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Spatial–spectral preprocessing for spectral unmixing
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ABSTRACT
Most techniques available in the endmember extraction rely on exploiting the spectral information of the data alone. In this paper, we improve the utilization of data information by dividing a pixel into four subpixels which are redefined by the scalar factor related to the spatial–spectral similarity. The spatial information is integrated into the spectral information in a certain spatial neighbourhood domain, which can make extracted endmembers more precisely, because the effect of noise and outliers can be suppressed with preprocessing (PP). Meanwhile, the accuracy of spectral unmixing will be improved without modification to the conventional methods applied to spectral-based endmember extraction. Experimental results with both synthetic and real hyperspectral images demonstrate the unmixing accuracy is better than that without PP.

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1. Introduction
The spectral resolution of hyperspectral image has been improved, but the spatial resolution is still low. Hyperspectral remote-sensing images are usually satellite-based spectrometers that acquire the spectral information of the ground target by collecting its spectral radiance. The instantaneous field of view of the spectrometer contains a certain area of space material on the ground. The farther the satellite from the ground, the larger the area contains, and which will lower the spatial resolution of hyperspectral images. Meanwhile, there are other factors such as atmospheric effects, illumination, and inherent spectral variability of the material itself which also result in a large number of mixed pixels in hyperspectral images. The mixed pixels contain several different substances, which reduce the classification accuracy and detection probability of small objects. In order to solve this problem, spectral unmixing is presented to extract pure spectral signal, which is called endmember extraction, and then the weight of each endmember is figured out in mixed pixels by inversion algorithms, called abundance inversion (Bioucas–Dias et al. 2012).

Hyperspectral unmixing methods mainly include three types: geometrical, statistical, and sparse regression-based approaches. At the end of the twentieth century, researchers have proposed some geometrical endmember extraction algorithms (Antonio et al. 2004), such as classic techniques that include pixel purity index (Boardman, Kruse, and...
Green 1995), N-FINDR (Winter 1999), automatic target generation process (ATGP) (Ren and Chang 2003), iterative error analysis (IEA) (Neville et al. 1999), vertex component analysis (Nascimento and Bioucas–Dias 2005), and others (e.g. Berman 2004; Miao and Hairong 2007; Chang et al. 2006; Wang and Chang 2006). However, these algorithms have some limitations. They may extract endmember in the transition areas of different objects and treat outliers as endmembers. It is generally believed that endmember mainly exists in the homogeneous region of the same object in the space, while mixed pixels exist in the transition zone between different objects. Other techniques for endmember extraction also have recently been proposed using both spatial information and spectral information to improve the unmixing accuracy (e.g. Zortea and Antonio 2009; Kowkabi, Hassan, and Ahmad 2016; Martín and Antonio 2011; Xu, Bo, and Liangpei 2014).

In this paper, a method of improving the utilization of data information by incorporating hyperspectral spatial–spectral information is proposed, which makes extracted endmembers more precisely and improves the unmixing accuracy. Each pixel is divided into four subpixels which are redefined by the scalar factor calculated by spatial–spectral information in the space window. New spectral values of central pixel in the space window is determined based on scalar factor. Endmembers are extracted from the obtained spectral image, and abundances are inverted by least squares method (Heinz and Chang 2001).

2. Preprocessing (PP) method

Let us assume that hyperspectral image data with $L$ bands is denoted by matrix $I$, in which the pixel at the discrete spatial coordinates $(i, j)$ of the image is represented by a vector $X(i,j) = \{x_1(i,j), x_2(i,j), \cdots, x_L(i,j)\}^T$. Under the linear mixture model assumption, each pixel vector in the original image can be modelled using the following expression (Guerra et al. 2015):

$$X(i,j) = E\alpha(i,j) + n(i,j)$$  \hspace{1cm} (1)

With

$$\sum_{z=1}^{P} \alpha_z(i,j) = 10 \leq \alpha_z(i,j) \leq 1$$  \hspace{1cm} (2)

where $E = (e_1, e_2, ..., e_P) \in \mathbb{R}^{L \times P}$ denotes the matrix of endmembers, and $P$ is the total number of endmembers, which can be automatically estimated using techniques such as the virtual dimensionality (Chang and Qian 2004) and the hyperspectral signal identification by minimum error (HySime) (Bioucas–Dias and Nascimento 2008). Abundance vector is denoted by $a(i,j)$ and $n(i,j)$ is noise vector. The abundance is generally subject to abundance sum-to-one constraint (ASC) and abundance non-negativity constraint (ANC).

2.1. Improving the utilization of data information

Hyperspectral image has outliers due to the influence of instrument and atmosphere, which leads to extract erroneous endmember and decreases the unmixing accuracy.
Endmember is usually in the homogeneous region of space, so integrating the spatial information into the spectral information can be used to distinguish outliers which are different from the neighbourhoods.

We improve the utilization of data information by dividing each pixel into \( n \) subpixels equally and incorporate the spatial information into the spectral information to redefine new spectral values. A pixel can be divided into multiple subpixels, but if the number of equally divided subpixels is too much, PP window will be larger to fuse the spatial information. Moreover, the amount of hyperspectral data will be increased excessively which will affect the processing speed. Therefore, we should consider the experimental effect and processing speed comprehensively. The divided pixel is regarded as independent pixel; therefore, the number of hyperspectral image pixel is \( n \) times as that of the original. When \( n \) is an odd number, the division method is shown in Figure 1(a); when \( n \) is an even number, the division method is shown in Figure 1(b), and the selection of \( n \) will be discussed in detail later.

The square space window of \( w \times w \) is adopted, assuming the variable \( w \) is set to an odd number and the radius of the spatial processed region is \( d = (w - 1)/2 \). It can be seen that the value of \( w \) is related to the number \( n \) of divided subpixels. If the number \( n \) of subpixels is large, the value of \( w \) should be larger to integrate the spatial information of the neighbourhood pixels. Let us consider that the central pixel is vector \( \mathbf{X} \) with

Figure 1. The pixel division method. (a) \( n \) is an odd number. (b) \( n \) is an even number.
spatial coordinates \((i, j)\), and the spatial coordinates of adjacent pixels are \((r, s)\). The calculation of the scalar factor depends on the spatial–spectral similarity between the central pixel and the adjacent pixels in the space window. The spectral value of the central pixel is redefined by the scalar factor to obtain new image data sets. The definition of the scalar factor is as follows:

\[
\varphi(r, s) = \beta(r, s)\gamma(r, s)
\]

where variable \(\beta\) and \(\gamma\) denote, respectively, the spatial similarity and spectral similarity between the central and adjacent pixels. After the weight is normalized, a new spectral for the central pixel spectral value is calculated in the space window:

\[
\hat{X}(i, j) = \sum_{r=i-d}^{i+d} \sum_{s=j-d}^{j+d} \hat{\varphi}(r, s)X(r, s)
\]

where \(\hat{\varphi}(r, s)\) denotes the normalised scalar factor, vector \(\hat{X}(i, j)\) is the new spectral.

### 2.2. Spatial similarity

Spatial objects have a clustering characteristic that makes the probability of aggregation higher in the same object. The endmembers mainly exist in the homogeneous region, while the mixed pixels are mainly in the boundary transition region of different substances. Spatial information has a great influence on the spectral value of the pixel. The closer the surrounding pixels are to the central pixel, the greater the impact. The spatial similarity is inversely proportional to the distance. The scalar factor of the spatial similarity \(\beta\) is measured by the Euclidean distance between central pixel vector \(X(i, j)\) and adjacent pixel vector \(X(r, s)\):

\[
\beta(r, s) = \frac{1}{\sqrt{((r - i)^2 + (s - j)^2)}}
\]

Taking \(n = 4\) as an example, each subpixel is taken as a central pixel, and the spatial weight of the central pixel in the space window is shown in Figure 2.

### 2.3. Spectral similarity

The more similar the spectrum between adjacent pixels, the higher the probability of the same object is. The spectral similarity weight of the adjacent pixel is determined by comparing the angles between central pixels and adjacent pixel. The smaller the angle of the spectral curve, the higher the similarity between the two spectra is. The angle between the two spectral curves is calculated by traditional spectral angle matching (SAM), which is calculated as follows (Miao and Hairong 2007):

\[
\text{SAM} = \cos^{-1} \frac{X(i, j)X(r, s)}{|X(i, j)||X(r, s)|}
\]

where \(|X(i, j)|\) and \(|X(r, s)|\) represent the norm of vector \(X(i, j)\) and vector \(X(r, s)\), respectively. In order to maintain the consistent trend between the spatial weight and the spectral weight, the cosine of the angle between the two spectral curves is used here. So
the range of the \( \cos(\text{SAM}) \) is \([0, 1]\). Furthermore, the square root of the cosine value is adopted to increase the effect of the spectral difference on the weight. So the spectral weight is defined as follows:

\[
\gamma(r, s) = \sqrt{\cos(\text{SAM})}
\]

(7)

The most widely used metric to evaluate the unmixing accuracy is the root mean square error (RMSE) which compares the difference between original image and reconstructed image. The RMSE is expressed as (Antonio et al. 2004):

\[
\text{RMSE} = \left( \frac{1}{L} \sum_{l} \left( \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} \left[ x(i, j) - \hat{x}(i, j) \right]^2 \right) \right)^{1/2}
\]

(8)

Where \( \hat{x}(i, j) \) denotes the pixel spectral values of reconstructed image which is the product of the endmember matrix and the abundance matrix. \( M, N, L \) denote the row column and bands of the hyperspectral images, respectively.

3. Experiments and result analysis

This section described a group of experiments by using synthetic and real hyperspectral dat, and combining standard endmember extraction algorithms to conduct a comprehensive analysis of the PP method. The difference of the unmixing accuracy was compared by using three representative endmember extraction algorithms with and without PP. Endmember extraction algorithms include N-FINDR, ATGP, and IEA. Abundance was estimated by the fully constrained least squares (FCLS) (Heinz and Chang 2001).

\[
\begin{array}{cccccc}
\frac{1}{2\sqrt{2}} & \frac{1}{\sqrt{5}} & \frac{1}{2} & \frac{1}{\sqrt{5}} & \frac{1}{2\sqrt{2}} \\
\frac{1}{\sqrt{5}} & \frac{1}{\sqrt{2}} & 1 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{5}} \\
\frac{1}{2} & 1 & 1 & 1 & \frac{1}{2} \\
\frac{1}{\sqrt{5}} & \frac{1}{\sqrt{2}} & 1 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{5}} \\
\frac{1}{2\sqrt{2}} & \frac{1}{\sqrt{5}} & \frac{1}{2} & \frac{1}{\sqrt{5}} & \frac{1}{2\sqrt{2}} \\
\end{array}
\]

Figure 2. Illustration of spatial information.
3.1. Synthetic hyperspectral image A

The reason for using simulated image as a complement to real data analysis is that all details of the simulated images are known in advance, so that we can evaluate the proposed method.

In this experiment, a commonly used remote-sensing simulation was adopted (Iordache, Bioucas-Dias, and Plaza 2012). Spectral curves of five different substances were selected randomly from the spectral library of the United States Geological Survey (USGS) digital spectral library as the endmembers to generate simulated data. The selection of endmembers spectra were arbitrary, as long as they were linearly independent, named Dolomite COD2005, Kaolinite CM3, Calcite CO2004, Gibbsite WS214, and Clinoptilolite GDS2. Five endmembers were represented by A, B, C, D, and E, respectively, and the background was expressed as F which was the average of the five endmembers. The spectral data contain 430 spectral bands covering wavelengths from 0.4011 to 2.976 μm. Figure 3 shows the simulated data of the 50th band and Figure 4 shows the endmembers’ spectral curves.

![Simulation data of the 50th band.](image)

**Figure 3.** Simulation data of the 50th band.

![Five endmembers spectral curves.](image)

**Figure 4.** Five endmembers spectral curves.
The size of the simulated data was 200 × 200 pixels. Simulated data had 5 row and 5 column cubes which had 25 × 25 pixels, and the rest was the background. The cubes satisfied the constraints described in Equation (2), and the weight of each endmember in the cube is shown in Table 1:

There would be noise in the real hyperspectral image. In order to make simulated data actually as much as possible, we added different degrees of zero-mean Gaussian noise into the simulated image, assuming the SNR was 10, 15, 20, 25, and 30 dB.

Hyperspectral data was dealt by the PP. Then, three methods based on geometry were used to extract endmembers with and without PP. Here, the pixel was divided into four subpixels, and the size of space window was 5 × 5, i.e. \( n = 4 \) and \( w = 5 \). Then, abundance was estimated by the FCLS. The number of the endmember is based on prior knowledge.

The performance of the PP was estimated by RMSE which could evaluate the unmixing accuracy. RMSE was compared at different signal noise ratio (SNR), shown in Table 2.

As is observed, RMSE values are lower at different SNR for all considered algorithms by PP to improve the utilization of data information. The smaller RMSE is, the higher the unmixing accuracy is. As SNR increases, the RMSE significantly decrease. The proposed PP method can make great progress for dataset in poor qualities, especially at 10 dB. It could be seen that the PP had suppressed the influence of noise effectively. But as the quality of the dataset increases, it seems that there is no effect. In fact, because the object spatial distribution of synthetic hyperspectral image A is simple, it makes surrounding pixels similar in the high SNR. Meanwhile, the mixing degree between substances is not complex, and the edge transition area is less. Overall, the results in Table 2 suggested that extracting endmembers in combination with spatial–spectral information is beneficial for reducing RMSE.

In order to verify the effectiveness of the PP, the more realistic simulated hyperspectral image is adopted in this paper, whose distribution is more complex and there are more edge transitions.

### Table 1. Weight of each endmember in the cube.

<table>
<thead>
<tr>
<th></th>
<th>First column</th>
<th>Second column</th>
<th>Third column</th>
<th>Fourth column</th>
<th>Fifth column</th>
</tr>
</thead>
<tbody>
<tr>
<td>First row</td>
<td>A</td>
<td>0.75A+ 0.25B</td>
<td>0.5A+ 0.5B</td>
<td>0.5A+ 0.5F</td>
<td>0.25A+ 0.25B+ 0.5F</td>
</tr>
<tr>
<td>Second row</td>
<td>B</td>
<td>0.75B+ 0.25C</td>
<td>0.5B+ 0.5C</td>
<td>0.5B+ 0.5F</td>
<td>0.25B+ 0.25C+ 0.5F</td>
</tr>
<tr>
<td>Third row</td>
<td>C</td>
<td>0.75C+ 0.25D</td>
<td>0.5C+ 0.5D</td>
<td>0.5C+ 0.5F</td>
<td>0.25C+ 0.25D+ 0.5F</td>
</tr>
<tr>
<td>Fourth row</td>
<td>D</td>
<td>0.75D+ 0.25E</td>
<td>0.5D+ 0.5E</td>
<td>0.5D+ 0.5F</td>
<td>0.25D+ 0.25E+ 0.5F</td>
</tr>
<tr>
<td>Fifth row</td>
<td>E</td>
<td>0.75E+ 0.25A</td>
<td>0.5E+ 0.5A</td>
<td>0.5E+ 0.5F</td>
<td>0.25E+ 0.25A+ 0.5F</td>
</tr>
</tbody>
</table>

### Table 2. RMSE in hyperspectral images A with different SNR.

<table>
<thead>
<tr>
<th>SNR</th>
<th>10 dB</th>
<th>15 dB</th>
<th>20 dB</th>
<th>25 dB</th>
<th>30 dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>N-FINDR</td>
<td>0.1532</td>
<td>0.1345</td>
<td>0.1006</td>
<td>0.0603</td>
<td>0.0342</td>
</tr>
<tr>
<td>N-FINDR + PP</td>
<td>0.0536</td>
<td>0.1173</td>
<td>0.0921</td>
<td>0.0550</td>
<td>0.0313</td>
</tr>
<tr>
<td>IEA</td>
<td>0.1516</td>
<td>0.1386</td>
<td>0.1010</td>
<td>0.0606</td>
<td>0.0346</td>
</tr>
<tr>
<td>IEA + PP</td>
<td>0.0718</td>
<td>0.1330</td>
<td>0.1002</td>
<td>0.0578</td>
<td>0.0313</td>
</tr>
<tr>
<td>ATGP</td>
<td>0.1562</td>
<td>0.1437</td>
<td>0.1032</td>
<td>0.0605</td>
<td>0.0344</td>
</tr>
<tr>
<td>ATGP + PP</td>
<td>0.0719</td>
<td>0.1263</td>
<td>0.1000</td>
<td>0.0579</td>
<td>0.0312</td>
</tr>
</tbody>
</table>
### 3.2. Synthetic hyperspectral image B

A database of five 100 × 100 pixel synthetic hyperspectral scenes has been created using fractals to generate distinct spatial patterns, described by Martín and Plaza (2012). Several natural objects could be simulated by fractals to a certain degree. In this way, we obtain complex spatial patterns to demonstrate the PP. We used five fractals images normalized as abundances which subject to the ASC and ANC. Figure 5 shows five fractal images.

**Figure 5.** Fractal images used in experiments as abundances. (a) Fractal 1. (b) Fractal 2. (c) Fractal 3. (d) Fractal 4. (e) Fractal 5. (f) Colour scale.
images used in the simulation. At the same time, endmember signatures were same as
the synthetic hyperspectral image A. The 300th band of the generated synthetic hyper-
spectral image B is shown in Figure 6. It could be seen that this was a mixture of five
fractal images, where fractal image 4 had a more pronounced effect on the 300th band
selected here.

Apparently, the distribution of object in the hyperspectral image B is relatively complex, and
there are many ways of mixing, which is more practical. At the same time, it can also be seen
that the mixing degree is high at the boundary of each object. The experimental conditions are
same as above, $n = 4, w = 5$. The RMSE of hyperspectral image B was compared at different SNR,
shown in Table 3.

Synthetic hyperspectral image B uses fractal images as abundances, with a higher degree of
mixing. Spatial–spectral information of the surrounding pixels is integrated in order to make
the extracted endmembers more accurate. From Table 3, it can be seen that the RMSE of PP is
approximately half that of non-PP at different SNR. Because spatial objects have clustering
characteristic, we divided pixels and incorporated spatial information to improve the purity of
pixel. Compared with the synthetic hyperspectral image A, B still has a good effect when the
SNR becomes high, indicating that the PP has a good effect on simple or complex synthetic
hyperspectral images.

**Figure 6.** The 300th band of the synthetic hyperspectral image B.

**Table 3.** RMSE in hyperspectral images B with different SNR.

<table>
<thead>
<tr>
<th>SNR</th>
<th>10 dB</th>
<th>15 dB</th>
<th>20 dB</th>
<th>25 dB</th>
<th>30 dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>N-FINDR</td>
<td>0.3429</td>
<td>0.1935</td>
<td>0.1597</td>
<td>0.1025</td>
<td>0.0661</td>
</tr>
<tr>
<td>N-FINDR+ PP</td>
<td>0.1536</td>
<td>0.1006</td>
<td>0.0898</td>
<td>0.0626</td>
<td>0.0396</td>
</tr>
<tr>
<td>IEA</td>
<td>0.3463</td>
<td>0.1934</td>
<td>0.1585</td>
<td>0.1019</td>
<td>0.0655</td>
</tr>
<tr>
<td>IEA+ PP</td>
<td>0.1849</td>
<td>0.1130</td>
<td>0.0831</td>
<td>0.0614</td>
<td>0.0363</td>
</tr>
<tr>
<td>ATGP</td>
<td>0.3416</td>
<td>0.2028</td>
<td>0.1590</td>
<td>0.1017</td>
<td>0.0655</td>
</tr>
<tr>
<td>ATGP+ PP</td>
<td>0.2094</td>
<td>0.1323</td>
<td>0.0957</td>
<td>0.0558</td>
<td>0.0403</td>
</tr>
</tbody>
</table>
In the experiment, \( n \) and \( w \) are two important parameters. We explored the relationship between the number of subpixel \( n \) and the size \( w \) of space window and their influence on the unmixing accuracy. Considering the processing rate and spatial fusion effects, both \( n \) and \( w \) should not be too large. We compared the effects of unmixing accuracy when \( n = 2, 3, 4, 5, 6 \), \( w = 3, 5, 7 \) (\( w \) is an odd number). Because the unmixing effect of IEA was best in the three algorithms, we chose the IEA algorithm to extract endmembers. When the SNR is 20 dB, synthetic hyperspectral data B was used to explore the relationship between \( n \) and \( w \). RMSE value and time of the IEA with PP at 20 dB are shown in Tables 4 and 5, respectively.

As can be seen from the table, when \( n = 4 \) and \( w = 5 \), RMSE is the smallest and the time spent is relatively few. In this paper, the amount of hyperspectral data was small, but as the data increases, the processing time would increase dramatically. Therefore, the value of \( n \) cannot be too large. When \( n \) takes a large odd number, it can be seen from the division method that the surrounding pixels of the central pixel have changed, which led the spatial information of the fused neighbourhood pixels less. In general, the larger the value of \( n \), the larger the value of \( w \) must be. On the one hand, the size of the \( w \) needs to contain all the neighbourhood pixels of the original hyperspectral data. On the other hand, the space window \( w \) cannot be too large to avoid integrating different types of spectral information in neighbourhood pixels. Taking into account the accuracy and time of the unmixing, the value of \( n \) is 4 and \( w \) is 5 in this paper.

### 3.3. Real hyperspectral image

Real hyperspectral image data set in the experiment covering the Cuprite mineral area in the United States captured by AVIRIS (Airborne Visible Infrared Imaging Spectrometer) in 1997, was used. A 200 × 200 pixels subset of the Cuprite was selected for the experiment, and the 50th band is shown in Figure 7. There were 170 spectral bands in the experiment, covering the wavelength range of 0.37–2.51 μm except low signal to noise ratio bands 1.27–1.56 μm and 1.76–1.95 μm.

The number of endmember in hyperspectral data was determined by the virtual dimension. When the false alarm rate was set to \( 10^{-6}–10^{-8} \), the number of endmember was 8. The proposed PP does not significantly affect the estimation of the

| Table 4. RMSE of the IEA with preprocessing at 20 dB. |
|---|---|---|---|---|---|
| \( w \) | \( n \) | 2 | 3 | 4 | 5 | 6 |
| 3 | 0.1056 | 0.1204 | 0.0955 | 0.1505 | 0.1271 |
| 5 | 0.0970 | 0.1185 | 0.0831 | 0.1424 | 0.1123 |
| 7 | 0.1042 | 0.1253 | 0.0823 | 0.1413 | 0.1101 |

| Table 5. Time (in seconds) of the IEA with preprocessing at 20 dB. |
|---|---|---|---|---|---|
| \( w \) | \( n \) | 2 | 3 | 4 | 5 | 6 |
| 3 | 47.21 | 50.62 | 56.36 | 75.51 | 130.84 |
| 5 | 50.54 | 53.15 | 60.20 | 82.13 | 146.66 |
| 7 | 54.61 | 60.58 | 72.20 | 90.25 | 164.20 |
number of endmembers. Three methods were used to extract endmembers, and then the least squares method was used to unmix. The unmixing accuracy with and without PP was compared. Unfortunately, no ground truth information about the endmembers and abundances was offered. So we evaluated the unmixing accuracy by the RMSE which was obtained by reconstructing the original image with the endmember and abundance matrix. The abundance of different algorithms with and without PP is shown in Figure 8.

Figure 8 shows each pixel RMSE obtained after reconstructing the original image using the endmembers obtained by different algorithms without PP (left column) and with PP (right column) using window with the size of $5 \times 5$. We could find that integrating spatial information with endmember extraction provided relatively better results in considered algorithms. The RMSE of most pixels were lower when the proposed PP method was used, especially in the transition areas with many kinds of objects, which indicated that the unmixing accuracy is improved. From the real hyperspectral image, we can know that this method is suitable for practical applications.

In order to visually compare the difference between the abundance distribution with and without PP and the true abundance distribution, a mineral map as true abundance was produced in 1995, shown in Figure 9 (Iordache, Bioucas–Dias, and Plaza 2012). It should be noted that the map is only available for hyperspectral data collected in 1995, while the publicly available AVIRIS Cuprite data was collected in 1997. Therefore, the two cannot be compared directly, but they can make a qualitative assessment. The abundance maps of each endmember is shown in Figure 10, which was a part of Figure 9.

It can be seen from the three methods that the abundance distribution with PP of each endmember is similar than that without PP, especially the IEA algorithm. Overall, the abundance maps with PP are more accurate, especially in transition region. It is
Figure 8. RMSE-based reconstruction errors. (a) N-FINDR. (i) N-FINDR without preprocessing (ii) N-FINDR with preprocessing. (b) IEA. (i) IEA without preprocessing. (ii) IEA without preprocessing. (c) ATGP. (i) ATGP without preprocessing (ii) ATGP with preprocessing. (d) Colour scale.
illustrated that the method of dividing pixels and combining spatial information presented in this paper is effective for geometric-based methods.

### 4. Conclusion

This paper has developed a simple and effective method which integrates spatial–spectral information to improve the unmixing accuracy. It is easy to perform and does not need change in the traditional endmember extraction methods. After the incorporation of spatial–spectral information, in a complex environment, it can also have better results and get higher unmixing accuracy.

In conclusion, the experiments, using both synthetic and real hyperspectral data sets, had proved that the PP was useful to improve the unmixing accuracy even in the complex environment. At the same time, it could suppress the effect of the noise and outliers on account of combining the spatial information. The proposed method could be applied to existing spectral-based endmember extraction algorithms without any modification and improve the unmixing accuracy. It has a promising applicability.
Figure 10. Abundance maps without preprocessing and with preprocessing. (a) N-FINDR without preprocessing: (i) abundance of endmember 1, (ii) abundance of endmember 2, (iii) abundance of endmember 3, (iv) abundance of endmember 4, (v) abundance of endmember 5, (vi) abundance of endmember 6, (vii) abundance of endmember 7, (viii) abundance of endmember 8. (b) N-FINDR with preprocessing: (i) abundance of endmember 1, (ii) abundance of endmember 2, (iii) abundance of endmember 3, (iv) abundance of endmember 4, (v) abundance of endmember 5, (vi) abundance of endmember 6,
Figure 10. (Continued). (vii) abundance of endmember 7, (viii) abundance of endmember 8. (c) IEA without preprocessing: (i) abundance of endmember 1, (ii) abundance of endmember 2, (iii), abundance of endmember 3, (iv) abundance of endmember 4, (v) abundance of endmember 5, (vi) abundance of endmember 6, (vii) abundance of endmember 7, (viii) abundance of endmember 8. (d) IEA with preprocessing: (i) abundance of endmember 1, (ii) abundance of endmember 2,
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No potential conflict of interest was reported by the authors.

References


(iii) abundance of endmember 3, (iv) abundance of endmember 4, (v) abundance of endmember 5, (vi) abundance of endmember 6, (vii) abundance of endmember 7, (viii) abundance of endmember 8. (e) ATGP without preprocessing: (i) abundance of endmember 1, (ii) abundance of endmember 2, (iii) abundance of endmember 3, (iv) abundance of endmember 4, (v) abundance of endmember 5, (vi) abundance of endmember 6, (vii) abundance of endmember 7, (viii) abundance of endmember 8. (f) ATGP with preprocessing: (i) abundance of endmember 1, (ii) abundance of endmember 2, (iii) abundance of endmember 3, (iv) abundance of endmember 4, (v) abundance of endmember 5, (vi) abundance of endmember 6, (vii) abundance of endmember 7, (viii) abundance of endmember 8.


