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Band Selection with CFI and Supervised Classification for Hyperspectral Images

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Abstract— **In this paper, we propose a new feature selection method for hyperspectral images. Firstly, the bands are selected by combining the information entropy, classification separability and correlation coefficients with the Choquet fuzzy integral. After that, maximum likelihood classification method is used for the classification. 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 or new features generated by linear combinations of the bands, i.e., feature extraction [2-4].

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 [5], [6]. These methods can be roughly summarized into three groups, search-based methods, transform-based methods and information-based methods. 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 [9]. 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 [7], [8].
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 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.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 Choquet fuzzy integral (CFI) to colligate the information entropy, correlation coefficients and classification separability to get an integrative index for bands selection. CFI are the natural generalizations of classical

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measures[9].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 [10]: (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) 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:

$$d = \frac{|\mu_i - \mu_j|}{\sigma_i + \sigma_j} \qquad (1)$$

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.

(2) 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 [11]:

$$h(u_k) = \frac{u_k - u_{k\min}}{u_{k\max} - u_{k\min}} \quad k = 1,2,3 \qquad (2)$$

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:

$$h(u_1) = \min\{h(u_1), h(u_2), h(u_3)\}$$
$$h(u_2) = \mathrm{mid}\{h(u_1), h(u_2), h(u_3)\}$$
$$h(u_3) = \max\{h(u_1), h(u_2), h(u_3)\} \qquad (3)$$

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

(3) 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:

In each subspace, let

$$S = h(u_1) + h(u_2) + h(u_3)$$
$$g(u_k) = h(u_k)/S \quad k = 1,2,3 \qquad (4)$$

(4) Determination of the CFI value

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

$$C = \sum_{i=1}^{3} g(h_{\partial i})(h(u_i) - h(u_{i-1})) \qquad (5)$$

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

(1) 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.

III. 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.

From the Table II, it can be seen that the classification accuracies with the selected bands are higher than that with the original bands.

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

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.

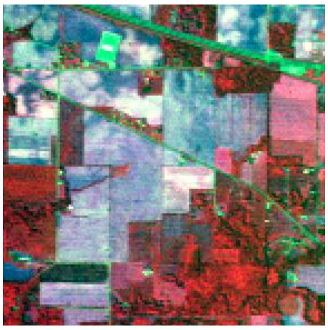

Figure. 1 AVIRIS image composed of band 90, band 5 and band 120.

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

IV. 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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