shown in Table 3, which measure the time cost of the training step and the time required to reconstruct one image of the ICVL dataset. Our proposed method is conducted using MATLAB R2015b on a computer with a 3.60 GHz CPU and 28 GB RAM. Similarly to the method of [11], any vast parallelism has not been used in this comparison. The results in Table 3 indicate that, our proposed method uses much less training and testing time than the methods of [8] and [11]. Considering the better or comparable spectral super-resolution performances shown in Table 2, our proposed methods is more efficient with less computing time and better performances than the other related methods. Besides, for the NUS dataset, our proposed method performs the best in both spectral and spatial domains than all the other related methods. Particularly, SAM is reduced over 0.88 than all the other related methods. Besides, for the NUS dataset, our proposed method performs well in the number of classes of typical pixels (c) with and (d) without the dark strip on the left edge of (a).

For the ICVL dataset, Table 2 also indicates the second best results (underlined). The spectral super-resolution results show that our proposed method is comparable to the method of [15] in RMSE_G and rRMSE_G, and performs the best in terms of other quality metrics. Besides, to compare the spectral super-resolution results in rRMSE with the results provided by [8] and [11], Fig.6 shows the average and variance of rRMSE at different wavelengths, and the spectral response functions of the RGB image (RGB SRFs) are also provided. The results in Fig. 6 show that our proposed method performs best with the lowest rRMSE and the smallest variance compared with that of the methods [8] and [11], even in the wavelength ranges such as 400-420 nm, which are not well covered by the spectral response functions of the RGB image. Additionally, the training time and the testing time of different methods are shown in Table 3, which measure the time cost of the training step and the time required to reconstruct one image of the ICVL dataset. Our proposed method is conducted using MATLAB R2015b on a computer with a 3.60 GHz CPU and 28 GB RAM. Similarly to the method of [11], any vast parallelism has not been used in this comparison. The results in Table 3 indicate that, our proposed method uses much less training and testing time than the methods of [8] and [11]. Considering the better or comparable spectral super-resolution performances shown in Table 2, our proposed methods is more efficient with less computing time and better performances than the other related methods. Besides, for the NUS dataset, our proposed method performs the best in both spectral and spatial domains than all the other related methods. Particularly, SAM is reduced over 0.88 than the method of [14], and RMSE is reduced over 0.4 than all the other related methods. From the spectral super-resolution results in Table 2, we can see that our proposed method performs comparable or better than the recent shallow CNN approach of [15], and significantly better than the recent deep CNN and sparse representation method of [11] and [8], and the approach of [13]. Additionally, the spectral super-resolution performance of our proposed method on typical spectrums of different datasets is shown in Fig.7. As can be seen in Fig.7, the spectrums are reconstructed with high accuracy using our proposed method.

### Table 3: Training time and testing time for spectral super-resolution of one ICVL image with a size 1300×1392×31.

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<tbody>
<tr>
<td>Training time</td>
<td>-</td>
<td>2.8h</td>
<td>5.7h</td>
<td>0.45h</td>
</tr>
<tr>
<td>Testing time</td>
<td>1.5h+100s</td>
<td>130s</td>
<td>110s</td>
<td>15s</td>
</tr>
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</table>

Fig.6 RGB SRFs and the averaged rRMSE at different wavelengths of three methods on the ICVL dataset.

**Discussion on Parameters Selection**

To evaluate the effect of the number of classes $k$ on the spectral super-resolution performance of our proposed method, the averaged RMSE and SAM curves of the reconstructed spectrums of HHS images on the CAVE dataset are shown in...
some extent. It indicates that the reconstructed spectrum $s$ of our proposed method can preserve more spatial and spectral information of the HHS counterpart is reconstructed from the classified given images. Then for a given test RGB image, each spectrum in its corresponding HHS image is predicted. The difference of RMSE and SAM are shown in Table 2. It can be due to the fact that, with more classes, the similarity of spectrums in each class is increased, which is more conducive for BPNNs to learn the spectral mapping in each class. Experimental results on three standard datasets demonstrate that our proposed method achieves a better spectral super-resolution quality than that of the other state-of-the-art methods.

### IV. CONCLUSIONS

In this paper, we proposed a new spectral super-resolution method to reconstruct an HHS image from an RGB image using class-based BPNNs. In this method, BPNNs are used to learn nonlinear spectral mappings using the classified spectrum-pairs of RGB images and their corresponding HHS images. Then for a given test RGB image, each spectrum in its HHS counterpart is reconstructed from the classified given RGB image using the trained BPNNs. Besides, an associative spectral classification is adopted to ensure the consistency of classes in the training stage and the spectral super-resolution stage. Experimental results on three standard datasets demonstrate that our proposed method achieves a better spectral super-resolution quality than that of the other state-of-the-art methods.

### REFERENCES


