A Band Selection Method For Hyperspectral Images Using Choquet Fuzzy Integral

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***Abstract*—Hyperspectral remote sensing images provide richer information about materials than that of multispectral images. The new larger data volumes of hyperspectral sensors bring new challenges for traditional image processing techniques. Therefore, conventional classification methods could fail without employing dimension reduction preprocessing. The dimensional reduction methods can be totally divided into two classes: feature extraction and feature selection. In this paper, a new feature selection method for hyperspectral images is proposed, which colligates the information entropy, classification separability and correlation coefficients with the Choquet fuzzy integral to select the bands. Experiments on the AVIRIS dataset show that the proposed method removes the redundant spectral bands effectively.**

***Index Terms*— hyperspectral images, image classification, fuzzy integral, spectral band selection, remote sensing**

I. INTRODUCTION

Recently, research work of optical remote sensing has gone through a step increase in number of spectral bands for acquired data, ranging from multispectral images to hyperspectral ones. Hyperspectral sensors can simultaneously measure hundreds of narrow and contiguous spectral bands with a fine spectral resolution. With enormous increase of input channels from tens to hundreds, hyperspectral imagery possesses much richer spectral information than multispectral imagery. However, the higher dimensional data space generated by the hyperspectral sensors generates a new challenge for conventional spectral data analysis techniques, It is necessary to have a minimum ratio of training pixels to the number of spectral bands for a reliable estimate of class statistics. The higher dimensional space implies that with limited training samples, much hyperspectral data space turns to be empty. When performing supervised classification, it is important that the number of training points is proportional to the number of bands. As the number of dimensions increases, the sample size of the training data will increase exponentially. Also, neighboring bands of hyperspectral data are strongly correlated. It has been proven that high dimensional data space has the following properties: the volume of a hypercube concentrates in the corner, and the volume of a hypersphere of hyperellipsoid concentrates in an outer shell [1]. Therefore, dimension reduction has become a significant part of hyperspectral image interpretation. Dimension reduction compresses data from high dimension to low dimension, which will conquer the curse of dimensionality. Reduction of the dimensionality can be achieved by making a selection of a few existing bands, i.e., feature selection [2]-[4] or new features generated by linear combinations of the bands, i.e., feature extraction [5],[6].

Your Feature selection methods process bands selection after considering the whole characteristics of hypersperal images. Therefore, these features contain the original characteristics of the images. Although there may be hundreds of bands available for analysis, not all bands contain the discriminatory information for classification. To limit the negative effects incurred by higher dimensionality, it is effective to remove parts of the spectral bands which convey little discriminatory information. Recently, many band selection techniques have been proposed [7]. These methods can be roughly summarized into three groups, search-based methods [8], transform-based methods [9] and information-based methods [10]. In this paper, we proposed a new information-based band selection method for hyperspectral band selection, which colligates the information entropy, class separability and correlation coefficients with Choquet fuzzy integral (CFI) to get an integrative index for band selection. This is considering that Choquet fuzzy integral is nonlinear functions combining multiple sources of uncertain information [14], [15]. And it can take into account the importance of the individual and subsets of souce. Choquet fuzzy integral have been used in remote sesing data processing [11], [12].

The remainder of the paper is organized as follows. Section II describes the common method of subspace decomposition for hyperspectral images. The basic concept of fuzzy integral is introduced in Section III. The

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band selection method based on Choquet fuzzy integral is provided in Section VI and experimental results are presented in Section V. Finally, concluding remarks are drawn in Section VI.

II. SUBSPACE DECOMPOSITION

Different ground objects have different electromagnetic characteristics. In general, the reflection characteristics of ground objects distribute in narrow frequency range relatively. There is discrepancy between the global statistical characteristic and the local statistical characteristics of the hyperspectral images. If the band selection is applied to the whole source area directly, it may lead to some loss of the local information. Selecting the bands on the base of the subspace decomposition will solve the problem effectively. At the same time, the subspace decomposition will help to reduce the data space, so as to improve the speed and efficiency of hyperspectral remote sensing data processing. The widely used subspace decomposition methods include:

(1) Uniform subspace decomposition

Uniform subspace decomposition (USD) is the simplest method to divide the source data, which distribute the hyperspectral data to the subspaces in average. The definition is as follows:

$$N_{bands} = N / N_{Source} \tag{1}$$

where N is the number of the bands of the original hyperspectral image data, N_{Source} is the number of the subspace, N_{bands} is the number of bands in each subspace. USD is the simplest subspace decomposition method; however, the method divides the source data averagely without considering the discrepancy of the spectral features of the ground objects.

(2) Subspace decomposition based on spectral range

Hyperspectral data covers the spectrum ranging from the visible light to the infrared light, so the spectral discrepancy can be used to divide the source data. For example, the source data can be divided into the range of visible, near infrared and shortwave infrared light. However, this method divides the data only in accordance with the spectral range without considering the spectral features of the specific data structure and relationship of the ground object.

(3) Adaptive subspace decomposition based on correlation filtering

Zhang et al. proposed a method of adaptive subspace decomposition [13]. The correlation coefficient $R_{i,j}$ between the bands i and j is calculated first. The larger the absolute value of $R_{i,j}$ is, the stronger the correlation between the bands is. Therefore, the correlation coefficients of any two bands $R_{i,j}$ compose the correlation coefficient matrix R. According to the matrix R, a threshold value T will be set and the adjacent bands, where $R_{i,j} \geq T$ will be combined into a new subspace. By adjusting the value of T, the number of the subspaces can be changed adaptively. With the increase of the value of T, the number of the bands in each subspace will reduce and the number of subspace will increase. The advantage of this method is that it not only reduces the data dimensionality, but also combines the bands which have strong correlation into one subspace.

(4) Automatic subspace decomposition based on local relevant minimum value

With this method, the correlation coefficient vector of the adjacent bands according to the correlation coefficient matrix is defined first. The definition of the correlation coefficient vector is $r = (r_{12}, r_{23}, ..., r_{i,i+1}, ...r_{l-2,l-1}, r_{l-1,l})^T$. The second step is to extract the locally relevant minimum from the vector. The original source data can be divided into N data subspaces according to the local relevant exacted automatically. The method makes use of the features of the correlation of the adjacent bands. The divided data subspaces have the similar spectral characteristics.

III. FUZZY MEASURE AND FUZZY INTEGRAL

A. Fuzzy measure

Fuzzy measures [14], [15] are the natural generalizations of classical measures. Let U be an arbitrary set, a set function $P(U)$ is defined over the power set of U, if the mapping $g: P(\boldsymbol{U}) \rightarrow [0, 1]$ has the following properties, then it is called a fuzzy measure.

(1) $g(\varnothing) = 0$, $g(U) = 1$

(2) $A, B \in P(\boldsymbol{U})$, and $A \subseteq B \Rightarrow g(A) \leq g(B)$

(3) $A_n \uparrow A \Rightarrow \lim_{n\to\infty} g(A_n) = g(A)$.

where g is the F measure, $(U, P(U), g)$ is the F measure space. Sugeno introduced so-called $\lambda - F$ fuzzy measure, if $g: P(U) \rightarrow [0,1]$ satisfies the additional property: $g(A \cup B) = g(A) + g(B) + \lambda g(A) g(B)$, where $\lambda \in (-1, \infty)$ and $A \cap B = \varnothing$.

B. Choquet fuzzy integral (CFI)

Let $(S, P(S), g)$ be the F measure space, $h \in h(s)$, $h(s)$ is the set of all the non-negative real-valued measurable functions defined in set S, $A \in P(S)$, Choquet integral of h on A relative to g is denoted as:

$$(c)\int_A hdg = \int_0^{+\infty} g(h_\partial \cap A) d\partial \tag{2}$$

where "$(c)\int_{\cdot}$" means Choquet integral, and $h_\partial = \{s / h(s) \geq \partial\}, \partial \in [0,1]$.

Let $S = \{s_1, s_2, ...s_n\}$ be a finite set, and $0 \leq h(u_1) \leq h(u_2) \leq \cdots \leq h(u_m) \leq 1$, then the Choquet integral with respect to formula (2) can be computed by:

$$(c)\int_S hdg = \sum_{i-1}^{n} g(h_{\partial_i})(h(s_i) - h(s_{i-1})) \tag{3}$$

where $h_{\partial_i} = \{s_i, s_{i+1}, \cdots, s_n\}$, $h(s_0) = 0$.

IV. THE BAND SELECTION METHOD BASED ON CFI

In this paper, we adopted the adaptive subspace decomposition method based on correlation filtering. After obtaining the subspaces decomposed with the correlation filtering, we make use of the feature of CFI to colligate the information entropy , correlation coefficients and classification separability to get an integrative index for bands selection. It not only guarantees the selected bands containing more comprehensive information in each subspace, but also guarantees the selected bands distributing in the whole data space reasonably. This method will avoid the loss of local information.

A. The band selection in the subspaces with CFI

For the band selection of hyperspectral data, the first step is to determine the criterion of band selection. There are two widely used criterions: one is that the combination of the selected bands must keep more information; the other is that the selected bands must be more useful for classification of the ground objects. Thus, the band selection should consider three factors [16]: (a) the information contained in the band or the band combination; (b) the correlation among the bands; (c) the spectral response of the ground objects to be identified. Bands that contain more information have little correlation with other bands, also, the bands with better spectral response of the ground objects are supposed to be the optimal bands. The proposed method makes use of the features of CFI which can integrate the multi-source information, colligates the above three factors to get an integrative index to select the bands.

The steps of the band selection are as follows:

(1) Denote the values of information entropy of the band in each subspace as $H(X)$, the definition of the information entropy is as follows:

$$H(X) = \sum_{i=0}^{255} P_i \log_2 P_i \tag{4}$$

where P_i is the probability of the gray scale value of i.

(2) Use the correlation coefficients to indicate the correlation between bands. Denote the image of band i as $f_i(x,y)$, band $i+1$ as $f_{i+1}(x,y)$, the definition of the correlation coefficient is as follows:

$$CC = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[f_i(x,y)-\mu_i][f_{i+1}(x,y)-\mu_{i+1}]}{\sqrt{(\sum_{x=1}^{M}\sum_{y=1}^{N}[f_i(x,y)-\mu_i]^2)(\sum_{x=1}^{M}\sum_{y=1}^{N}[f_{i+1}(x,y)-\mu_{i+1}]^2)}} \tag{5}$$

where $\mu_i = \frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N} f_i(x,y)$, $\mu_{i+1} = \frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N} f_{i+1}(x,y)$, $f_i(x,y)$ is the value of the pixel in the position (x,y) of band i, and $f_{i+1}(x,y)$ is the value of the pixel in the position (x,y) of band $i+1$.

(3) The standard distance of the mean values between two classes stands for the spectral separability. As there are more than two kinds of ground objects in the hyperspectral images, the averaged standard distance of mean values between different classes should be calculated. The definition of the standard distance of mean value is as follows:

$$d = \frac{|\mu_i - \mu_j|}{\sigma_i + \sigma_j} \tag{6}$$

where μ_i, μ_j are the mean values of two different types of ground objects i and j respectively, σ_i, σ_j are the values of the variance of two different types of ground objects i and j, respectively.

(4) Determination of the belief function

Set $U = \{u_1, u_2, u_3\}$, where u_1, u_2 and u_3 represent the information entropy of each band，the correlation coefficient among each band, and the average distance of mean value, respectively. The relationship of the single index and the band selection can be described as follows:

① The larger the value of the information entropy is, the more information included in the selected bands is.

② The smaller the correlation coefficient among each band is, the higher the degree of the independence of the bands is.

③ The larger the value of the average standard distance of the mean value among the ground objects classes is, the better the classification separability is, and the selected bands will be more helpful to the classification.

Suppose there are N subspaces obtained from the original source data, according to the condition: $0 \le h(u) \le 1$, in each subspace, denote the maximum value of the single index u_i as $u_{i\max}$, denote the minimum value of the single index as $u_{i\min}$. The belief function is defined as follows [17]:

$$h(u_1) = \frac{u_1 - u_{1\min}}{u_{1\max} - u_{1\min}}$$

$$h(u_2) = \frac{u_{2\max} - u_2}{u_{2\max} - u_{2\min}}$$

$$h(u_3) = \frac{u_3 - u_{3\min}}{u_{3\max} - u_{3\min}} \tag{7}$$

According to the condition: $0 \le h(u_1) \le h(u_2) \le \cdots \le h(u_m) \le 1$, rearrange the above formula, we have:

$$h(u_1) = \min\{h(u_1), h(u_2), h(u_3)\}$$

$$h(u_2) = \mathrm{mid}\{h(u_1), h(u_2), h(u_3)\}$$

$$h(u_3) = \max\{h(u_1), h(u_2), h(u_3)\} \tag{8}$$

where $h(u_1)$, $h(u_2)$ and $h(u_3)$ are the minimum, middle and maximum values, respectively.

(5) Determination of the fuzzy measure

How to determine the fuzzy measure g is another pivotal problem. In this paper, the importance degree of the single index can be used to determine the fuzzy measure. For the belief functions arranged in a non-decreasing order, the one which has larger value is considered as higher importance. The definition of fuzzy measure in this paper is as follows [18]:

In each subspace, let

$$S = h(u_1) + h(u_2) + h(u_3)$$

$$g(u_k) = h(u_k)/S \quad k = 1,2,3 \tag{9}$$

(6) Determination of the CFI value

In each subspace, the CFI value of every band can be calculated as:

$$C = \sum_{i=1}^{3} g(h_{\partial i})(h(u_i) - h(u_{i-1})) \tag{10}$$

where $h_{\partial i} = \{u_i, u_{i+1}, ...u_n\}$, and $h(u_0) = 0$.

(7) Band selection in each subspace

In each subspace, the first N bands according to the value of CFI are selected to construct the new feature subspace. There are three methods to determine the number of the bands to be selected.

① Select the bands with the same number in each subspace.

② Set the threshold value of the CFI, and select the bands whose CFI value is bigger than the chosen threshold value to compose the new feature subspace. The threshold value can be adjusted according to specific application.

③ In each subspace, suppose the bands have been ranged in the descending order according to the values of CFI. The ratio P is used to select the bands in each subspace. The first N bands are selected by the ratio P.

Because of the asymmetry of band number in each subspace, it is hard to choose and guarantee acquiring bands with same number in each subspace. In addition, since the value of fuzzy integral gotten from each subspace is different, it is also hard to confirm the threshold value. Therefore, the third method is adopted to decompose the subspace in this paper.

V. EXPERIMENTS

A. Experimental Data

In this paper, hyperspectral test data were obtained from the AVIRIS imaging spectrometer. We focused on the collection of Indiana's Indian Pines Data set taken on 1992. The tested data consists of 145×145 pixels by 224 bands. We intercepted a subimage with size of 128×128 from the original images in the experiments. The source images are shown in Fig.1.

B. Supervised Classification Method

In our experiments, the Maximum Likelihood Classification (MLC) method is used, which is one of the most commonly used method in supervised classification applications. The effectiveness of the MLC depends on reasonably accurate estimation of the mean vector and the covariance matrix for each spectral class.

C. Experimental Results

Besides the bands polluted severely by noise, we kept 179 bands from the original bands in our experiments. When the correlation threshold T is set as 0.5, five data sources are obtained. There are bands 5 to 36, band 37, bands 38 to 87, bands 88 to 111 and bands 112 to 216. In each subspace, the bands are ranged according to the values of the CFI. The bands with the largest values of the CFI in each subspace are shown in Fig.2 (a)-Fig.2 (e).

Seven kinds of ground objects are chosen for classification, and the numbers of samples for training and testing are shown in Table I.

The experiments were performed with the bands selected according to the different proportion P. When the values of P are 1, 1/7, 1/6, 1/5, 1/4, the corresponding classification accuracies are shown in Table II. The graph of the classification accuracies is shown in Fig.3.

From the Table II, it can be seen that the classification accuracies with the selected bands are higher than that with the original bands. From Fig.3, it is apparent that the classification accuracy with the bands selected by the proportion 1/6 is higher than the other accuracies, which means only with 1/6 of the original bands, highest classification accuracy can be obtained. The high correlated bands and the band selection can save more storage space and communication bandwidth. When the proportion P is 1/6, the band numbers and the corresponding CFI values are shown in Table III.

The original demarcated image of the ground objects is shown in Fig.4 (a), and the images of the classification results with the bands selected by the ratio 1, 1/7, 1/6, 1/5 and 1/4 are shown in Fig.4(b)~Fig.4(f) respectively, where orange represents the ground objects of class 1, lake blue represents the ground objects of class 2, green represents the ground objects of class 3, blue represents the ground objects of class 4, purple represents the ground objects of class 5, red represents the ground objects of class 6, yellow represents the ground objects of class 7, and black represents the other ground objects which are not chosen for classification.

Comparing the accuracy of the proposed method to those presented in [10], when the value of P are 1/7, 1/6, 1/5, 1/4, the corresponding classification accuracy are better than that of [10].

From the images of the classification results, it can be concluded that the classification accuracies with the bands selected by the values of the CFI are higher than the classification accuracy with all the bands. Experimental results demonstrate the efficiency of the proposed method. It also can be seen that when the value of the proportion P is 1/6, the classification accuracy of

the ground objects improves apparently, which means that the best classification accuracy may be obtained with some particular proportion P and not all bands contain useful information.

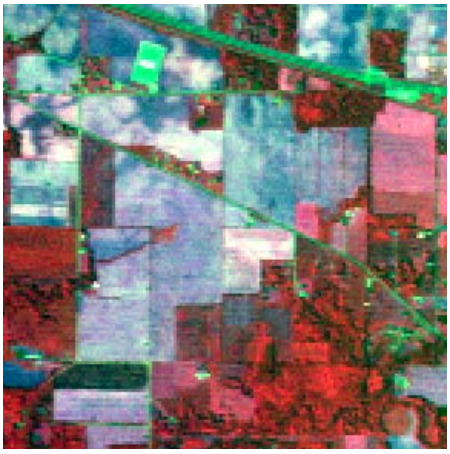

Figure. 1 AVIRIS image composed of band 90, band 5 and band 120.

Figure.2(a) The band with the largest value of the CFI in the first subspace.

Figure.2(b) The band with the largest value of the CFI in the second subspace.

Figure.2(c) The band with the largest value of the CFI in the third subspace.

Figure.2(d) The band with the largest value of the CFI in the fourth subspace.

Figure.2(e) The band with the largest value of the CFI in the fifth subspace.

TABLE I.
NUMBERS OF TRAIN SAMPLES AND TEST SAMPLES

Classes	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Training Samples	68	147	120	152	547	100	348
Testing Samples	72	162	140	171	616	127	353

TABLE II.
THE CLASSIFICATION ACCURACIES WITH THE BANDS SELECTED BY DIFFERENT RATIO *P* (%)

P	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Accuracy
1	65.00	96.46	100	64.50	88.48	64.10	98.25	86.25
1/7	93.33	99.56	100	89.69	92.12	87.82	99.34	94.40
1/6	87.50	99.12	100	92.37	93.33	83.97	99.34	94.54
1/5	68.33	99.12	100	90.84	94.18	77.56	99.56	93.22
1/4	51.67	97.79	100	83.21	95.64	59.62	99.56	90.53

TABLE III.
THE BAND NUMBER AND THE CORRESPONDING CFI VALUE WITH 1/6 BANDS

Subspace 1		71	0.965	119	0.9709
Band Number	Index Value	74	0.965	117	0.9704
5	0.9665	75	0.9641	120	0.9704
17	0.9539	70	0.9636	121	0.9702
11	0.9487	69	0.9633	122	0.9698
16	0.9465	72	0.9629	123	0.9694
10	0.9429	**Subspace 4**		124	0.9689
Subspace 2		Band Number	Index Value	183	0.9688
Band Number	Index Value	87	0.9886	184	0.9687
37	1	88	0.9202	125	0.9686
Subspace 3		**Subspace 5**		185	0.9686
Band Number	Index Value	Band Number	Index Value	193	0.9686
73	0.9659	118	0.9709	188	0.9683

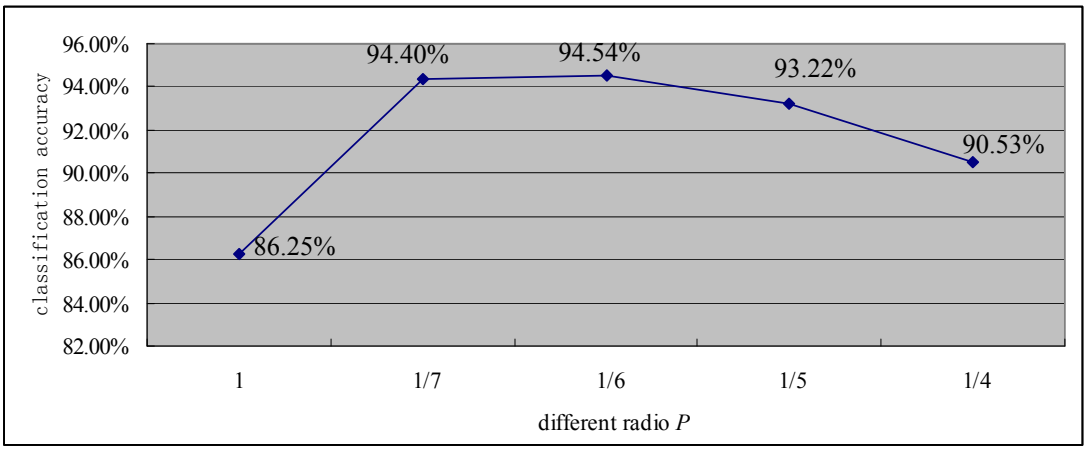

Figure. 3 Classification accuracies with the bands selected by different ratio P .

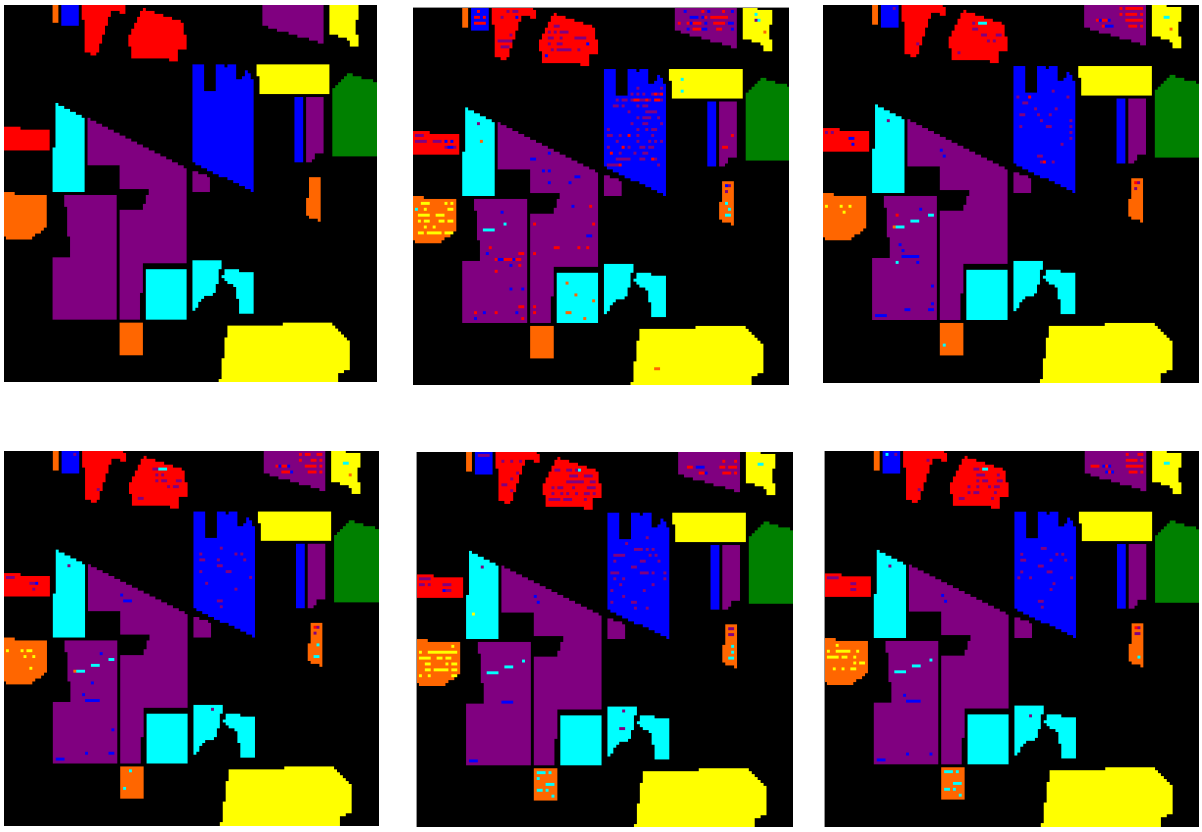

Figure.4 The original demarcated image and the images of the classification results with the bands selected by different ratio P .

VI. Conclusion

This paper presents a band selection method based on CFI. The experimental results indicate that the proposed method saves the storage space and improves the processing speed on the basis of keeping the classification accuracy. Our future work will focus on developing a new band selection approach by combining several features together. In addition, the set of the indexes can be chosen according to the actual needs.

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