Transactions on Aeronautics and Astronautics (2020) 1: 1-14
Clausius Scientific Press, Canada
DOI: 10.23977/tranaa.2020.010101
ISSN 2616-1737

Feature dimension reduction method of multi-source remote sensing image based on spatial information

Yulong Zhao[1,*], Min Hu[1]

Space Engineering University, Beijing, 101416, China

Keywords: Spatial information; Multi-source remote sensing image; Feature dimensionality reduction; Shadow detection and removal

Abstract: The dimension reduction method of multi-source remote sensing image based on spatial information is proposed because of the influence of shadow on band selection and feature extraction. According to the separability of feature parameters, candidate feature parameters are selected to determine the classification threshold between samples. The feature parameters with separability greater than 6 are selected as the standard basis to construct the feature space of multi-source remote sensing image, so as to collect the feature space information of multi-source remote sensing image. According to the process of shadow detection algorithm, the original shadow image is transformed into HSV space to separate the dark area, and the dark area is denoised to get the shadow area. After shadow preprocessing, removing and post-processing, the boundary line is weakened and the undistorted information is obtained. According to the data structure of the multi-source remote sensing image, the image of each band in the multi-source remote sensing image can be expanded into one-dimensional vector by using the collected spatial information, and the independent components can be obtained by further solving. The independent component analysis (ICA) mathematical model was constructed to centralize the original mixed data and eliminate the mean value. The multi-source remote sensing image is whitened to form a new low-dimensional image. The experimental results show that the method is effective in dimensionality reduction.

1 Introduction

The existing dimensionality reduction methods can be divided into two categories: band selection and feature extraction. Band selection can reduce dimension by selecting a subset of bands from the original band, while feature extraction can reduce dimension by transforming the original data to another space. The dimensionality reduction method based on band selection can also calculate the amount of information and the distance between classes for multispectral images, but for the hyperspectral remote sensing images of hundreds of bands, the amount of calculation is huge; at the same time, because only a few bands are selected, the information of other bands is lost artificially. However, the dimension reduction method based on feature extraction changes the physical characteristics of the original band, which is not conducive to the maintenance of spectral characteristics. None of the above dimensionality reduction methods consider the unique spectral features (especially the diagnostic spectral features) of the target image. However, the dimensionality reduction method based on spatial information is a landmark feature different from other images. This feature interval is a whole, and its information is particularly important relative to other band intervals. If the spectral integrity of this interval is not considered, its diagnostic spectral feature information may be Other information interference. Therefore, the relationship between the diagnostic spectral features and the amount of information is studied, and a feature dimensionality reduction method based on spatial information is proposed.

2 Collection of feature spatial information of multi-source remote sensing image

Cloud has a high reflection coefficient in the visible light band, and often presents a large-scale coverage area. Therefore, most of the cloud regions in the image show continuous high brightness characteristics. However, most of the images have low reflection coefficient and low brightness in the images. The average gray level can be used as a characteristic parameter to distinguish the two. From the physical origin of clouds, clouds are gradually condensed by water droplets, ice crystals and their mixed particles in the atmosphere, which is similar to the growth process of crystals, and shows certain self-similarity in space. It is fractal geometry of nature and has specificity. However, most of the images do not have fractal characteristics. Therefore, fractal dimension can be used to distinguish the two. In addition, the uneven and variable Texture Features of the image can also be used to identify the texture of the image, such as high spatial resolution and uneven texture.

According to the difference between cloud and image imaging attributes, the average gray level, fractal dimension and texture parameters are taken as candidate feature parameters. The texture features can be calculated by sum difference histogram or gray difference vector, including angle second-order moment, texture entropy, correlation, inverse moment and texture contrast. There are 12 candidate feature parameters. The separability of characteristic parameters is defined by formula (1) to screen the candidate feature parameters.

$$D = \sqrt{\frac{\left\| O_1 - O_2 \right\|^2}{s_1 s_2}} \quad (1)$$

In formula (1), O_1 and O_2 represent the class center of two types of samples respectively, $\left\| O_1 - O_2 \right\|$ is the class spacing, indicating the degree of inter class dispersion of samples; s_1、s_2 are the standard deviation of two types of samples, representing the degree of within class dispersion of samples, and separability measures the degree of feature parameters conducive to classification. It can be seen from the definition that the larger the distance between classes, the smaller the dispersion within the class, and the greater the separability of samples, the more conducive to clustering.

By setting the separability threshold, selecting the corresponding characteristic parameters, considering the same distribution of two types of one-dimensional samples, as shown in Figure 1.

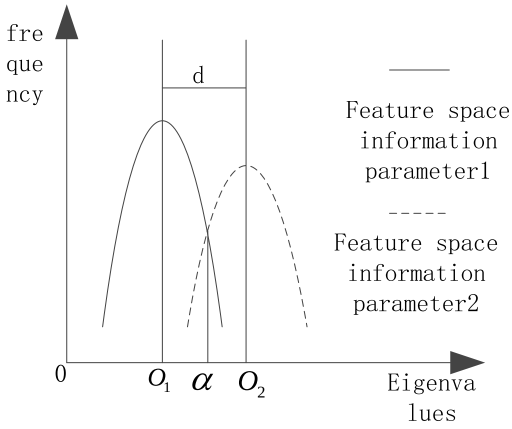


Fig.1 Spatial feature distribution of multi-source remote sensing images

Suppose that two types of samples satisfy normal distribution, $N(0,\sigma)$ and $N(d,\sigma)$, where $N(\mu,\sigma)$ represents the normal distribution of mean value μ and mean square deviation of σ; d is the distance between classes. In order to make the sample redundancy a small probability event, the classification threshold α between samples should meet the following requirements:

$$|\alpha - O_1\| = 3\sigma \quad (2)$$

At the same time:

$$\|\alpha - O_1\| = \|O_2 - \alpha\| = \frac{d}{2} \quad (3)$$

500 image blocks of quickbird2 and IKONOS cloud and their underlying surface were selected as samples for feature selection. The separability of the above 12 feature parameters was calculated. The feature parameters with separability greater than 6 were selected as the standard basis to construct the multi-source remote sensing image feature space. The final expression of sample 2 in the feature space is as follows:

$$x_i = [\text{ gray }, fd, asm, ent, \text{ cor }]^T \quad (4)$$

In the formula, i is the sample number, and the feature parameters are average gray level, fractal dimension, angle second moment and entropy, and texture feature parameters are spatial information parameters of multi-source remote sensing images.

3 Shadow detection and removal technology of spatial information parameters

Because the relative position and geometric orientation of pixels in multi-source remote sensing images are not consistent with the sun, the difference of light irradiance of pixels on different slopes changes the pixel value on the image, thus producing shadow pixels. The gray value of pixels in these areas is low, and the information contained is distorted, which seriously affects the final results of image processing. The shadow makes the image difficult to process and analyze. This is because the overall gray information of the shadow area is low, which makes the color and shape information of the original image in the shadow area seriously distorted. Therefore, the shadow processing technology of multi-source remote sensing image is very important for the subsequent processing of shadow image.

The main spectral characteristics of the shadow are as follows: 1

(1) The gray value of shadow areas is low, that is to say, the intensity of sunlight reflection in these areas is significantly lower than that of surrounding areas;

(2) In the shadow and non shadow regions, the texture features of the image are continuous, that is, the texture features of the image surface will not change due to the shadow;

(3) In some color spaces, individual bands remain invariant to shadows.

The histogram of multi-source remote sensing image can be obtained by statistical gray distribution range of multi-source remote sensing image. In the histogram, the shadow area is concentrated in the lower gray value side, while the higher gray value side is the non shadow area. Therefore, the image with shadow often presents the characteristics of "two peaks" which are relatively concentrated in the shadow and non shadow areas. Usually, the gray value corresponding to the valley bottom between two peaks is selected as the threshold to distinguish shadow from non shadow.

The image has the following characteristics in HSV space: (1) the shadow area of remote sensing image can be separated after two HSV transformations; (2) this transformation brings more noise to the image. Generally, before shadow extraction, denoising should be carried out, otherwise the classification accuracy will be affected; (3) shadow and water can not be effectively distinguished in HSV space, so it needs to be in the final The algorithm adds some extra steps to separate water and shadow. The shadow removal of multi-source remote sensing image includes shadow area detection and shadow area removal.

3.1 Shadow area detection

According to the analysis, the hyperspectral images with shadows have obvious differences in HSV color space. The shadow detection algorithm based on the characteristics of HSV color space can better solve the shortcomings of common methods. According to the special properties of the original shadow image transformed into HSV space, the shadow area is obtained by denoising the dark area. The specific flow of shadow detection algorithm is shown in Figure 2.

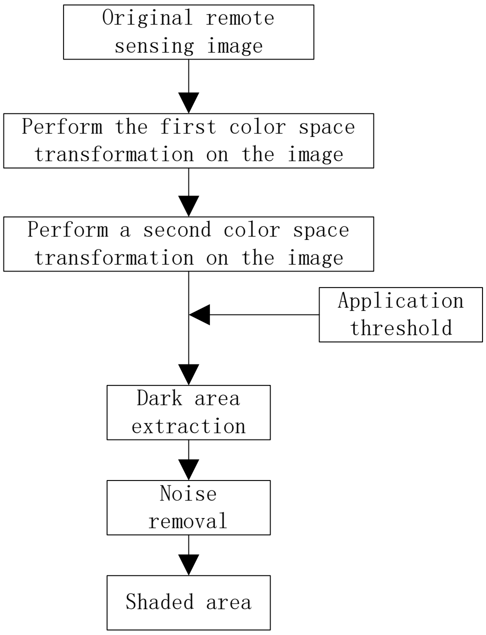


Fig.2 Data detection shadow algorithm flow

3.1.1 Color space conversion

Color space transformation refers to transforming RGB space of image into HSV space through formula (5). The original image is transformed into HSV space pixel by pixel

$$\begin{cases} V = \max(R,G,B) \\ H = \begin{cases} \theta, & \text{if} \quad G \geq B \\ 2\pi - \theta, & \text{others} \end{cases} \\ S = 1 - \dfrac{\min(R,G,B)}{\max(R,G,B)} \end{cases} \qquad (5)$$

Normalize hue (H), saturation (s) and brightness (V). Then, the first result is transformed into color space according to the previous step, and the final result is normalized. Through some previous processing, there are many bands left in the data, and representative bands are selected to form the effective bands of true color map.

3.1.2 Dark area extraction

The method of extracting dark area based on HSV spatial characteristics of shadow image is more flexible, and there is no high requirement for threshold selection. After two HSV transformations, the chroma space and RGB image have obvious bimodal characteristics. According to the chroma histogram, another peak between the two peaks which are close to each other is selected as the threshold, and the shadow area of the image is extracted by using the threshold.

3.2 Shadow removal technology

Shadow removal technology is to restore the shadow area image information detected in the previous step, which is the core part of shadow processing process, because the previous operation is the foundation of shadow removal, and the effect of this step directly affects the final processing results.

3.2.1 Shadow pretreatment stage

The shadow in the image is mainly caused by the sun, which is a single light source. The sunlight is usually regarded as a parallel light source. The transition between shadow and non shadow area in remote sensing image is obvious. There is a very narrow transition area between the shadow and the surrounding scenery in the real remote sensing image. The extracted shadow area may contain such transition area. Although the visual angle analysis of such area is not obvious, in the subsequent processing, the existing color scale is stretched, that is, the difference between the shadow area and the transition area is magnified, forming a line The obvious transition zone usually corrodes 2 to 4 pixels for the shadow part distinguished in the first stage.

3.2.2 Shadow removal stage

After preprocessing, in the HSV space transformation of the image, its essence is to do spatial mapping of image pixel values. The specific process is to stretch the color scale of the shadow area, which can improve the quality of image processing. However, the overall performance of the shadow area is not natural enough, and the hue is quite different from the surrounding non shadow area. Usually, the RGB image with adjusted color level is converted to HSV color space, and then the chroma and saturation value of the image in the shadow area are adjusted to the average value of the chroma and saturation of the same surrounding non shadow area respectively, and finally transformed back to RGB space.

After adjusting the color level of the image, the real shadow recovery operation is carried out. Shadow recovery is mainly based on the statistical characteristics of pixels in the shadow and its adjacent non shadow areas. First, adjust each channel, then return to RGB space, and then do some necessary post-processing. After the color adjustment is adjusted, the image will be adjusted in the HSV space, which is adjusted based on the shadow and the pixels in the adjacent area. The specific process of pixel adjustment in shadow area is shown in flow chart 3.

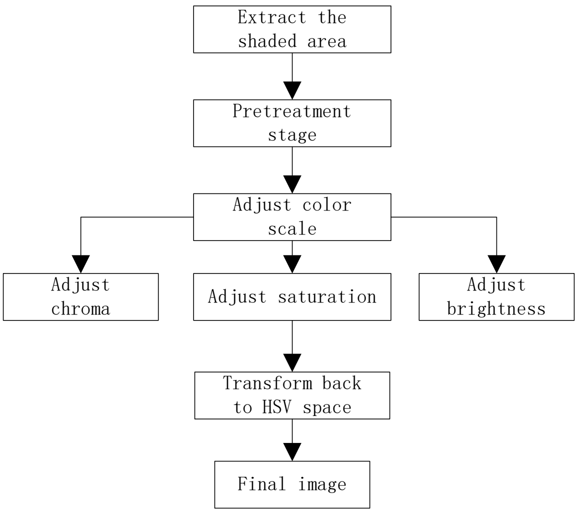


Fig.3 Flow chart of shadow recovery algorithm

3.2.3 Post treatment stage

The post-processing stage is a necessary link after shadow removal. This step is mainly to modify the processed image, that is to do some edge processing on the image. In the previous operation, the shadow area was treated separately, and the excessive problem of shadow and non shadow area was not considered. Therefore, a sharp boundary line appeared on the periphery of the shadow after processing. A 3 × 3 Gaussian filter is used to filter along the boundary line to weaken the boundary line.

4 Dimensionality reduction of multi-source remote sensing image features

Due to the huge amount of multi-source remote sensing image data, it is necessary to reduce the dimension of the data. The dimension reduction of multi-source remote sensing images is realized by using the collected spatial information. Firstly, the experimental data obtained by band filtering are read into the array. In the process of reading, according to the data structure of the multi-source remote sensing image, the image of each band in the multi-source remote sensing image can be expanded into a one-dimensional vector. If the image has m bands and each band has $a \times b$ pixels, then the three-dimensional $m \times a \times b$ hyperspectral image is converted into a two-dimensional array of $(a \times b)$ columns in m row, and then a two-dimensional image matrix is established, in which each row represents the image of a band.

Let $U = a \times b$, then the mathematical expression of multi-source remote sensing image is $\mathbf{X} = [x_d]_{m \times U}$, where $d \in \{1, 2, \cdots, m\}$ is the band index, m is the total number of image bands, $i \in \{1, 2, \cdots, U\}$ is the pixel index, U is the total number of pixels in the image.

The main purpose of this step is to remove the correlation between different bands and reduce the computational complexity of the algorithm, which can provide help for the next step of calculation. Then, ICA algorithm is used to solve the unmixing matrix W. finally, the independent component s can be obtained by further solving according to the characteristic distribution diagram of the collected spatial information. The specific process is shown in Figure 4.

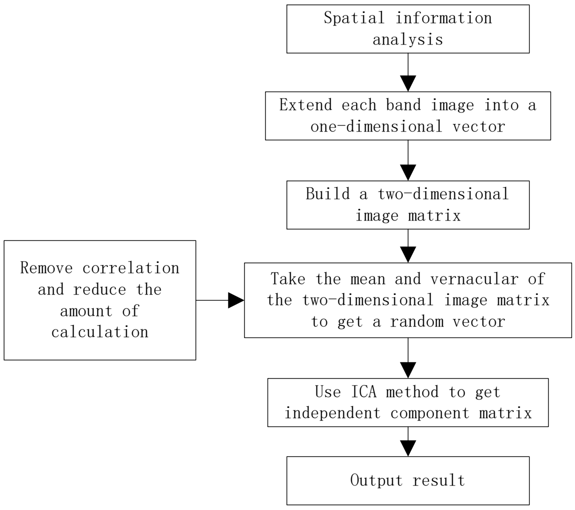


Fig. 4 Multi source remote sensing image unmixing flow chart

As a linear dimensionality reduction method, ICA is widely used in hyperspectral image processing and analysis. Moreover, ICA has the advantages of simple theory and high efficiency. ICA takes non Gaussian as the standard of independence. The greater the non Gaussian, the stronger the independence, otherwise the weaker. In this paper, the relationship between independent components and the original image is fully explored, and the dimension reduction of hyperspectral image is realized by band selection. In hyperspectral image processing and analysis, some representative band subsets are selected from the original band to replace the original image, so as to reduce the dimension of the data.

The mathematical model of independent component analysis can be expressed as follows:

$$\mathbf{X} = WS \quad (6)$$

In formula (6), each line can be regarded as an independent component in the multi-source remote sensing image. According to the basic principle of the central limit theorem, using the statistical independence and non Gaussian characteristics of each independent component as the objective function, the appropriate transformation matrix is found, and then the approximate independent component process is obtained. According to the basic theory of information theory, the maximum of negative entropy is used as the objective function to solve the independent components under the constraint conditions. As a fixed-point iterative algorithm, this method has the characteristics of fast convergence, simple calculation and good robustness.Using this method, the multi-source remote sensing image is decomposed to obtain the unmixing matrix and approximate independent components.

The specific dimension reduction steps are as follows:

Step1: centralize multi-source remote sensing images. In order to avoid losing generality, assume that the mixed variable is zero mean, which can simplify the complexity of the algorithm to a certain extent. If the actual situation does not meet the assumption of zero mean value, we can achieve this goal through a mean operation. In other words, the original mixed data is centralized before ICA operation. Namely:

$$X^{'} = X - E\{X\} \quad (7)$$

In formula (7), $E\{X\}$ represents the mean value of the original mixed data, and thus X' has zero mean value. At the same time, due to:

$$E\{\mathbf{S}\} = W^{-1}E\{\mathbf{X}\} \quad (8)$$

The independent component is also changed to zero mean value, and the mixed matrix remains unchanged before and after preprocessing, so the centralization of variables can not affect the estimation of independent components. For the data with zero mean, after estimating the mixed matrix and independent components by the algorithm, subtracting the mean value can be reconstructed by adding $W^{-1}E\{\mathbf{X}\}$ to the independent component of zero mean.

Step2: whiten the multi-source remote sensing image $\mathbf{X}$ after removing the mean value, and the uncorrelation is a weakening form of independence. If the covariance of two random variables is zero, it can be said that the two variables are uncorrelated.The whitened random variables are uncorrelated and have unit variance. It can also be described as that the covariance matrix of the random vector P is a unit matrix. Namely:

$$E\left\{PP^{\mathrm{T}}\right\} = R \quad (9)$$

Firstly, the eigenvalues of covariance matrix are decomposed

$$E\left\{PP^{\mathrm{T}}\right\} = EGE^{\mathrm{T}} \quad (10)$$

E on the right side of the above formula is the orthogonal matrix composed of its eigenvectors, and G is the diagonal matrix composed of its eigenvalues. Therefore, the whitening matrix is set as follows:

$$F = G^{-\frac{1}{2}}E^{T} \quad (11)$$

The whitened data P is obtained by formula (11):

$$P = FX \quad (12)$$

In the unmixing matrix w obtained by ICA, W_{ij} represents the independent component weight of the j band. It can also be expressed as: W_{ij} represents the independent component information contained in the j band. Therefore, the average absolute weight coefficient W_{j} can be used to evaluate the amount of independent component information contained in each band:

$$w_j = \frac{1}{m}\sum_{i=1}^{m}\left|w_{ij}\right| \quad (13)$$

After sorting the W_{j}, the original image corresponding to the band with larger average absolute weight coefficient is selected to replace the original data, thus forming a new low dimensional image. Because the selected band image represents most of the feature information of the original image and does not change its physical characteristics, it can be considered that the dimension reduction of multi-source remote sensing image is realized.

5 Experiment

In order to verify the rationality of the research on feature dimension reduction method of multi-source remote sensing image based on spatial information, simulation experiments are carried out.

5.1 Experimental environment

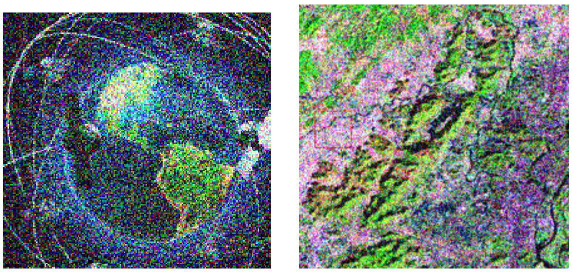
The experimental environment settings are shown in Table 1.

Table 1 Experimental Environment

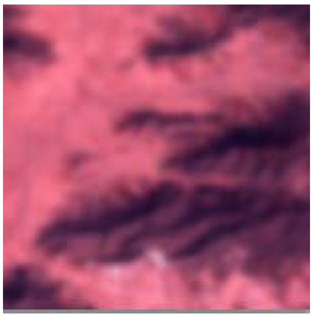
Hardware environment	
PC	2 sets One for Managers One for users
Memory	5G
Development platform	MagicARM2410
Software environment	
Operating system	Microsoft Windows Xp Pro_ Sp2
Microsoft platform generator	Microsoft Platform Builder
Microsoft embedded vision	Microsoft eMbedded Visual C++ 4.0+SP4
Synchronize software version	Microsoft ActiveSync4.5
System debugging	

5.2 Experimental results and analysis

Three standard remote sensing images are used for experimental analysis, which are image 1, image 2 and image 3. The schematic diagram of each data image is given in Figure 5.



(a) Image 1 (b) image 2

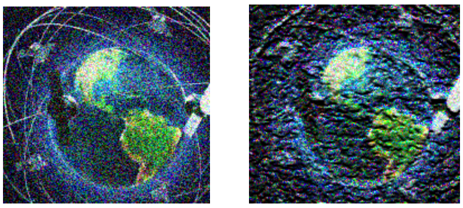


(c) Image 3

Fig. 5 Schematic diagram of image set

(1) Image 1

For image 1 remote sensing image feature dimensionality reduction, band selection, feature extraction and spatial information feature dimensionality reduction methods are compared respectively, and the dimension reduction effect as shown in Fig. 6 is obtained.



(a) Dimension reduction method of band selection

(b) feature extraction method

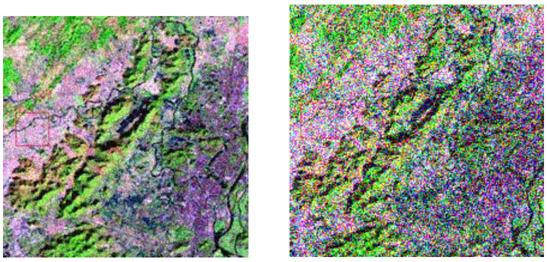
(c) Dimension reduction method based on spatial information features

Fig. 6 Comparison and analysis of dimension reduction effect of three methods in image 1

It can be seen from Fig. 6 that although the rough outline of the image can be seen by using the method of band selection and feature extraction, there are obvious turtle cracks and patching lines. The method of dimensionality reduction based on spatial information features can clearly show the contour line features and the meaning of the whole image.

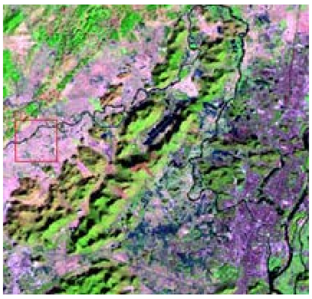
(2) Image 2

For image 2 remote sensing image feature dimensionality reduction, band selection, feature extraction and spatial information feature dimensionality reduction methods are compared respectively, and the dimension reduction effect as shown in Figure 7 is obtained.



(a) Dimension reduction method of band selection

(b) feature extraction method



(c) Dimension reduction method based on spatial information features

Fig. 7 Comparative analysis of dimension reduction effect of three methods in image 2

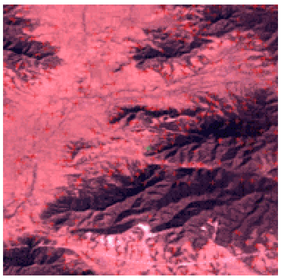
As can be seen from Figure 7, the dimension reduction effect of the band selection method is better than that of the feature extraction method, and the image texture can be seen more clearly, but there is noise, while the dimension reduction method based on spatial information features does not have noise, and can clearly display the image content.

(3) Image 3

For image 3 remote sensing image feature dimensionality reduction, band selection, feature extraction and dimensionality reduction based on spatial information feature are compared, and the dimension reduction effect as shown in Fig. 8 is obtained.

(a) Dimension reduction method of band selection

(b) feature extraction method



(c) Dimension reduction method based on spatial information features

Fig. 8 Comparison and analysis of dimension reduction effect of three methods in image 3

It can be seen from Fig. 8 that the dimension reduction methods of feature extraction using band selection can display image features, but there are noises. However, the feature extraction dimensionality reduction method can not display the image features completely, but the dimensionality reduction method based on spatial information features clearly shows the image features.

Through the above comparison, it can be seen that the dimension reduction method based on band selection and feature extraction is not careful in processing the details of multi-source remote sensing image, resulting in the image features can not be displayed, and the dimension reduction method based on spatial information features has good dimensionality reduction effect.

6 Conclusion

This paper proposes a method of multi-source remote sensing image feature dimensionality reduction based on spatial information. By collecting the feature spatial information of multi-source remote sensing image and considering the diagnostic spectral feature in the process of dimensionality reduction, the loss of spectral information of image in the process of dimensionality reduction is minimized. Experiments show that the dimension reduction effect is improved by considering the feature space information of multi-source remote sensing images.Because of the different characteristics of different remote sensing images, the method can be used to classify the features of multi-source remote sensing images, which has certain universality and practical value. Due to the different characteristics of different remote sensing images, the subspace divided according to one kind of image is not suitable for the other. For the study area with more classification categories, it is necessary to consider automatic extraction of diagnostic spectral interval and automatic division.

References

[1] Huang Hong, Shi Guangyao, Duan Yule, et al. Dimensionality reduction method of hyperspectral remote sensing image based on weighted space-spectrum joint preservation and embedding[J]. Acta Geomatica Sinica, 2019, 11(8):1014-1024.

[2] Lu Jianqiang, Li Wangzhi, Lan Yubin, et al. Agricultural aerial remote sensing image registration algorithm based on point feature detection[J]. Transactions of the Chinese Society of Agricultural Engineering, 2020, 36(3): 71-77.

[3] Liu Yongmei, Ma Xiao, Men Chaoguang. Hyperspectral remote sensing image classification method based on multiple spatial information[J]. Chinese Space Science and Technology, 2019, 039(002): 73-81.

[4] Zhang Yan, Sun Jie, Yu Changchun, et al. Study on Quaternary Coverage Classification Method Based on Multi-source Remote Sensing Data: A Case Study of 1:50,000 Mapping of Qigandianzi Sheet in Inner Mongolia[J]. Geological Science and Technology Information , 2019, 38(02):287-296.

[5] Cheng Bo, Liu Yueming, Liu Xunan, et al. Research on high-resolution remote sensing image offshore aquaculture area extraction method based on multi-source feature fusion[J]. Remote Sensing Technology and Application, 2018, 33(2):296-304.
[6] Miao Kaichao, Luo Xichang, Zhang Shujing, et al. Feature extraction and grade recognition method of fog image based on color gamut analysis[J]. Science Technology and Engineering, 2019, 019(035):228-233.
[7] Tian Qinglin, Pan Wei, Li Hanbo, et al. Comparative study of alteration information extraction based on multi-source remote sensing data[J]. Geological Science and Technology Information, 2018, 37(06):224-231+244.
[8] Li Yunfeng, Gan Le, Lin Cong, et al. An urban rice field distribution extraction method based on multi-source and multi-temporal remote sensing information[J]. Geography and Geo-Information Science, 2018, v.34(03):53- 59.
[9] Long Yuhang, Wu Desheng. Three-dimensional virtual reconstruction simulation of spatial feature information of high-altitude remote sensing images[J]. Computer Simulation, 2019, 036(012):57-61.
[10] Meng Qingyan, Sun Yunxiao, Zhang Jiahui, et al. Analysis of the vertical distribution characteristics and spatial configuration of greening in the building area based on multi-source remote sensing——A case study of Szekszbek, Hungary[J]. Remote Sensing Technology and Application, 2018, 33 (002):370-376.