MULTISPECTRAL REMOTE SENSING IMAGE CLASSIFICATION WITH MULTIPLE FEATURES

QIAN YIN¹, PING GUO¹,²

¹Image Processing and Pattern Recognition Laboratory, Beijing Normal University, Beijing 100875, China
²School of Computer Science and Technology, Beijing Institute of Technology, Beijing 100081, China
E-MAIL: yinqian@bnu.edu.cn; pguo@ieee.org

Abstract:
In this paper, we propose to combine the spectral and texture features to compose the multi-feature vectors for the classification of multispectral remote sensing image. It usually is difficult to obtain the higher classification accuracy if only considers one kind feature, especially for the case of different geographical objects have the same spectrum or texture specialty for a multispectral remote sensing image. The spectral feature and the texture feature are composed together to form a new feature vector, which can represent the most effective features of the given remote sensing image. In this way we can overcome shortcomings of only using the single feature and raise the classification accuracy. The system classification performance with composed feature vector is investigated by experiments. By analysis of results we can learn how to combine the multi-feature vector can obtain a higher classification rate, and experiments proved that the proposed method is feasible and useful in multispectral remote sensing image classification study.

Keywords:
Spectrum feature; Texture feature; Multispectral remote sensing image; Feature combination; Classification.

1. Introduction

In the last decades, remote sensing imagery utility has proved a powerful technology for monitoring the earth’s surface and atmosphere at a global, regional, and even local scale. The volume of remote sensing images continues to grow at an enormous rate due to advances in sensor technology for both high spatial and temporal resolution systems. As a consequence, an increasing quantity of multispectral image acquired in many geographical areas is available. There are many applications in analysis and classification of remote sensing image, such as in geology remote sensing, water area remote sensing, vegetation remote sensing, soil remote sensing, multi-spectrum remote sensing and so on. In all these applications, to recognize the interesting regions from the multispectral remote sensing image is the key processing step. In order to effective raise the classification accuracy, it is important to extract the most effective features to represent the image under study. With extracted features, a classifier is built to recognize the interested objects in remote sensing imagery. There are two kinds of classification: supervised and unsupervised. In general, when we have little knowledge about given image, we have to adopt unsupervised classification techniques. Among the unsupervised methods, the finite mixture model analysis has some advantages and it attracts many researchers’ interest in image segmentation as well as other applications [1]. When building a classifier, we assumed that the data in the feature space as a mixture of Gaussian probability density distribution, and the finite mixture model is used to cluster the extracted features [4].

Spectral feature is regarded as one of the most important pieces of information for remote sensing image interpretation. This kind feature can be used to characterize most important contents for various types of the remote sensing images. It is believed that the gray value plays an important role in the visual systems for recognition and interpretation of the multispectral remote sensing image data.

On the other hand, the texture describes the attribution between a pixel and the other pixels around it [3]. Texture features represent the spatial information of an image, can be regarded as an important visual primitive to search visually similar patterns in the image. However, no universally accepted mathematical definition of texture exists, and texture analysis is even more difficult in remote sensing images [10]. Reed and Buf present a detailed survey of various texture methods for image analysis [11].

However, in classification, it has the shortcomings if only adopting the texture analysis method, such as the edge between different classes may be incorrectly classified, because texture feature extraction must be considered based on a small region, not a single pixel. Spectral feature such as gray value can be extracted based on a single pixel, but it
has limitation as the representative information of an image. Nowadays, most existing classification studies for remote sensing image adopt only simple spectral or texture feature, or investigate with independent manner [5][14]. to efficiently extract useful features from remote sensing image and to building a classification system with higher accuracy become a challenge.

In this paper, we propose to combine the spectral and texture features to compose the multi-feature vectors for the classification of multispectral remote sensing image. The spectral features and the texture features, which are extracted in the same image, are composed to construct a new feature vector in multi-feature space for classification.

2. Methodology

Basically, for multispectral remote sensing imagery, its data amount is large and makes it become difficult to extract the main features if only considering one spectral characteristic; especially for the different geographical objects have the same spectrum. When its resolution is high, it has abundant texture information. This becomes difficult to distinguish some geographical objects when interested area has complicated texture information. Also, the spectral characteristic is uncertainty if the geographical objects have complicated surroundings. Sometimes different objects have the same spectrum, or same geographical objects have different spectrum. While texture refers to a pattern, it has properties of homogeneity that does not depend on the presence of only a single color or intensity. Previous attempts at modeling texture include the following approaches: Markov random field, co-occurrence matrices and Gabor filters and so on [11].

The approaches of extracting the features should be guided by the following concerns: The features should carry enough information about the image and should include domain-specific knowledge for their extraction. They should be easy to compute in order for the approach to be feasible for a large image collection and rapid clustering. They should relate well with the remote sensing image characteristics since users will finally determine the suitability of the classified images.

2.1. Spectral Features

Spectrum is an important characteristic for the analysis of various types of the remote sensing images. In the previous work, five dimension reduction methods, such as the Euclid distance measurement method (EDM), the discrete measurement criteria function method (DMCF), the minimum differentiated entropy method (MDE), the probability distance criterion method (PDC), and the principle component analysis method (PCA) are adopted to extract the most available features form multispectral images [9]. The purpose for dimension reduction is that extracted spectral feature may not be redundancy and the parameters can be estimated well in lower feature space in which the multispectral remote sensing image is relative easy investigated.

We can suppose the original remote sensing image has $D$ bands and the processed data has $d$ dimensions after we decrease the bands. And we can define the original data vector as $y = [y_1, y_2, \ldots, y_D]^T$, the processed data vector as $x = [x_1, x_2, \ldots, x_d]^T$. And the transformation formula is:

$$x = W^T y$$  \hspace{1cm} (1)

A number of bands are reduced into a single one in this paper, so a multispectral image can be displayed in the gray scale form. The detail description of each dimension reduction method can be found in reference [9].

2.2. Texture Features

We will adopt the following approaches for texture feature modeling problem: the gray level co-occurrence matrix (GLCM) [3], the histogram measures (HM) [12], the texture spectrum (TS) [13], and the gray difference statistical quantity ($GDSQ$) [3].

2.2.1. Gray Level Co-occurrence Matrix

For the GLCM texture feature, we use the angular second moment (ASM), also called the energy, the dissimilitude (DIS), also called inertia, and the inverse difference moment, and also called homogeneity (HOM). In order to increase computation efficient, we introduce an improved method to avoid calculating the zero values in the gray level co-occurrence matrix. The improved GLCM is constructed by $p(i, j)$, and the corresponding measures are:

$$p(i, j) = \frac{\text{graynum}(i, j)}{(\max N - \min N)^2}$$, \hspace{1cm} (2)

$$i, j = \min N, \ldots, \max N$$

$$\text{ASM} = \sum_{i=1}^{N} \sum_{j=1}^{N} p(i, j)^2$$, \hspace{1cm} (3)
\[ HOM = \sum_{i=1}^{N} \sum_{j=1}^{N} P(i, j) \left[ 1 + (i - j)^2 \right], \quad (4) \]

\[ DIS = \sum_{i=1}^{N} \sum_{j=1}^{N} |i - j| P(i, j). \quad (5) \]

### 2.2.2. Histogram Measures

For the HM feature we adopt the average value (AVE), the standard covariance (STDCOV) and the entropy (ENT) measures. Suppose the number of pixels in an image is \( P \), for each gray value, the pixel number is \( p_k \), the frequency histogram \( H \), can be expressed as

\[ H(k) = \frac{p_k}{P}, \quad k = 0, 1, \ldots, 255. \quad (6) \]

It is used to describe the probability density curve of the given image. And those measures are expressed as

\[ AVE = \frac{1}{256} \sum_{k=0}^{255} H(k), \quad (7) \]

\[ STDCOV = \frac{1}{256} (H_k - AVE)(H_k - AVE)^T, \quad (8) \]

\[ ENT = -\sum_{k=0}^{255} H_k^2 \log(H_k^2). \quad (9) \]

### 2.3. Texture Spectrum

The TS feature we adopted are angular second moment (ASM), the average value (AVE) and the standard covariance (STDCOV). The definitions of these measures are as follow [14].

\[ ASM = \sum_{i=1}^{N} S(i)^2, \quad (10) \]

\[ AVE = \frac{1}{N^2} \sum_{i=1}^{N} S(i) \quad (11) \]

\[ STDCOV = \sum_{i=1}^{N} S(i) - \frac{1}{N^2} \sum_{i=1}^{N} S(i) \quad (12) \]

where \( S(i) \) is the \( i \)th value of texture spectrum.

### 2.4. Gray Difference Statistical Quantity

For the GDSQ feature, we adopt the following measures: the contrast, the angular second moment (ASM), the entropy (ENT) and the average value (AVE). The definitions for these measures are [12]:

\[ ASM = \sum_{i} i^2 p_{\alpha}(i), \quad (13) \]

\[ ENT = -\sum_{i} p_{\alpha}(i) \log p_{\alpha}(i), \quad (14) \]

\[ AVE = \frac{1}{m} \sum_{i} ip_{\alpha}(i), \quad (15) \]

where \( p_{\alpha} \) is the gray difference statistics.

### 3. Finite Mixture Model Analysis

The unsupervised classification method is adopted because we can get better results in the case where there is a lack of prior knowledge about remote sensing images.

From the detailed description of each dimension reduction method [9], we know that except the PCA method, all the other methods need to label each pixel in the original multispectral remote sensing image. But we have little knowledge about which pixel should belong to which class. In order to resolve this problem, in this work we adopt the random sample method. That means, we first assign a class label for each pixel randomly. The finite mixture model is adopted to analyze and the Expectation-Maximization (EM) algorithm [4] is used to estimate the model parameters. With the iterative EM algorithm, the mixture parameters can be estimated until the likelihood function \( L(\Theta) \) reaches a local minimum value.

\[ L(\Theta) = \prod_{a=1}^{N} p(x^a) = \prod_{a=1}^{N} \sum_{j=1}^{k} p(x^a | j) p(j). \quad (16) \]

The joint probability distribution can be expressed as

\[ p(x, \Theta) = \sum_{j=1}^{k} \alpha_j G(x, m, \Sigma), \quad (\alpha_j \geq 0, \sum_{j=1}^{k} \alpha_j = 1). \quad (17) \]

Where

\[ G(x, m, \Sigma) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left[ -\frac{1}{2} (x-m)^T \Sigma^{-1} (x-m) \right] \quad (18) \]

is a general expression of multivariate Gaussian distribution. \( x \) denotes a random vector, \( d \) is the dimension of \( x \), and the parameter \( \Theta = \{ \alpha_j, m_j, \Sigma_j \}_{j=1}^{k} \) is a set of finite mixture model parameters vectors. Here \( \alpha_j \) is the mixing
weights, $m_j$ is the mean vector, and $\Sigma_j$ is the covariance matrix of the $j$th component of the mixture model. Actually, these parameters are unknown, and using how many Gaussian component densities can best describe the joint probability density is also unknown.

Redner [6] had proved that the likelihood function was convergent and assured it could be close to a local minimum value. Under the pre-assigned region number $k$, the posterior probability can be described as: $P(j=1|x), P(j=2|x), \ldots, P(j=k|x)$ . We use Bayes decision to classify $x_i$ into cluster $j^*$. This procedure is called Bayesian probabilistic classification.

4. Experiments and Result Analysis

4.1. Experiments

In Figure 1, the spectrum images obtained from one multispectral remote sensing image with different feature extraction methods are displayed, these images are used in the experiments. For these spectral remote sensing image, the extracted texture measures are shown in Table 1 with image format. By analyzing the experimental results, we can know that though $ASM$ measure can better describe this image’s $GLCM$ texture features, $STDCOV$ measure can better describe this image’s histogram texture features, compared with $AVE$ measure for $GDSQ$ texture features, these two measures do not good in representing this image’s texture feature. Therefore, in constructing the multi-feature vector which can contain more effective texture information, we finally adopt the $AVE$ measure in $GDSQ$ texture features as one component.

In principle, we can construct a high dimensional vector using as many spectral and textural features as possible. However, it will become very difficult to analyze the properties of combined vector for classification. In this work, we only consider a simple case, that is, to construct the multi-feature vector with one spectral component and one textural component. In the experiments, the combination of various spectral features with the different texture features together is investigated intensively. The classification results by using texture feature and different spectral information combination are shown in table 2 in image form representation. Table 3 shows the classification accurate rates for original multispectral remote sensing image.

4.2. Results

By analyzing the experimental results in table 3, we can find from the results shown in the row, when the same spectral feature extraction method is adopted, for different texture feature, the histogram measures method can better describe texture characteristics, texture spectrum feature takes second place in accuracy. From the results shown in the column, we can know when the same texture feature is adopted, for different spectral feature extraction methods, the DMCF method can better describe the spectrum characteristic, the EDM method take the second place in classification accuracy.

If the gray difference statistical quantity texture feature is adopted, with the MED, PCA and PDCM spectral feature extraction methods, it cannot get the better classification results. These measures are not suitable to describe the features of the multispectral remote sensing image. From the experimental results, we also know that
for different geographical objects, the edge of the objects can be better separated by the histogram measures method. Then we can conclude that with HM and DMCF combined feature vector, the higher classification accuracy can be reached.

Table 1. the texture features images with different measures

<table>
<thead>
<tr>
<th>Texture / Spectrum</th>
<th>GLCM</th>
<th>HM</th>
<th>TS</th>
<th>GFSQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLCM</td>
<td>ASM</td>
<td>DIS</td>
<td>HOM</td>
<td></td>
</tr>
<tr>
<td>HM</td>
<td>AVE</td>
<td>STDCOV</td>
<td>ENT</td>
<td></td>
</tr>
<tr>
<td>TS</td>
<td>ASM</td>
<td>AVE</td>
<td>STDCOV</td>
<td></td>
</tr>
<tr>
<td>GFSQ</td>
<td>ASM</td>
<td>ENT</td>
<td>AVE</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. The classification results with different feature combination

<table>
<thead>
<tr>
<th>Texture / Spectrum</th>
<th>GLCM</th>
<th>HM</th>
<th>TS</th>
<th>GDSQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>DMCF</td>
<td>94.86%</td>
<td>98.66%</td>
<td>95.86%</td>
<td>95.58%</td>
</tr>
<tr>
<td>EDM</td>
<td>94.40%</td>
<td>97.60%</td>
<td>95.66%</td>
<td>95.60%</td>
</tr>
<tr>
<td>MDE</td>
<td>92.84%</td>
<td>95.59%</td>
<td>93.20%</td>
<td>83.11%</td>
</tr>
<tr>
<td>PCA</td>
<td>91.92%</td>
<td>95.92%</td>
<td>92.63%</td>
<td>82.16%</td>
</tr>
<tr>
<td>PDCM</td>
<td>93.98%</td>
<td>93.90%</td>
<td>95.52%</td>
<td>88.06%</td>
</tr>
</tbody>
</table>

Table 3. the classification accuracy for combining different spectral and texture features

5. Conclusions

In this paper, we propose to construct multi-feature vector to raise the multispectral remote sensing image classification accuracy. Five methods are adopted to extract spectral feature, and four methods are used to extract texture features of the image. Various combinations of spectral and textural features are experimental investigated in order to find the most effective feature vector to represent the image. From the results we can conclude that applying proposed methodology can get the higher accuracy in classifying multispectral remote sensing image. In the future work, we intend to combine more features to form a multi-feature vector, we also intend to apply genetic algorithm to find the optimal combination of spectral and textural features in order to improve the performance of multi-source data classifier in high dimension space.

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