HYBRID FEATURE EXTRACTION FOR OBJECT-BASED HYPERSPECTRAL IMAGE CLASSIFICATION

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ABSTRACT: The purpose of feature extraction is to reduce the dimensionality of hyperspectral images to solve classification problems caused by limited training samples. In this study, a hybrid feature extraction method which integrates spectral features and spatial features simultaneously is proposed. Firstly, the spectral-feature images are calculated along the spectral dimension of hyperspectral images using wavelet decomposition because wavelet has been proven effective in extracting spectral features.
Secondly, ten different kinds of spatial-features, which are calculated along the two spatial dimensions of hyperspectral images, are implemented on the wavelet spectral-feature images. Then a feature selection method based on the optimization of class separability is performed on the extracted spectral-spatial features to get the hybrid features which could be suitable for classification applications. In this study, the object-based image analysis (OBIA) is used for hyperspectral image classification. The experiment results showed that the overall accuracy for the classification of a real hyperspectral data set using our proposed approach could reach approximately 94%. Moreover, it is worth mentioning that the hybrid features and OBIA classification could significantly increase the overall accuracy of hyperspectral images which contain poor separability between classes, after the spectral features were extracted. The experiment result also showed that the overall accuracy would go up by 20% by using our proposed approach on hyperspectral images with poor class separability.

1. INTRODUCTION

Hyperspectral images contain rich and fine spectral information. However, we have to extract the useful information for classification to avoid facing curse of dimensionality（Bellman, 1961）, which refers to the fact that the sample size required for training a specific classifier grows exponentially with the number of spectral bands. There are two ways to avoid curse of dimensionality, which are increasing training samples and reducing the dimensionality of hyperspectral image. As it is time-consuming and labor-intensive to collect the ground truth data ,which means it is not easy and convenient to increase training samples. Hence, reducing the dimensionality is preferred generally.
With the improvement in spatial resolution of remote sensing, images contain richer textural information. Moreover, it has been proved that the textural analysis improves the classification accuracy of multispectral images indeed （Cheng, 2007; Shen, 1998）. Textural interpretation could increase the information for classification by considering the relation between every pixel and its' adjacent pixels. However, most of studies related to hyperspectral classification classified the images right after reducing the dimensionality. Therefore, if texture is considered as one of the factors during classification, it will improve the classification rate.
The most of classifications of remote sensing images focus on pixel-based approaches, which results in pepper-salt effect and fragmented edge. In order to improve this situation, the OBIA classification would be used for hyperspectral image classification in this study.
Therefore, we design a classification procedure for hyperspectral images. Firstly, the spectral-feature images are calculated along the spectral dimension of hyperspectral images using wavelet decomposition because wavelet has been proven effective in extracting spectral features. Secondly, ten different kinds of spatial-features, which are calculated along the two spatial dimensions of hyperspectral images, are implemented on the wavelet spectral-feature images. Then a feature selection method based on the optimization of class separability is performed on the extracted spectral-spatial features to get an optimal hybrid feature subset which could be suitable for classification applications. Finally, the OBIA classification is conducted on the hyper features.

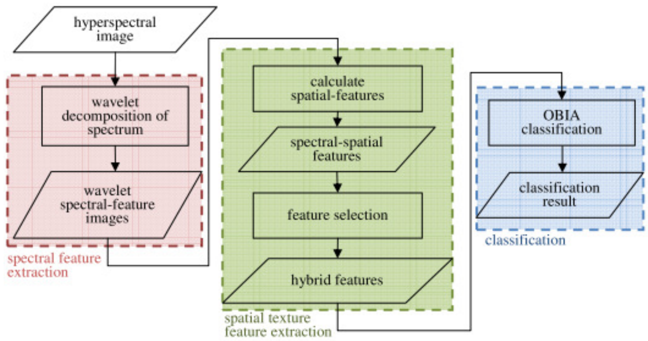

Figure 1　Flow chart of the hyperspectral classification procedure which is presented in this study

2 METHODOLOGY

2.1 Wavelet decomposition of spectrum

Hsu（2003）proposed that wavelet decomposition of spectrum method is actually better than other common dimensional reduction approaches such as principal components transformation （PCT）, discriminant analysis feature extraction（DAFE）, and decision boundary feature extraction（DBFE）. Wavelet decomposition of spectrum method is unsupervised feature extraction method; hence, it could avoid the lack of training samples. Due to the above-mentioned reasons, wavelet decomposition of spectrum method is used for extracting wavelet-based spectral features in this study.

As shown in Figure 2, a wavelet transformation is implemented on the hyperspectral data such as the original spectrum x with 16 elements, which means the image contain 16 bands. Then one approximation coefficient and several detail coefficients are obtained after the wavelet decomposition. Sort these wavelet coefficients in decreasing order, and select 6 largest amplitude wavelet coefficients, which are shown as yellow blocks in Figure 2, as the important spectral features of x. This is how wavelet decomposition of spectrum method reduces the dimension of hyperspectral images.

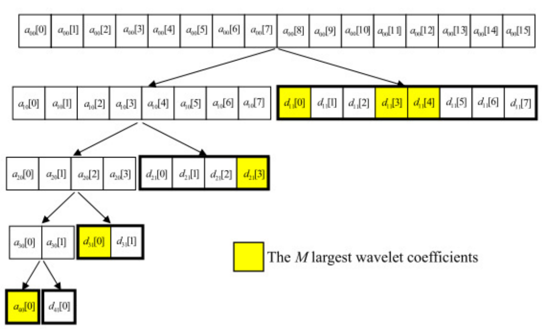

Figure 2　An example of wavelet decomposition spectrum（Hsu, 2003）

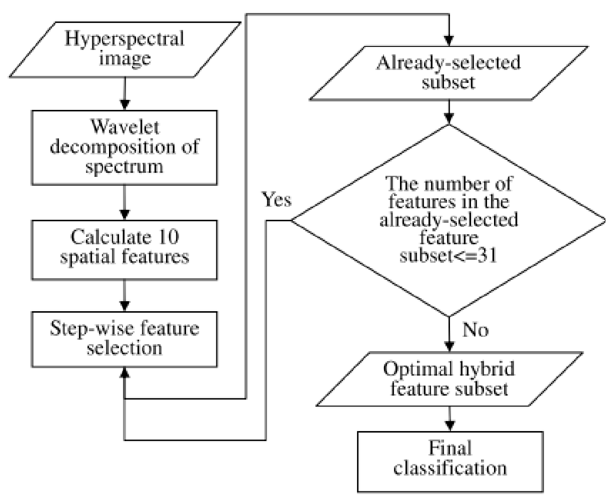

Figure 3　Spatial texture feature extraction algorithm

2.2 Spatial texture feature extraction

Manian and Jimenez（2007）proposed a spatial-feature selection and classification method for AVIRIS images. However, they did not reduce the dimensionality of the AVIRIS image firstly, but used 200 bands to calculate 10 kinds of spatial features, which are shown in Table 1, and the size of the window implemented the convolution is n_1

$\times n_2$. Hence, 2000 spatial texture features were obtained from the calculation. Then a feature subset applicable to classification was selected from these 2000 spatial texture features. However, this procedure would be time-consuming; therefore, in this study, wavelet decomposition of spectrum method is used to reduce the dimensionality to 10 spectral features firstly then calculate 10 kinds of spatial features; 100 spectral-spatial features are obtained. Finally, the feature selection is implemented on these 100 spectral-spatial features only, which would save a lot of computing time. Figure 3 shows the flow chart of the spatial texture feature extraction. First of all, 10 spatial features, which contain statistical features（f1~f6）and wavelet features（f7~f10）, are calculated for each spectral feature after wavelet decomposition of spectrum. Then 100 spectral-spatial features are obtained from the calculation of spatial features. Next, a feature selection process that selects features step by step by adding features that result in the highest increase in classification rate（CR）, which is defined by Eqs.（1）, is applied. Each spectral-spatial feature is classified by using minimum distance classifier, and the feature providing the maximum classification rate is selected as the already-selected subset, which is called hybrid feature subset also. Another feature is randomly selected and appended to the already-selected subset. The fitness of the new feature subset with this feature added is evaluated using the criterion that this new subset should result in the maximum increase in CR. Feature selection is stopped when the number of features in the already-selected subset is over 31. Finally, an optimal hybrid feature subset is generated, which is suitable for classification applications.

Table 1 The information about 10 spatial features

Spatial feature	Equation	Meaning
f1	$f_1 = \frac{1}{n_1 n_2}\sum_{i=1}^{n_1}\sum_{j=1}^{n_2} X(i,j)$	Average
f2	$f_2 = \sqrt{\sum_{i=1}^{n_1}\sum_{j=1}^{n_2}\left(X(i,j) - f_1\right)^2}$	standard deviation
f3	$f_3 = \frac{1}{n_1 n_2}\sum_{i=1}^{n_1}\sum_{j=1}^{n_2}\left\lvert X(i,j) - X(i+1,j)\right\rvert + \left\lvert X(i,j) - X(i,j+1)\right\rvert$	average deviation of gradient magnitude
f4	$f_4 = \frac{1}{n_1 n_2}\sum_{i=1}^{n_1}\sum_{j=1}^{n_2}\left\lvert X(i,j) - f_1\right\rvert$	average residual energy
f5	$f_5 = \frac{1}{n_1 n_2}\sum_{i=2}^{n_1-1}\sum_{j=1}^{n_2}\left\lvert X(i,j) - X(i-1,j) + \frac{X(i+1,j)}{2}\right\rvert$	average deviation of the horizontal directional residual
f6	$f_6 = \frac{1}{n_1 n_2}\sum_{i=1}^{n_1}\sum_{j=2}^{n_2-1}\left\lvert X(i,j) - X(i,j-1) + \frac{X(i,j+1)}{2}\right\rvert$	average deviation of the vertical directional residual
f7	$f_7 = \frac{1}{N}\sum_{k=1}^{N_j}\left\lvert A_{j,k}\right\rvert$	average of the approximation coefficients
f8	$f_8 = \left[\frac{1}{N}\sum_{k=1}^{N_j}\left\lvert A_{j,k} - M\right\rvert^2\right]^{1/2}$	standard deviation of the approximation coefficients
f9	$f_9 = \frac{1}{N}\sum_{k=1}^{N_j}\left\lvert D_{j,k}\right\rvert$	average of the detail coefficients
f10	$f_{10} = \left[\frac{1}{N}\sum_{k=1}^{N_j}\left\lvert D_{j,k} - M\right\rvert^2\right]^{1/2}$	standard deviation of the detail coefficients

$$\text{classification rate(CR)} = \frac{\text{number of samples correctly classified}}{\text{total number of sample classified}} \times 100 \qquad (1)$$

2.3 Object-based image analysis (OBIA)

OBIA classification differs from pixel-based classification. OBIA classification is based on image object, and pixel-based classification is based on pixel. In the beginning of the OBIA classification, an image is segmented into several pieces, which are called image objects. The characteristics of the image objects, which are also called features, are the basis of OBIA classification. The image object provides more information for the classification than the pixel does. The process of OBIA classification is split into four steps : image segmentation, feature extraction of the objects, class hierarchy, classification.

3 EXPERIMENTAL RESULTS USING REAL HYPERSPECTRAL IMAGE

There are three experiments in this study. The main purpose of experiment I is to test the hybrid feature extraction using different numbers of training samples in terms of classification accuracy. In experiment II, there were 12 cases to test the necessity of the hybrid feature extraction, and an optimal hybrid feature subset was decided at the end of this experiment. Finally, in experiment III, OBIA classification was used to classify the hybrid feature image instead of minimum distance classification. Figure 4 shows the image of the test AVIRIS data set which is available in the website of School of Electrical and Computer Engineering at Purdue University（https://engineering.purdue.edu/~biehl/MultiSpec/）The image covers an agriculture field on northwest Indiana in 1992. The original data set has 224 spectral bands from 0.4 to 2.45 µm with 10 nm spectral resolution. The image size of the test field is 145×145. The number of bands is 220 after removing 4 noisy bands. The ground truth data shown in Figure 5 includes seven classes: Corn-notill, Corn-min, Grass/Trees, Hay-windrowed, Soybeans-notill, Soybeans-min, and Woods. These chosen classes are plants, and the separability between them is poorer than the chosen classes in the AVIRIS image of Jasper Ridge Biological Preserve, which Li（2011）used as an experimental image.

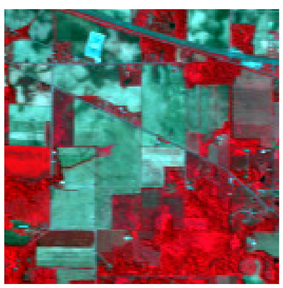

Figure 4 Test AVIRIS image

Figure 5 Ground truth map

3.1 Experiment I：Hybrid feature extraction and classification using different numbers of training samples

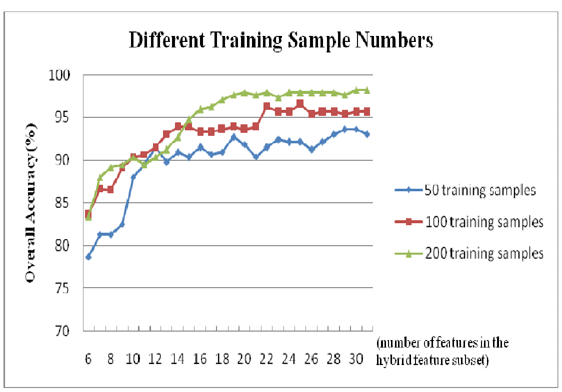

Figure 6 Classification results using different training sample numbers

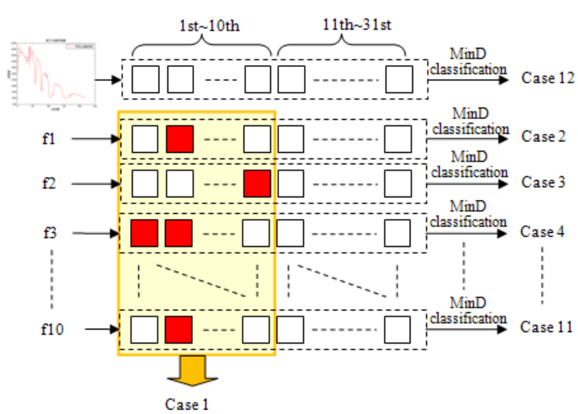

Figure 7 Frame of 12 cases

The main purpose of experiment I is to test the hybrid feature extraction using different numbers of training samples in terms of classification accuracy. There are three different kinds of training sample numbers which are 50 per class, 100 per class, and 200 per class. The process of hybrid feature extraction follows Figure 3. Db1 was used to do the wavelet decomposition of spectrum. In terms of the calculation of wavelet features(f7~f10), db2 was used, and the window size was 8x8. Figure 6 is the result of this experiment.

It is shown in Figure 6 that the classification accuracies with different training samples grow gradually when the number of features in the hybrid feature subset rises, and they have the same increasing trend, which is increasing more steeply in the beginning and going up gently later. More the number of training samples is; better the classification accuracy is, and vice versa. Generally speaking, all of these three cases have fine classification accuracies. Even in the case using 50 training samples per class, The classification accuracy could maintain above 90%, when the feature number is over 10.

3.2 Experiment II：The necessity of the hybrid feature extraction

The purpose of experiment II is confirming the necessity of hybrid feature extraction. There are 12 cases in the experiment II. Figure 7 is the frame of these 12 cases. Case 2 implements the wavelet decomposition of spectrum to extract Y spectral features firstly then calculates f1 of each spectral feature. After that, there are Y spectral-spatial features. Next, combine these Y spectral-spatial features into an image cube, and classify it with the minimum distance classifier. The value of Y is from 6 to 31. Regarding case 3 to case 11, the f1 is substituted by f2 ~ f10; other parameters are the same as case 2. Case 1 uses the hybrid features extraction. Figure 7 shows that case 1 implements the wavelet decomposition of spectrum to extract 10 spectral features then calculates f1~f10 of each spectral feature. After that, there are 100 spectral-spatial features setting in the yellow block in Figure 7. Next, L spectral-spatial features shown red in Figure 7 are the hybrid features chose by using the feature selection method mentioned in chapter 2.2. Then these L spectral-spatial features are combined into an image cube, and classify it with the minimum distance classifier. The value of L is from 6 to 31. Case 12 does not implement any spatial feature calculation. It executes the wavelet decomposition of spectrum to extract K spectral features firstly. Then it combines these K spectral features into an image cube and classifies it directly. The value of K is from 6 to 31.
Regarding the parameters in experiment II, Db1 was used to do the wavelet decomposition of spectrum. In terms of the calculation of wavelet features（f7~f10）, db2 was used, and the window size was 8×8. All of them are the same as the parameters in experiment I.

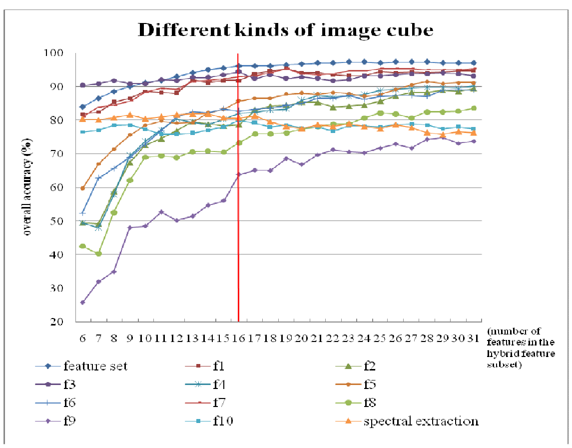

Figure 8 Classification results of 12 cases

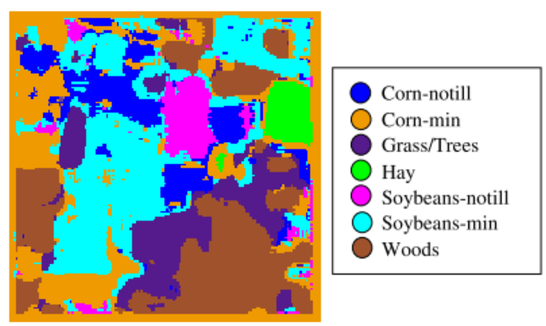

Figure 9 The classified image of the optimal hybrid feature subset

Figure 8 is the classification result of these 12 cases. In the legend, “feature set” is case 1; from “f1” to “f10” are case 2 to case 10, and “spectral extraction” is case 12. It is obvious that the classification result of hybrid feature extraction（case 1）is the best one. The classification accuracy of hybrid feature extraction is better than the classification accuracy of any single spatial feature. By comparing case1 to case12, it is worth mentioning that the hybrid feature extraction could improve the classification accuracy after spectral feature extraction about 3%~20%. In addition, generally speaking, the statistic features（f1~f6）perform better than the wavelet features（f7~f10）.
The result of experiment II proves that the hybrid feature extraction could improve the classification accuracy effectively. Therefore, we use the hybrid feature extraction method to extract hybrid features for classification. In Figure 8, the increasing trend of classification accuracy of hybrid feature extraction（case 1）slows down gradually when the number of features in the hybrid feature subset arrive at 16. Hence, 16 previous hybrid features are chosen for minimum distance classification. Figure 9 is the classified image of these 16 hybrid features. The overall accuracy is 96.20%; the Kappa index is 0.96. It is obvious that the result image contain the pepper-salt effect, and the edges of the ground patches are fragmental; therefore, in experiment III, we try to use OBIA classification in order to ameliorate these situations.

3.2 Experiment III：OBIA classification

Experiment III classifies 16 hybrid features chosen at the end of experiment II by using OBIA classification. Figure 10 is the classified image of OBIA classification. The overall accuracy is 94.46%; the Kappa index is 0.94. Compare with Figure 9, OBIA classification would not generate the pepper-salt effect, and it could improve the situation of the fragmental edges.

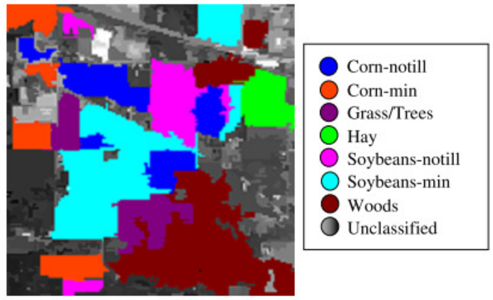

Figure 10   The classified image of OBIA classification

4 CONCLUSIONS

In this study, a hybrid feature extraction method which integrates spectral features and spatial features simultaneously is proposed. The experiment results showed that the overall accuracy for the classification of a real hyperspectral data set using our proposed approach could reach approximately 94%. Moreover, it is worth mentioning that the hybrid features and OBIA classification could significantly increase the overall accuracy of hyperspectral images which contain poor separability between classes, after the spectral features were extracted. The experiment result also showed that the overall accuracy would go up by 20% by using our proposed approach on hyperspectral images with poor class separability.

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