Integrating genetic algorithm method with neural network for land use classification using SZ-3 CMODIS data*

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Abstract This paper presents a methodology on land use mapping using CMODIS (Chinese Moderate Resolution Imaging Spectroradiometer) data on-board SZ-3 (Shenzhou 3) spacecraft. The integrated method is composed of genetic algorithm (GA) for feature extraction and neural network classifier for land use classification. In the data preprocessing, a moment matching method was adopted to remove the stripes in the images. Then by using the reproduction, crossover and mutation operators of GA based on the mechanism of "natural selection", and with Jeffries-Matusita distance as its discriminate rule and the training samples, the optimal band combination for land use classification was obtained. To generate a land use map, the three layers back propagation neural network classifier is used for training the samples and classification. Compared with the Maximum Likelihood classification algorithm, the results show that the accuracy of land use classification is obviously improved by using our proposed method, the selected band number in the classification process is reduced, and the computational performance for training and classification is improved. The result also shows that the CMODIS data can be effectively used for land use/land cover classification and change monitoring at regional and global scale.

Keywords: CMODIS, genetic algorithm, band selection, neural network, land use classification.

The development of imaging spectrometry remote sensing technologies combining imaging technologies and spectrometry technologies is significant progress in the Earth Observation Programm. This technology can provide both high spatial and high spectral data with high signal/noise ratio[1]. The first NASA Earth Observing System (EOS) Satellite Terra (EOS-AM1) was launched on December 18, 1999, which was thought to be a milestone in moderate resolution remote sensing, proving marked increase in our observation capability[2—4]. Launched on March 25, 2002, the Chinese Moderate Resolution Imaging Spectroradiometer (CMODIS) aboard the SZ-3 spacecraft has similar function to MODIS on-board Terra. CMODIS, which indicates a new development of civil remote sensing technologies in China, is designed to provide 34 bands with wavelength in the range of 403—12500 nm among which the spectral resolution is 10 nm in the visible range and 20 nm in the near and middle infrared ranges and with high ground resolution of 400—500 m. Data from CMODIS will have prospective and meaningful applications in the fields of natural resource and environment, land use/cover, ocean and coastal investigation research, etc.

However, the increase in band number results in relatively high correlationship between neighborhood bands, which often implies high data redundancy. Meanwhile, the band increase implies that the amount of training sample must increase exponentially, so that the classifier can more effectively discover the patterns disguised in feature space, which makes land use classification for high dimensional data distinctly different from traditional multispectral data classification. Therefore, it is necessary to study how to transform the hyperspectral data from high dimension to low dimension so as to diminish the difference of samples among the same class and to augment the difference of samples between different classes.

As for the classifier selection, the Neural networks have been proven to be the most significant improvement in information extraction in remote sensing in the last years. Examples and applications have become increasingly common, for example, MODIS Land Cover Product adopts Neural networks Algo-

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rithm for classification[5]. Some previous study concluded that Backpropagation Neural Network classifiers have successfully classified remote sensed data and yielded similar (or slightly higher) accuracy compared to conventional methods[6,7], such as the maximum likelihood classifier.

In this paper, we will present a method of land use mapping using SZ-3 CMOIDS data, which adopts the genetic algorithm (GA) for feature extraction and the neural network classifier for land use classification. Our result shows that this method can not only reduce the volume of data size and save time for training and classifying, but also raise the computational performance. Moreover, the method is very efficient for improving the land use classification accuracy.

1 Data and methods

1.1 Data preprocessing

In this paper, SZ-3 CMODIS data acquired on May 22, 2002 is used for studying land use classification, and the Beijing-Tianjin region is selected as a key study area, which is a flat and agricultural area located within E 111°8′45″—123°21′41″, N 34°2′24″—42°8′56″. Fig. 1 shows the location of the study area with white rectangle in a true color CMODIS composite image.

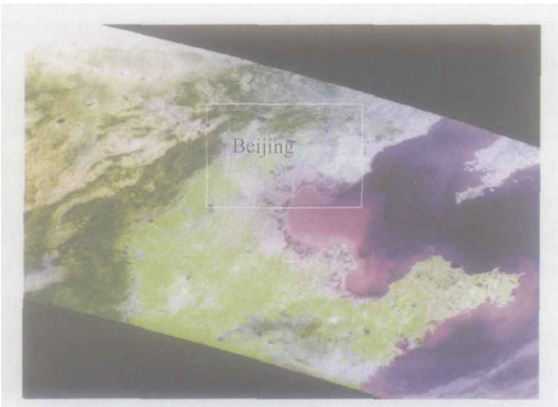

Fig. 1. Location of the study area in true color image of CMODIS data (bands 20, 11, 5).

There are much strip noises in the initial CMODIS image like data forming other sensors onboard, which normally results from the radiometric variation, optical characteristics between different charge coupled device (CCD) sensors, scanning movement, and position of sensors platform. Many researchers[8,9] have studied the causes and the methodologies for removing these noises. In this paper, the moment matching method is adopted to remove strip noise[10—12]. The method is described as follows:

Ideally, the spectral response function of CCD can be assumed as a linear function within the spectral dynamic range for most ground objects and shift invariant, which can be expressed as

$$Y_i = k_i X + b_i + \varepsilon_i(X), \tag{1}$$

where i denotes the ith CCD and Y_i is the response function value of the ith CCD, which represents the image grey value; X is the value from the surface diffuse reflection received by the ith CCD; k_i and b_i are the gain of the ith CCD and its offset; and ε_i is the random noise which can be expressed by using a Gaussian distribution function.

When the image has high signal to noise ratio, the intensity of $\varepsilon_i(X)$ can be safely omitted, thus Eq. (1) can be simplified as

$$Y_i = k_i X + b_i. \tag{2}$$

From Eq. (2), we can find that different values of k_i and b_i can lead to different grey values for the same incidence radiant intensity X. If Y_i can be normalized by a standardized reference Y, the noise strip can be efficiently removed or at least diminished from the image.

Suppose that the ground surface is Lambertian and homogenous and the data are acquired from CCD scanning line by line, the mean of incidence radiant intensity is similar to its variance. In the moment matching method, one CCD element is chosen as the reference and the others are to be corrected to this reference. The normalization equation is given as

$$Y = \frac{\sigma_r}{\sigma_i} X + \mu_r - \mu_i \frac{\sigma_r}{\sigma_i}, \tag{3}$$

where X, Y are the grey values of one pixel in the ith CCD scan line for the original image and corrected image; σ_r, μ_r are the mean and variance of the reference CCD scan line; σ_i, μ are the mean and variance of the ith CCD scan line.

The striping noise caused by CCD radiation difference can be effectively removed using the above described approach. However, on the edges of swath where is far from the nadir, the noise phenomena resulting from the "double vision" effect still exist. Fortunately, our interested area in the image is near the nadir and has little geometry distortion which has little effect on classification, so the supplementary positioning coordinate data in each pixel is used to make simple rectification.

The preliminary geometric correction of the CMODIS image can be achieved by combining the spacecraft attitude and positioning data. This paper also uses the land use map of China at a scale of 1:1000000 to conduct geometric correction for each band of CMODIS image precisely with the errors maintaining between 1 and 2 pixels. The destriping result is shown in Fig. 2.

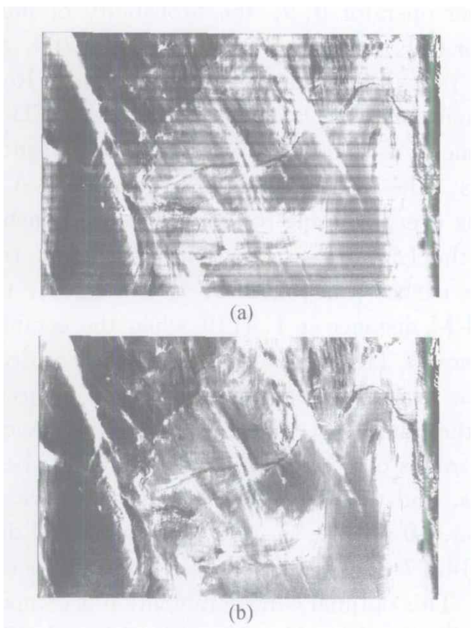

Fig. 2. CMODIS subimage (a) before destriping and (b) after destriping.

1.2 Feature selection of CMODIS image for land use classification

1.2.1 Methods

Although the CMODIS has moderate spatial resolution, it is a typical imaging spectroradiometer with high spectral resolution. Its data will be more useful for global and regional land use/land use classification relative to AVHRR data. Hughes phenomenon[13], however, shows that the classification accuracy will not necessarily improve with the increasing dimensionalities of the remote sensing data, and sometimes the classification accuracy and computing efficiency will severely decrease. Previous researches indicate that for a given dataset, there may exist an optimum number of input features to describe the characteristics of the training data well enough for these descriptions to be generalized to the image under consideration. So optimum feature selection is very important to improve the land use classification accuracy[14]. In this paper, the genetic algorithm is adopted for feature selection of the CMODIS data, our aim is to find the band combination which has the least bands numbers as well as the best interclass separability.

When applying a genetic algorithm for optimal feature subset selection, the evaluation function should be defined to evaluate the separability of different band combinations represented by different chromosomes to determine which kind of band combinations is the best for a number of given samples. This evaluation function can be expressed as an average class divergence index. In this paper, the J-M distance regarded as one of the most suitable indexes for increasing interclass separability[14] is used and can be expressed as

$$B_{ij} = 1/2(M_i - M_j)^{\mathrm{T}}\left[\frac{(V_i + V_j)}{2}\right]^{-1}(M_i - M_j) + 1/2\ln\frac{|(V_i + V_j)/2|}{\sqrt{|V_i||V_j|}}, \tag{4}$$

$$d_{ij} = \sqrt{2(1 - \mathrm{e}^{-B_{ij}})}, \tag{5}$$

$$d = \frac{1}{n^2}\sum_{1}^{n}\sum_{1}^{n}(p_i p_j d_{ij}), \tag{6}$$

where $\boldsymbol{V}_i$ and $\boldsymbol{V}_j$ are the covariance matrix between class i and class j; $\boldsymbol{M}_i$ and $\boldsymbol{M}_j$ are the corresponding mean vectors of classes i and j; B_{ij} is the well known Bhattacharyya distance; p_i and p_j are the prior probabilities for classes i and j; d_{ij} is the J-M distance between classes i and j, and d is the average J-M distance. The superscript T denotes matrix transpose operation.

Since the J-M distance matrix is a symmetrical triangle matrix, Eq. (6) can be rewritten as

$$d = \frac{2}{n(n+1)}\sum_{i=1}^{n-1}\sum_{i=j+1}^{n}(p_i p_j d_{ij}). \tag{7}$$

1.2.2 The optimal feature selection by Genetic Algorithm (GA)

Genetic Algorithm was first proposed by Goldberg in 1985[15], who was enlightened by the natural selection of biology. It was supposed that individuals with more adaptability in current generation would have better capability of survival and breeding in the next generation. One of the most important advantages of GA is that it can make use of the limited search processes to find the optimal or near-optimal result in the solution space automatically. In the basic GA process, each possible solution is represented by an individual of the population, namely a chromosome. Each chromosome is composed of several genes. Each gene can be expressed by using a specific encoding strategy, e.g. the Hamming encoding strategy. A Simple GA (SGA) produces the new generation of offspring by its reproduction, crossover and mutation operators[14].

The proposed framework of optimal band selection of CMODIS data based on GA for land use classification is as follows: The first step is to randomly generate different band combinations, in which each band combination is encoded as a chromosome with each integer-valued gene representing its band number. Meanwhile, it is assumed that each gene is not equal to any other genes existed in this chromosome. This phase is repeated till it meets the request for specified population size. The second step is to calculate the average J-M distance between each band combinations (chromosomes). Based on the average J-M distance, the fitness of each chromosome is evaluated, and dominant individuals will be selected for genetic operation according to the selection strategy, e.g. the Roulette Wheel Selection[15]. The third step is to actually perform the reproduction, crossover and mutation operators to produce the new generation of individuals. This process will continue until individuals in the population meet the required conditions or the maximal number of iterations is reached.

2 Results

2.1 Land use classification

In this study, there are only 20 bands available in the study area in this experiment, which extends from 0.403 μm to 0.803 μm. Fig. 3 is the false color map of Beijing-Tianjing study area combined with bands 20, 11 and 5 of CMODIS data.

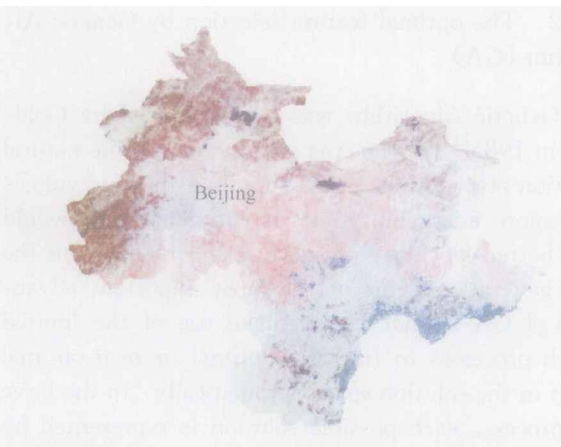

Fig. 3. The false color image combined with CMODIS bands 20, 11, 5 after geometrical correction of the study area.

The Real Number Steady State Genetic Algorithm is adopted for feature selection after the CMODIS data has been preprocessed. Ten percent of most excellent individuals in each population are automatically added in the next generation of genetic operation and the others are created by the selection, crossover, and mutation operators. The selection algorithm is Roulette Wheel with the probability of crossover operator 0.9, the probability of mutation operator 0.1, total size of the population 200, and iteration time 300. The National Territorial Resource and Environmental Database in 2000 (NTRED-2000) at a scale of 1∶1000000 are used to collect and train samples. The feature selection is based on GA incorporating every training sample. The relationship between the J-M distance and the number of training samples is shown in Figure 4. In this figure, the average J-M distance is 1.4119 when the combination bands are 4. The amplitude of J-M distance decreases with the increase of band number and it keeps steady when the number of band tends to be 10. According to the trends of J-M distance variation, Hughes phenomena, and the capability of neural network generalization, 10 suitable spectral bands with J-M distance of 1.414207 were finally selected for land use classification. This optimal band combination is composed of 2, 4, 7, 9, 10, 11, 15, 16, 18 and 20 from CMODIS data, which covers visible, near infrared and especially short infrared wave. Compared with the common used data, such as NOAA and Landsat TM, these fine spectral and spatial data can reflect the spectral characteristic and the difference in various land use types.

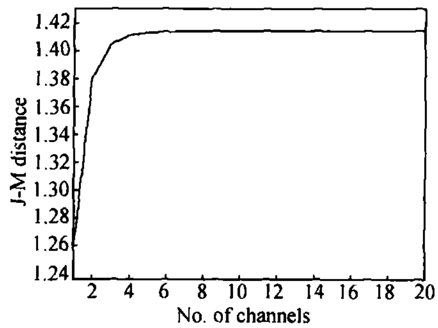

Fig. 4. Relationship between the optimal average J-M distance and band numbers.

After the optimal band combination was selected, the classification was performed with Backpropagation Neural Network classifier under PCI Geomatics

7.0 software environment. The classifier, whose activation function is sigmoid function defaulted by PCI, is three layers neural network including 12 hidden nodes, learning speed 0.95, and the momentum 0.05. A small momentum will be more useful for precise solution solving. The total normalized mean square error (MSE) is converged to 0.059, as shown in Fig. 5.

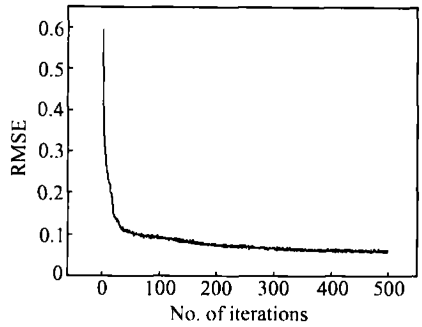

Fig. 5. Normalized RMSE error convergence neural according to network training iterations.

2.2 Classification result

There are 9 kinds of land use classes that have been distinguished: forest, bush and grassland, paddy field, irrigated field, no-irrigated field, water bodies, wetland, salt pan, and urban and town land. The land use classification result based on the above described methods for the study area is shown in Fig. 6 (a) and (b). They both used the optimal band combination for dassification. From Fig. 6(b), it can be seen that the classification resulting areas of urban and town, bush and grassland, and irrigation are not the same as the result from Backpropagation Neural Network classifier.

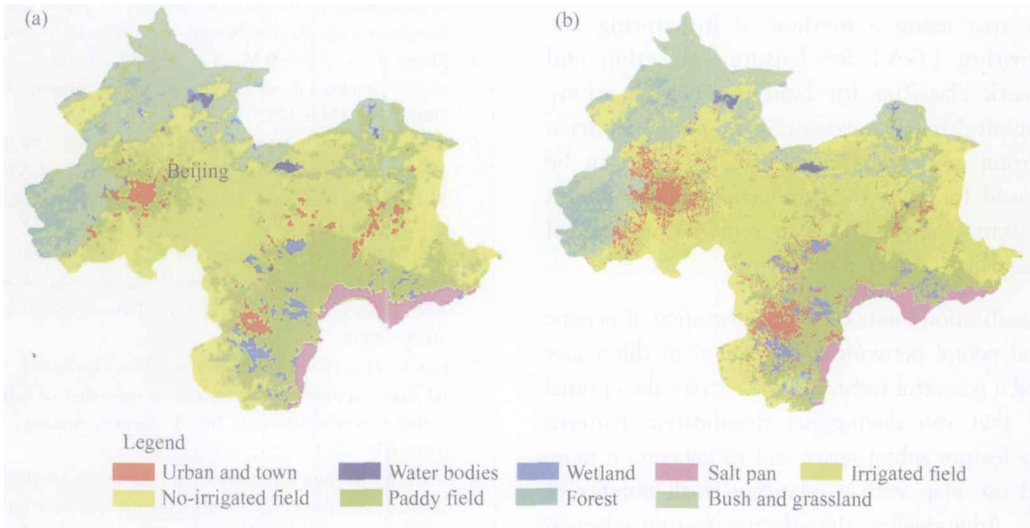

Fig. 6. Land use map from CMODIS data in the study area. (a) Backpropagation Neural Network classifier; (b) Maximum Likelihood classifier.

3 Discussion

To assess the land use classification accuracy, a suitable and reasonable assessment criterion was established. The National Territorial Resource and Environmental Database in 2000 (NTRED-2000) at a scale of 1∶1000000 is available and can be used as a reference for land use classification evaluation. The NTRED-2000 was constructed based on Landsat TM data in 2000 through computer-aided interpretation. A total of 1000 samples, whose types have a broad special continuous distribution in the NTRED-2000 database and are not easy to change during the two years, were selected carefully to test the classification accuracy. Then 509 out of the 1000 Samples were randomly selected and compared with their corresponding reference data from NTRED-2000 database to assess their consistency. Results show that the average classification accuracy is 87.2% in this study (Table 1).

To assess the effectiveness of the feature selection technique, two additional experiments for comparison were conducted under PCI Geomatics 7.0 software environment with the same samples. In one experiment, all bands of CMODIS data from 1 to 20 were used for land use classification with Neural Network algorithm without band selection and optimization. In another experiment, 10 optimal bands of CMODIS data, which was proposed by the feature selection method in this study, were used for the Maximum Likelihood algorithm, which is commonly used in land use classification. The results indicate that with the Backpropagation Neural Network classifier, the classification accuracy can be improved 2.2% using the selected optimal bands than using all bands; the Neural Network algorithm has approximately 6.1% accuracy improvement than the Maximum Likelihood algorithm classifying with the ten optimal bands. In addition, the proposed band feature selection method can not only reach similar land use classification accuracy as the method without feature selection, but also save the time for training and classification.

Table 1. Accuracy[a] assessment of the land use classification using CMODIS data

	Urban and town	Water bodies	Wetland	Salt pan	Irrigated field	No-irrigated field	Paddy field	Forest	Shrub and grassland	Overall accuracy (%)
[b] GA & NN	86.5	100	74.4	100.0	95.0	86.5	79.9	73.7	92.5	87.2
[c] NN	86.0	100	65.4	100.0	94.2	72.3	77.0	73.1	91.0	85.0
[d] ML	70.3	100	63.2	98.3	84.2	78.5	74.3	72.7	85.4	81.1

a) User accuracy; b) Genetic and Neural Network algorithm with bands feature selection; c) Neural Network algorithm without bands feature selection; d) Maximum Likelihood algorithm with bands feature selection.

4 Conclusion

The general objective of this study is to use CMODIS data to generate the land use map in Beijing-Tianjin area using a method of integrating the genetic algorithm (GA) for feature extraction and neural network classifier for land use classification. The experimental results presented in this paper have provided strong evidence that CMODIS data can be effectively used for land use/land cover classification and have potential applications in regional and global scale land use/ land cover monitoring.

The classification methods with integration of genetic algorithm and neural network implemented in this paper have provided a powerful technology to extract the optimal band subset that can distinguish classification patterns clearly in the feature subset space and to generate a more accurate land use map with a relatively small number of image bands. Additionally, the effective feature selection technologies can improve the computational performance and save the computational time.

Unfortunately, the CMODIS infrared data are unavailable for this study area, thus some land use types (brushwood land and grassland) are not able to be classified more precisely. If these data become available, the land surface temperature (LST) derived from CMODIS infrared will be added as additional feature to improve the land use/cover classification accuracy.

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