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**Spatial resolution enhancement of
hyperspectral images based on
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Spatial resolution enhancement of hyperspectral images based on redundant dictionaries

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Abstract. Spatial resolution enhancement of hyperspectral images is one of the key and difficult topics in the field of imaging spectrometry. The redundant dictionary based sparse representation theory is introduced, and a spatial resolution enhancement algorithm is proposed. In this algorithm, a pixel curve instead of a pixel patch is taken as the unit of processing. A pair of low- and high-resolution respective redundant dictionaries are joint trained, with the constraint that a pair of high- and low-resolution corresponded pixel curves can be sparse represented by same coefficients according to the respected dictionaries. In the process of super-resolution restoration, the low-resolution hyperspectral image is first sparse decomposed based on the low-resolution redundant dictionary and then the obtained coefficients are used to reconstruct the corresponding high-resolution image with respect to the high-resolution dictionary. The maximum *a posteriori* based constrained optimization is performed to further improve the quality of the reconstructed high-frequency information. Experimental results show that the pixel curve based sparse representation is more suitable for a hyperspectral image; the highly spectral correlations are better used for resolution enhancement. In comparison with the traditional bilinear interpolation method and other referenced super-resolution algorithms, the proposed algorithm is superior in both objective and subjective results. © The Authors. Published by SPIE under a Creative Commons Attribution 3.0 Unported License. Distribution or reproduction of this work in whole or in part requires full attribution of the original publication, including its DOI. [DOI: [10.1117/1.JRS.9.097492](https://doi.org/10.1117/1.JRS.9.097492)]

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1 Introduction

Hyperspectral imaging is a major breakthrough in the field of earth observation that occurred at the end of the last century. It combines the techniques of imaging and spectroscopy, fuses the spatial and spectral information of the imaging targets.¹ With hyperspectral imaging, an observing target can be imaged in dozens to hundreds of spectral bands, covering the range from ultraviolet to microwave, which far exceed the limit of human vision. Therefore, it can detect both spatial and spectral characteristics of the target, and provide more effective information for analyzing and distinguishing the properties. Currently, application of hyperspectral remote sensing has been extended from the traditional fields of military reconnaissance and topographic mapping to urban planning, resources investigation, environmental monitoring, traffic management, etc. Thus, it is playing a more and more important role in the fields of remote sensing and earth observation.

Spatial resolution and spectral resolution are the two most important indicators when measuring the quality of hyperspectral images. Spatial resolution describes the ability to resolve spatial details in the target that are being imaged, while spectral resolution measures the ability to resolve electromagnetic spectrum features. How to increase both the spatial and spectral resolutions is a key topic of the hyperspectral imaging technology. However, due to the constraint of

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imaging mechanisms, the two goals cannot be achieved simultaneously. This is because the spectral bandwidth of a hyperspectral imaging system is very narrow, and thus, a large field of view is needed to collect enough light quanta to maintain an acceptable signal-to-noise ratio.² Therefore, spectral resolution enhancement of a hyperspectral image is often at the cost of spatial resolution decreasing. Because of this, the spatial resolution of hyperspectral images is much lower than that of the common visible or panchromatic images. Fortunately, super-resolution (SR) restoration,^{3,4} a signal processing based resolution enhancement method, provides a new choice to resolve this problem without any hardware costs. This technique has been widely investigated for visible images/videos. However, few of them were specially designed for hyperspectral images. In most cases, a hyperspectral image was taken as a sequence of gray images with somewhat complementary information between each band and then was reconstructed by traditional SR methods band by band.⁵ However, hyperspectral images are quite different from visible images. One of the most significant characteristics is that it has much higher spectral correlations than other image sequences, while the spatial correlations are quite low. Traditional spatial based SR methods may not achieve as good performance as for visible images. In addition, SR algorithms are often computation-intensive and time-consuming, when applied to dozens of hyperspectral bands separately, the computations that required were unbearable.

In the field of visible image SR, a sparse representation based algorithm⁶ has shown good performance. However, for the aforementioned reasons, it is not suitable to be directly used for hyperspectral images. On the other hand, a pixel curve based sparse method has been proven effective for describing hyperspectral images and has shown good performances in spectral unmixing and classification applications, but few for SR. In this paper, the sparse representation based SR method⁶ is specially investigated for hyperspectral images and a redundant dictionary based hyperspectral image SR restoration algorithm is proposed. According to the specific characteristics of the hyperspectral images, the pixel curve (formed by the pixels located on the same coordinate point through the bands) instead of the pixel patch is considered as an atom of the dictionary. During the process of dictionary training, a pair of high resolution (HR) and low resolution (LR) corresponding training sets are created by pixel curves from HR hyperspectral images and their simulated degraded images. Then the dictionary pair is jointly trained from the set of pixel curves with the constraint that when a pixel curve from the HR hyperspectral image and its degraded image is decomposed according to the HR and LR dictionary pair, respectively, we can get the same sparse coefficients. In the process of SR restoration, each pixel curve from the LR hyperspectral image will first be decomposed according to the LR dictionary of the dictionary pair to obtain a set of sparse coefficients, then the corresponding HR curve is reconstructed by the LR coefficients and the HR dictionary. When all the curves are SR reconstructed, all the bands of the estimated HR image are optimized by a maximum a priori (MAP) based algorithm to further improve the quality. In this algorithm, the hyperspectral images are sparsely decomposed as a whole for each pixel on the spectral dimension. In this way, the pixel curves are regarded as a unit during the entire process; spectral features that are often described by the curves are effectively preserved. The pixel curve based sparse representation is more suitable for hyperspectral images in order to make better use of its high spectral correlations. At the same time, as the number of bands (corresponding to number of values in a pixel curve) is often larger than the number of pixels in the traditional image patches, the total computation is also saved. The experimental results are compared with the following related algorithms including bilinear interpolation, MAP based SR, and the traditional pixel patch based sparse SR method. The proposed algorithm is superior in both objective and subjective results.

The structure of this paper is as follows. In Sec. 2, the related background of the proposed algorithm and the framework of the algorithm are introduced. In Sec. 3, the basic principle of hyperspectral image sparse decomposition is described. The core of the proposed algorithm is elaborated in Sec. 4, that is, the design and training process of the redundant dictionary pair. In Sec. 5, the process of the HR hyperspectral images reconstruction is presented. In Sec. 6, experimental results of the algorithm are given and the validity of the algorithm is verified.

2 Algorithm Outline

2.1 Related Background

Redundant dictionary based sparse decomposition is a new kind of signal representation method¹ that was proposed in the 1990s. It has changed the traditional idea of orthogonal basis based methods, in that the traditional orthogonal basis was substituted by the redundant dictionary, which consisted of a set of overcomplete functions. The dictionary was called redundant because it consisted of several basis functions to be used selectively. In the decomposition process, the best basis functions were selected according to the characteristics of a certain signal in order to represent it more effectively. In this way, sparser representation coefficients may be obtained by selecting a set of more suitable bases. Neurological researches have shown that overcomplete representation was more compliant with the biology of a mammal's visual system.⁷ Moreover, nonlinear approximation theory also proved that the approximation of an overcomplete system was superior to the known orthogonal basis. In the field of image processing, the overcomplete sparse representation method has shown better results in denoising, restoration, and segmentation applications. It also brought significant improvements to compression and equalization applications.⁸

In the field of hyperspectral images analysis, the sparse based method was designed in a pixel curve based way. For example, an unsupervised learning based sparse coding method was improved for hyperspectral images in Ref. 9. Experimental results showed that the redundant dictionary created by learning could describe the spectral features of hyperspectral images better than orthogonal transform based ones, thus coding the features of the images in a sparser way. Moreover, when the sparse coding method was used for classification, both the complexity of the classifier and number of required samples were decreased. A spectral unmixing method for a hyperspectral image based on sparse decomposition was proposed in Ref. 10. The redundant dictionary was trained by the spectral library samples, dependence on end member extraction accuracy, as done by other algorithms was avoided, and good results were obtained. The researches mentioned above indicated that the features in the hyperspectral images could be better described with less data by redundant dictionary based sparse representation methods.

In this paper, the sparse representation based visible image SR algorithm⁶ is improved for hyperspectral images. A redundant dictionary based hyperspectral image SR restoration algorithm is proposed. By using of more effective redundant dictionary based hyperspectral image representation method, better performance has been achieved.

2.2 Algorithm Framework

The block diagram of the proposed redundant dictionary based SR restoration algorithm for hyperspectral images is shown in Fig. 1. In this algorithm, a pair of HR and LR corresponding redundant dictionaries is precreated by joint learning, with the constraint that the respective HR and LR pixel curves would have the same sparse representation coefficients when decomposed according to the respective dictionaries. When turning to SR restoration, the input LR hyperspectral image is first bilinearly interpolated to the expected resolution so as to have the same

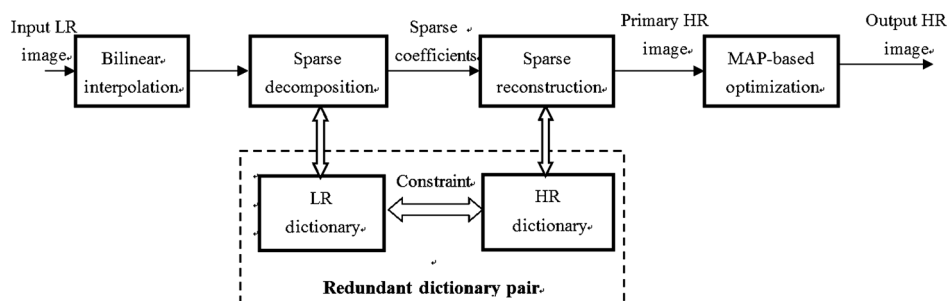


Fig. 1 Block diagram of the proposed algorithm.

number of spectral curves as the HR images. Furthermore, each pixel curve in the interpolated LR images is sparsely decomposed based on the LR redundant dictionary of the dictionary pair. Then the HR hyperspectral image is reconstructed by using the obtained sparse representation coefficients and the corresponding HR redundant dictionary. Finally, each band of the reconstructed primary HR image is optimized by the MAP based method to further improve the performance.

3 Principle of Pixel Curve Based Sparse Decomposition of the Hyperspectral Image

Hyperspectral image is a kind of image that can image a target to dozens of bands. For a certain target material to be imaged, all the pixels located on the same coordinate point through the bands form a curve, named the spectral curve. This curve reflects the spectral features of the imaged material. Any material has its own spectral curves, and similar materials have similar ones. In applications, any pixel curve in the image is related to the target material's spectral curve or can be considered as a combination of several spectral curves, when the target area is related to several kinds of materials. That is similar to the ways that the redundant dictionary based method do. The most typical pixel curves were selected by training and were considered as atoms of the redundant dictionary. Thus, any pixel curve can be represented by a combination of several atoms. Some researches¹⁰ suggested that by redundant dictionary based sparse decomposition, the atoms of the trained redundant dictionary reflected the spectral features of the imaging materials. Most of the atoms were consistent with a certain spectral curve of the material.

The creation of the redundant dictionary is the core of the algorithm. Currently, the mainstream method is based on learning, all the atoms of the dictionary are generated by training of the data. That is to say, the most representative elements are selected from a large number of training samples, then they are taken as the atoms to constitute the redundant dictionary. In this way, any pixel curve can be described in the manner of an optimal linear combination of the atoms. For example, the method of optimal direction,¹¹ the generalized principal component analysis method,¹² the method of kernel singular value decomposition (K-SVD),^{9,13} and the method of sparse dictionary learning¹² are all typical methods for dictionary training. In this study, the method of K-SVD is used.

K-SVD¹³ is a dictionary learning algorithm via an SVD approach. It is a generalization of the k-means clustering method and works by iteratively alternating between sparse coding the input data based on the current dictionary and then updating the atoms in the dictionary to better fit the data. The goal of the algorithm is to resolve the optimization problem of Eq. (1).

$$\min_{D,C} \|X - DC\|_2^2, \quad \text{subject to } \forall_i, \|c_i\|_0 \leq T_0, \quad (1)$$

where D is the dictionary created through training and X is the set of training pixel curves. C is the coefficient matrix of the sparse representation for pixel curves X , and T_0 is the subjective assumption of sparsity satisfying $T_0 < K$, where K is the number of atoms in the dictionary. As presented in Ref. 13, this problem can be resolved by alternative optimization of the dictionary D and the coefficients C . That is, first assuming that D is fixed, pursue the optimal representation vectors c_i by solving the following equation:

$$c_i^* = \arg \min_{c_i} \|x_i - Dc_i\|_2^2, \quad \text{st, } \|c_i\|_0 < T_0. \quad (2)$$

Then update the dictionary by minimizing the overall representation error.

$$E_k = X - \sum_{j \neq k} d_j c_T^j. \quad (3)$$

As a method for dictionary training, the input multidimensional signal can be represented in the sparse linear form of the atoms in the dictionary by using the K-SVD algorithm. The atoms obtained through training are usually independent, but are not necessarily linearly uncorrelated. For the hyperspectral image, each atom obtained through training usually represents the spectral curve of a certain ground material that is imaged by the spectrometer. Moreover, any pixel curve

of the image is the imaging result of a single material or a mixture of several ground materials. Therefore, the pixel curves can be decomposed into a linear combination of several atoms.

In practical applications, $st, \|c_i\|_0 < T_0$ is usually substituted by $st, \min \|c_1\|$ to simplify the solution process of Eq. (2). Thus, the problem above is solvable without subjective estimation of T_0 . Moreover, c_i is normalized to satisfy $0 \leq c_i \leq 1$. The following can be obtained by merging the objective functions:

$$c^* = \arg \min \|x - Dc\|_2^2 + \lambda \cdot \|c\|_1, \tag{4}$$

where $x \in R^p, c \in R^K, D \in R^{p \times K}$, and λ is the equilibrium factor which is used to equilibrate the weight between the convergence precision and sparsity of sparse representation. In general, according to experience, good results can be obtained when $\lambda = 0.001$.

4 Training and Creation of the Redundant Dictionary Pair

The training method for the LR and HR corresponding redundant dictionary pair is designed on the basis of the K-SVD based redundant dictionary training algorithm, as shown in Fig. 2.

In the diagram, the degradation model of the hyperspectral image is first created according to the imaging principle and the degradation process of hyperspectral images, and is usually composed of the stages of subsampling and blurring. The training data are created as follows: first, a group of HR hyperspectral images expected to contain sufficient spectral features are selected. Then the corresponding LR images are generated by first applying the degradation model to the HR images and then bilinearly interpolating to regain the original number of pixel curves. That is to say, the LR image has the same number of pixel curves as the original HR images. The only difference is that it carries less high-frequency information because of the loss during the sub and upsample processes. During the training process, the HR and LR corresponding pixel curves from the respective images are used to construct the dictionary pair. The HR hyperspectral image is denoted by X_h , and the corresponding LR image is X_l . Hence, the corresponding HR and LR dictionaries can be obtained by minimizing the following objective equation:

$$\{D_h^*, D_l^*, \Lambda^*\} = \arg \min_{D_h, D_l, \Lambda} \{\|X_h - D_h \Lambda\|_2^2 + \|X_l - D_l \Lambda\|_2^2 + \lambda \|\Lambda\|_1\}, \tag{5}$$

where Λ is the vector consisting of the sparse coefficients α . Through training, D_h^* and D_l^* are the obtained optimal redundant dictionary pair, respectively. $\lambda \|\Lambda\|_1$ is a normalization item for solving the above optimization problem. In the optimization procedure, the HR and LR sparse coefficients are jointly designed. That is to say, coefficients of an HR pixel curve based on the HR dictionary are enforced to be similar to that of the LR pixel curves based on the LR dictionary. Therefore, in the SR restoration process, the HR image can be reconstructed by using the coefficients obtained by the LR pixel curve and the corresponding HR redundant dictionary.

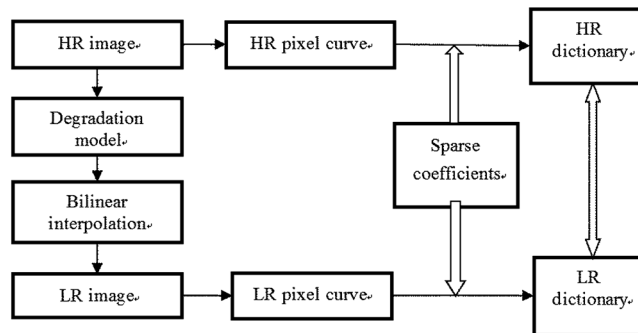


Fig. 2 Diagram of the design process of the redundant dictionary pair.

5 Super-Resolution Reconstruction of Hyperspectral Images

When the HR and LR corresponding redundant dictionary pair is created, for any pixel curve x_l^i in the LR hyperspectral image, its sparse representation coefficients can be obtained through Eq. (6).

$$\alpha^* = \arg \min_{\alpha} \{ \|x_l^i - D_l \alpha\|_2^2 + \lambda \|\alpha\|_1 \}. \quad (6)$$

Then the estimated HR pixel curve \hat{x}_h^i can be reconstructed according to Eq. (7).

$$\hat{x}_h^i = D_h \alpha^*, \quad (7)$$

where D_l and D_h are the pair of HR and LR corresponding redundant dictionaries.

In the proposed pixel curve based manner, the pixel curve is considered as a unit during the whole process of decomposition and reconstruction. Spectral complementary information is fully used for resolution enhancement. However, the spatial correlation, although much lower than in common images, may also contribute to the SR work. Thus each band of the reconstructed HR image is further optimized by the MAP based algorithm. Under the framework of MAP probability, each band of the reconstructed HR image should satisfy

$$\hat{b}_h^{(j)} = \arg \max \log Pr(b_h^{(j)} | b_l^{(j)}) = \arg \max \{ \log Pr(b_h^{(j)}) + \log Pr(b_l^{(j)} | b_h^{(j)}) \}. \quad (8)$$

Here, to distinguish from the pixel curves denoted by $x_l^{(i)}$ and $x_h^{(i)}$, respectively, $b_h^{(j)}$ and $b_l^{(j)}$ are used for denoting the respective HR and LR image bands j . $Pr(b_h^{(j)} | b_l^{(j)})$ is a *posteriori* probability of the HR band $b_h^{(j)}$ when the LR band $b_l^{(j)}$ is known. $Pr(b_h^{(j)})$ is the priori distribution of the HR band, described by the Huber-Markov model.¹⁴ Conditional probability $Pr(b_l^{(j)} | b_h^{(j)})$ reflects the distribution of error between the LR estimate band obtained after the subsampling of $\hat{b}_h^{(j)}$ and the actual LR band $b_l^{(j)}$. It is considered to obey Gaussian distribution.

$$Pr(b_l^{(j)} | b_h^{(j)}) = \frac{1}{2\pi^{\frac{M_1 N_2}{2}} \sigma^{(j) N_1 N_2}} \exp \left\{ -\frac{1}{2\sigma^{(j)2}} \|b_l^{(j)} - D b_h^{(j)}\|^2 \right\}, \quad (9)$$

where M and N are the number of pixels in the row and column of LR band $b_l^{(j)}$, respectively. $\sigma^{(j)}$ is the variance of error distribution of the j 'th band. D is the subsampling matrix. Each band of the HR image obtained by the above sparse based method is the initial value of b_h^j . By solving Eq. (8) iteratively, the estimated HR band of the image is obtained. During the iteration, the LR model constraint¹⁵ is employed for each iteration result. Thus, the stability of the algorithm can be further promoted.

6 Experimental Result and Analysis

The test data are a set of 128-band hyperspectral images collected by the OMIS image spectrometer. One of them named OMISr02, which contains most of the imaged materials, is selected as the training data. The spatial resolution of the training data is 512×512 pixels. The 113th band of the image, which corresponds to the visible range, is shown in Fig. 3.

The test data include the training image r02 and another group of test images, r01 and r03.

6.1 Visible Bands Tests

First, the 113th bands of OMISr02 and OMISr03 are used to evaluate the performance on visible images. Comparison of the experimental results are shown in Fig. 4, where the image OMISr03 is divided into four pieces to show more details. The comparing algorithms include bilinear interpolation, a traditional MAP based visible image SR method proposed in Ref. 14, and the sparse based SR method proposed in Ref. 6. In this experiment, the SR scale is set to



Fig. 3 The 113th band of the training image OMISr02.

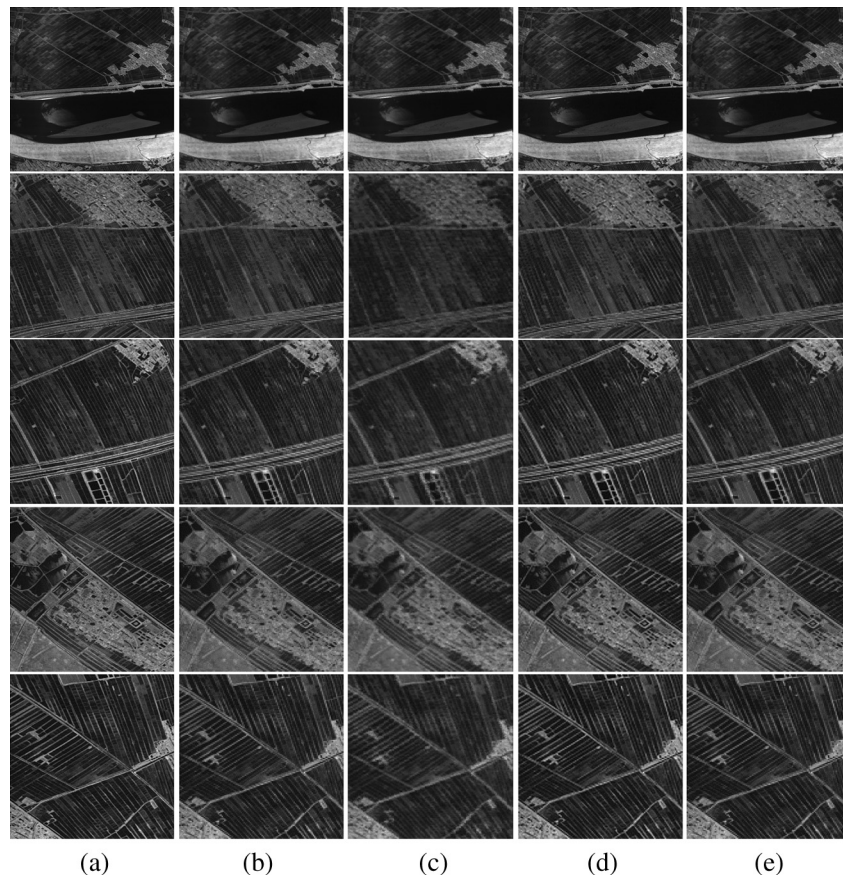


Fig. 4 Subjective comparison of the experimental results (band 113): (a) the original high-resolution image, (b) bilinear interpolation, (c) the sparse based method,⁶ (d) the maximum a priori based algorithm,¹⁴ and (e) the proposed algorithm.

2×2 , which means that both the vertical and horizontal resolutions of the image are amplified by 2.

As shown in Fig. 4, the first column is the 113th band of the original HR images. The second column shows results from the bilinear interpolation of the LR images. The third and fourth

Table 1 113th band peak signal-to-noise ratio (PSNR) value comparison.

Test image	Bilinear	Sparse ⁶	Maximum a prior ¹⁴	Proposed
OMISr02_113	27.709227	28.889757	29.864555	30.112765
OMISr03_113_a	26.223614	27.566919	27.970005	28.242410
OMISr03_113_b	23.288805	23.928974	24.898954	25.302387
OMISr03_113_c	24.445230	25.253573	27.390677	27.533555
OMISr03_113_d	23.279052	23.332022	26.154882	26.328987
Average	24.989186	25.794249	27.255815	27.504021

columns are the reconstruction results from the sparse based method proposed in Ref. 6 and the MAP based algorithm proposed in Ref. 14, respectively, and the last column shows results from the method proposed in this paper. It can be seen from the results that for either the training data or the test data, the quality of the reconstructed images by the proposed algorithm is better than that of the other algorithms. The texture structures in the images are much clearer. The comparison of PSNR values of the 113 bands of the image is further shown in Table 1. It can be seen that for both the training image (r02) and the test images (r03_a to r03_d), the results of reconstruction by the proposed method are better than those by the other algorithms, and the PSNR values are significantly increased.

6.2 All Bands Test

To evaluate the performances though all the spectral bands, more bands of the test images are used in the following experiment. The comparison of PSNR values is shown in Table 2. Here the SR factor is set to 4×4 . Considering that the MAP based method is time-consuming and too much time is required when it is applied for all the bands, in this experiment only the sparse

Table 2 All bands PSNR value comparison.

Test image	Bilinear interpolation	Sparse based algorithm ⁶	Proposed algorithm
OMISr01_av	32.767359	33.141606	33.944164
OMISr01_26	28.676791	29.284466	29.813128
OMISr01_68	37.295503	37.069088	37.713118
OMISr01_101	32.860224	32.846843	33.292267
OMISr01_114	25.518575	26.378652	26.894301
OMISr02_26	28.210120	29.508768	30.122543
OMISr02_68	37.529728	37.332852	37.930697
OMISr02_101	32.566524	32.630394	33.043938
OMISr02_114	25.301015	26.967337	27.959817
OMISr03_26	27.039738	27.550315	28.226109
OMISr03_68	35.099324	34.791296	35.757244
OMISr03_101	31.538935	31.522329	32.089051
OMISr03_114	22.544934	23.255279	23.929798
Average	30.534521	30.944556	31.593552

Table 3 Time consumption comparison.

Stage	Sparse based algorithm ⁶ (s)	Proposed algorithm (s)	Improvement (%)
Dictionary training	19,604.179	18,775.620	4.23
Sparse decomposition	24,104.719	9251.284	61.62
Super-resolution reconstruction	61.047	31.347	48.65

based algorithm is compared with the proposed one. The first line of Table 2 shows an average PSNR value of all the 128 bands of OMISr01, and the following are several single bands of the test images. The average PSNR value of the listed bands is given in the last line. It can be seen from the results that for any band of the image, the PSNR values are significantly increased.

At last, time consumption of the algorithm when applied to all bands of OMISr01 is listed in Table 3. It can be seen that for any stage of the algorithm, less time is required for the proposed algorithm. For the sparse decomposition and SR reconstruction period steps, the time required is decreased by more than 60% and 40%, respectively. This is very important because the decomposition and reconstruction operations are needed during the whole process of super resolution. So efficiency improvements of these two stages are far more meaningful in practical applications.

Moreover, it can be seen from all the above experimental results that there is no obvious difference between the results of the training data (OMISr02) and test data (OMISr01 and OMISr03). That is to say, for a certain hyperspectral imaging device, when the redundant dictionary pair is trained by a set of images that contain most of the imaged materials, it can be used for other images collected by the same device. So the dictionary pair can be trained beforehand and can be generally used for other applications. That will further reduce the computing burden of training the dictionaries.

7 Conclusion

In this paper, a redundant dictionary based hyperspectral image SR restoration algorithm is proposed. This proposed method takes full advantage of both spectral and spatial information to enhance the spatial resolution of the hyperspectral images. A sparse representation based SR method is specially redesigned by using pixel curves instead of patches as the processing units. In this manner, spectral correlations of the image are better used for resolution enhancement. Moreover, a MAP based spatial SR method is used band by band to take further advantage of the spatial information. Experimental results show our method's superior performance compared to other similar algorithms. Not only the objective and subjective qualities of the reconstructed images are obviously improved, but the time required is reduced.

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