A Multi-Criteria Band Selection Method of Hyperspectral Images

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Abstract: Hyperspectral remote sensing images are characterized by many bands and large amounts of datum, which require the dimensionality reduction, but band selection is one of the basic methods for dimensionality reduction of hyperspectral datum. For this reason, this paper proposes a multi-criteria band selection method. Firstly, the intrinsic dimensionality of hyperspectral image is calculated by virtual dimension, then the subspace is divided according to the band correlation criterion; and secondly, the information criterion is adopted to select the high-quality exponential bands in each subspace; and finally, the most suitable bands in each subspace are selected by class separability criterion to form the optimal band subset. Various experiments show that, compared with the optimum index factor and adaptive band selection methods, the proposed method has better performance in the measurement of information volume and information redundancy.

1. introduction

Hyperspectral remote sensing technology is the leading technology in the field of remote sensing, and is widely used in military, medical, agricultural and environmental monitoring and other fields[1]. Hyperspectral images have nanometer-level resolution, which can accurately describe the spectral features of ground objects, making it possible to identify ground objects from spectral dimensions. However, with the increase in the number of bands, the amount of hyperspectral datum have also increased dramatically, and how to improve its processing efficiency has become a hot topic.

Research on hyperspectral image dimensionality reduction has been carried out at home and abroad. The feature selection and extraction of hyperspectral remote sensing images are generally focused on band selection. Chavez proposed the Optimum Index Factor, which combines the band standard deviation and the correlation coefficient between bands to form an optimal index, to select the band combination[2,3]. Alarm proposed an Adaptive Band Selection method to fully consider the relationship between band information and correlation[4]. Combined with joint entropy, Su Hongjun put forward the band combination[5]. Chang proposed the virtual dimensionality to characterize the intrinsic dimensionality of hyperspectral datum, and then determine the number of subspaces and band selection[6]. The above research improves the technology system of hyperspectral remote sensing...
information processing. However, most of the above methods only consider a single band selection criterion, which affects the band selection quality[7]. This paper proposes a band selection method that integrates three criteria: first, the number of subspaces of hyperspectral datum is determined according to the virtual dimensionality, and the subspaces are divided using the correlation coefficient criterion; then, the high-quality bands are chosen in each subspace according to the optimal band index that characterizes the relationship between the band information and correlation; finally, the best band combination is determined by using the inter-class separability of the spectral angles of ground objects.

2. Band selection method

2.1. Optimum Index Factor

The optimal index Factor (OIF) considers the information content of single-band image data and the correlation between the bands, which is expressed as follows.

\[
OIF = \frac{\sum_{i=1}^{n} \sigma_i}{\sum_{i=1}^{n} \sum_{j=1}^{n} |R_{i,j}|}
\]

In the formula, \(\sigma_i\) is the standard deviation of the \(i\)th band datum, \(R_{i,j}\) is the correlation coefficient between the \(i\)th and \(j\)th band, its expression is defined as follows.

\[
R_{i,j} = \frac{\sum_{k=1}^{M \times N} (f_{i,k}(x,y) - \bar{f}_i)(f_{j,k}(x,y) - \bar{f}_j)}{\sqrt{\sum_{k=1}^{M \times N} (f_{i,k}(x,y) - \bar{f}_i)^2 \sum_{k=1}^{M \times N} (f_{j,k}(x,y) - \bar{f}_j)^2}}
\]

Where \(\bar{f}_i\) and \(\bar{f}_j\) are the average gray values of the \(i\)th and \(j\)th band datum, respectively.

However, OIF has some limitations. The correlation coefficient of non-adjacent bands is certainly smaller than that of adjacent bands, and the farther the band interval is, the smaller the correlation coefficient is. Therefore, it is impossible to guarantee the maximum information of band combination.

2.2. Adapative Band Selection

According to the amount of information and the correlation criterion, an Adaptive Band Selection method (ABS) was presented. ABS tries to select bands with a large amount of information, and ensures the weakest correlation between the selected bands.

According to the above description, a mathematical model of the band selection method was indicated by the \(Index_i\), which is the ratio of the standard deviation \(\sigma\) of the \(i\)th band image to the average \(\mu\) of the band correlation coefficients.

\[
Index_i = \frac{\sigma_i}{\mu_i}
\]

\[
\mu_i = \frac{R_{i-1,i} + R_{i,i+1}}{2}
\]

The smaller the correlation coefficient between the two bands, the greater the independence of the two bands and the lower the information redundancy. The larger the \(Index_i\) is, the greater the corresponding amount of information is. Therefore, first, calculate the \(Index_i\) in each band of hyperspectral image; second, arrange these indexes by the descending order; finally, Select the bands in numerical top ranking as the optimal band combination.
3. The proposed method
This paper comprehensively considers the three basic criteria for hyperspectral band selection. First, the number of subspaces is calculated from the number of signal terminals\[8\], then select the band with the largest band index in the subspace, finally a subset of bands with small correlation, large amount of information, and good separability between classes are chosen by the criterion of the spectral angle separability of ground objects.

3.1. Virtual dimension determines the number of subspaces
A non-transformation method is used to project the hyperspectral datum from the high-dimensional space to the low-dimensional space. The dimension of the virtual dimension space is the number of Terminal source\[9\]. Suppose that the hyperspectral datum set \( S \) has \( N \) bands, the covariance matrix of \( S \) is \( K \), and the autocorrelation matrix is \( R \), and its eigenvalue sets are \( \{\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_N\} \) and \( \{\overline{\lambda}_1 \geq \overline{\lambda}_2 \geq \ldots \geq \overline{\lambda}_N\} \). From the viewpoint of mathematics, the determination of the signal source can be regarded as a binary hypothesis testing problem:

\[
H_0 : z_i = \overline{\lambda}_i - \lambda_i = 0, H_1 : z_i = \overline{\lambda}_i - \lambda_i > 0
\]

According to the Neyman-Pearson criterion\[9\], when \( \lambda_i - \overline{\lambda}_i \geq \mu \), it indicates the existence of a signal source and the total number of signal sources are the virtual dimensionality.

3.2. Spectral angle matching
Spectral angle matching (SAM)\[10\] is a classification method based on the spectral characteristics of ground objects. First, each pixel is represented as an \( N \)-dimensional vector, and the target spectrum of the hyperspectral image is matched with the reference spectrum in the \( N \)-dimensional space to determine the ground object separability.

In the classification of hyperspectral datum, the lower the separability between ground objects, the lower the classification accuracy. Within a certain waveband range, due to the physical reflection characteristics if ground object, the its spectral curve will change. But, the spectral responses and response ranges of different ground objects will be different. Therefore, the spectral angle is often used to identify the ground objects. In actual engineering, by calculating the spectral angle between the pixel spectrum and standard spectrum, the similarity between them is determined. The formula for calculating the spectral angle is as follows.

\[
\theta = \arccos \frac{\sum_{i=1}^{n} (x_i y_i)}{\sqrt{\sum_{i=1}^{n} x_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}}
\]

Where \( n \) is the number of bands, and \( x_i \) and \( y_i \) are the radiance values of the \( i \)th band, \( x \) and \( y \) are the spectral vectors of the ground objects in the \( i \)th band.

4. Experiment and Result Analysis
4.1. Experimental conditions and data sources
In this experiment, the radiation spectrum datum set Jasper Ridge was used. The original datum set has 224 bands, the wavelength range is from 380nm to 2500nm, and the spectral resolution is 9.46nm. 26 band datum which were seriously affected by dense water vapor were filtered out, and 198 band datum were preserved. The datum set includes four end elements, namely roads, silt, water, and trees, shown in Figure 1.
4.2. Experiment procedure

The experiment in this paper is realized by the following 4 steps.

Step1: Calculate the number of end elements of hyperspectral signal by virtual dimensionality, then determine the minimum number of intrinsic signal sources. In the experiment, the false alarm probability is $10^{-6}$, and the number of intrinsic signal sources in the datum set is calculated to be 4, that is, 4 bands are finally selected as the optimal band subset.

Step2: Calculate the correlation coefficient between any two adjacent bands, shown in Figure 2.

![Figure 2. Correlation coefficient between any two adjacent bands](image)

By calculating the correlation coefficient $R_{i,i+1}$ between the $i$th and $(i+1)$th adjacent bands, the correlation coefficient distribution is shown in Figure 2, where the minimum values are in the 33th, 104th and 145th bands, respectively. Therefore, the hyperspectral image space can be divided into the following four subspaces: 1-33, 34-104, 105-145 and 146-198 bands.

Step3: Calculate the band index in each subspace according to the formula (3), and order the indexes from largest to smallest, then select the bands corresponding to the three largest indexes in these subspaces, displayed in Table 1.

![Table 1. The bands corresponding to the three largest indexes in each subspace](image)

| Subspace  | 1-33   | 34-104 | 105-145 | 146-198 |
|-----------|--------|--------|---------|---------|
| Band      | 5,12,22| 51,76,92| 108,122,1| 147,182,1|
|           |        |        |         | 32      |
|           |        |        |         | 83      |

Step4: The spectral angle thresholds of various types of ground objects are set by the geographic remote sensing software ENVI. Starting from 0° and incrementing by 0.5° every time, the spectral angles, which make the classification accuracy of ground objects higher, are selected as the classification thresholds, shown in Table 2.

![Table 2. Threshold of spectral angle of each ground object](image)

| Object | River | Road | Tree | Silt |
|--------|-------|------|------|------|
| Threshold (°) | 18.52 | 21.73 | 9.47 | 6.28 |
The pixel spectra of the above four end elements are used as the target spectrum, and the average values of spectral angles of various objects are used as the standard angles. According to the thresholds in Table 2, the spectral angle of each object is calculated separately, ranked from largest to smallest, and the bands corresponding to the three largest indexes in all subspaces are listed in Table 3.

| River  | Band | Spectral angle(°) |
|--------|------|-------------------|
|        | 5    | 19.73             |
|        | 12   | 19.16             |
|        | 51   | 18.78             |
| Load   | 76   | 22.38             |
|        | 51   | 21.93             |
|        | 92   | 21.79             |
| Tree   | 108  | 11.78             |
|        | 132  | 10.67             |
|        | 122  | 10.16             |
| Silt   | 147  | 7.56              |
|        | 182  | 7.31              |
|        | 132  | 6.34              |

In the Table 3, it is shown that the spectral angles of the fifth, 76th, 108th and 147th bands are the largest indexes of the rive, load, tree and silt ground objects respectively. Therefore, the \{5, 76, 108, 147\} bands are taken as the optimal band subset.

4.3. Experiment analysis
In order to analyze the band combination in this paper, the ABS, OIF and proposed method in this paper were used to perform the band selection contrast experiment on the hyperspectral image datum set Jasper Ridge. The band combination is shown in Table 4.

| Band selection method | Band combination |
|-----------------------|------------------|
| ABS                   | 8,12,50,134      |
| OIF                   | 7,23,92,180      |
| The proposed method   | 5,76,108,147     |

In order to objectively evaluate the performance of the three methods, the band combination information entropy \(H_{sum}\), sum of correlation coefficient \(R_{sum}\) and correlation coefficient variance \(S^{[4]}\) are adopted to measure. The greater \(H_{sum}\) is, the greater the information volume is. The smaller \(R_{sum}\) and \(S\) are, the smaller the information redundancy reflecting the band combination are. The calculated \(H_{sum}, R_{sum}\) and \(S\) in the band combination of Table 4, are shown in Table 5.

| Band selection method | Band combination | \(H_{sum}\) | \(R_{sum}\) | \(S\)  |
|-----------------------|------------------|-------------|-------------|--------|
| ABS                   | 8,12,50,134      | 25.686      | 2.839       | 0.137  |
| OIF                   | 7,23,92,180      | 25.752      | 2.843       | 0.146  |
| The proposed method   | 5,76,108,147     | 26.285      | 2.793       | 0.123  |

According to the data analysis in Table 5, the proposed method has the largest \(H_{sum}\), and the \(R_{sum}\) and \(S\), calculated by the proposed method, are less than that of the ABS and OIF methods. In summary, the band combination performance, adopted by the presented method, is better than that of the ABS and OIF methods.

5. Conclusions
This article has considered several basic criteria for hyperspectral band selection. First, the hyperspectral space is divided into several subspaces with virtual dimensionality; then, the band index
with the smallest spectral similarity is selected by the SAM to form the best band subset. After the experimental verification, the band combination adopted by the proposed method has better performance and the classification accuracy of hyperspectral images is improved with the presented method.

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