Land use classification using CBERS-1 data

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Abstract

This paper discussed and analyzed results of different classification algorithms for land use classification in arid and semiarid areas using CBERS-1 image, which in case of our study is Shihezi Municipality, Xinjiang Province. Three types of classifiers are included in our experiment, including the Maximum Likelihood classifier, BP neural network classifier and Fuzzy-ARTMAP neural network classifier. The classification results showed that the classification accuracy of Fuzzy-ARTMAP was the best among three classifiers, increased by 10.69% and 6.84% than Maximum likelihood and BP neural network, respectively. Meanwhile, the result also confirmed the practicability of CBERS-1 image in land use survey.

Key words: CBERS-1 image, Fuzzy-ARTMAP neural network, Land use

1. Introduction

Go West Project is ongoing now in China, arid and semiarid areas cover some half of the country in China and most of these areas locate in western parts, these areas are facing serious challenges about rational use of limited water resource and reasonable land resource management in order to realize the sustainable development of resources. Compared with other countries, standard of living in these areas is always lower, meanwhile, the illogical utilization of limited land and water resources led to serious environment degradation. Water and land resources are the determinative factors that influence the ecological environment, human survival and economic development in the arid and semiarid areas, and the scientific management and efficient utilization of the water and land resources are the basic requirements for region development and ecological environment construction.

Land cover and land use classification is a new concept to the land classification with the development of Remote Sensing technology. Land cover and land use survey has become a basic work for the land use prediction, natural disaster prevention, land plan and management and environment protection. Land use automatic classification is a main study direction. Since the successful launch of Landsat in 1972, there have been a lot of studies about land cover and land use classification with multi-spectral data.

China and Brazil Earth Resources satellite 1(CBERS-1) launched at October 14, 1999 is the first resource satellite manufactured by China. CBERS-1 filled up the blankness about resource satellite in our country and provided another data source for the macroscopical, integrated, quick and dynamic monitoring to our country's land resource, therefore, it make the situation changed which we have used foreign satellite data for a long term and promote the development of resource satellite career in our country. In this paper in order to find a classification method suitable for western areas in China we have a compare between three classifiers by using CBERS-1 image, meanwhile, the result also confirmed the practicability of CBERS-1 image in land use survey.

2. Study area

Study area in this paper is selected in Shihezi, Xinjiang. Shihezi city locates in the middle of northern foot of Mountain Tianshan, southern Zhungeer basin, north to Guerbantonggu desert. It covers from 80° 58′ E to 86° 24′ E longitudes and 44° 1′ N- 45° 20′ N latitudes, the altitude is 300~500m from the sea level. Shihezi belongs to typical oasis area, its natural condition such as water, land, light and heat is advantageous to agricultural production, so it became a base for provision and cotton production in Xinjiang.

It belongs to typical territorial desert climate in Shihezi with characteristics of cold in winter and cool in summer, lack of rain and strong evaporation. There distributes a large area of Gobi and desert in Shihezi with little vegetation, there is enough land resource but with low quality and serious salinity.

3. Multispectral data and its preprocess

Remote sensing image in this paper is China and Brazil Earth Resources satellite 1(CBERS-1) data supplied by China Center for Resources Satellite Data & Application. The image was received in 34/50 (path/row) in June 13, 2001. Band combination for the image is CH1、CH2 and CH4 and their wavelength range from 0.52～0.59μm、0.63～0.69μm and 0.77～0.89μm, respectively. The spatial resolution of image is 19.5m. There are other data in this study such as 1:00000 relief map, 1:00000 digital landuse map in 2000 and 1:250000 digital landuse map.

Preprocess for satellite image including image geometric correction, image stretch and enhancement and noises removal are required before classification, which make spatial texture information more clear and wipe off noises. During geometric correction with PCI software strict registration between the CBERS-1 image and 1:100000 relief map was performed, using quadratic as –model and resampling from the image, study error was controlled within 0.5 pixel.

Firstly, main land use categories suitable to remote sensing should be defined in Shihezi. Based on the CBERS-1 image, land cover classification system should be established according to utilization, management characteristic, using manner and cover character of land. In this study, because desert and salinity cover a large area in Shihezi, but forest and grass area is small and crop distribution is extensive, forest and grass are not included in the classification system. The information source of this study is CBERS-1 image received in June 13, 2001. During this time wheat is in tassel period, young cotton comes out shortly, so the difference of spectral intensity between them is very large, especially in the band 3, theoretically they can be classified by computer automatically. In CBERS-1 image of Shihezi, spectral intensity of desert and resident are very close in band 2, 3 and 4 and are difficult to be distinguished by computer, so we take them as one category. Therefore the land use system is defined to include six categories – wheat, cotton, salinity, desert and resident, water and irrigated land.

4. Methodology

In order to find a automatic land use classification method suitable to arid and semi-arid areas remote sensing image, three types of supervised classifier: maximum likelihood classifier, Backpropagation neural network and Fuzzy ARTMAP classifier, were adopted in this study. The two latter types of classifiers are neural network classifying method applied in fields such as pattern recognition, image processing and combination optimization, etc. Compared with traditional supervised classifier, one notable character of neural network is that the distribution of data sources is random.

4.1 Maximum likelihood classifier

Maximum likelihood classifier is one of supervised classification methods used frequently. During classification, attributive probability of every pixel to each category should be calculated, then the pixel will be classified into one category with biggest attributive probability.

4.2 Fuzzy—ARTMAP neural network classifier

Fuzzy ARTMAP incorporates fuzzy logic in its ART 1 modules and has fuzzy set-theoretic operations instead of ART 1's binary set-theoretic operations. It learns to classify either analog or binary inputs by a fuzzy set of features (or a pattern of fuzzy membership values between 0 and 1), which indicate the extent to which each feature is present.

Fuzzy ARTMAP integrates the "fuzzy recognition" characteristics of fuzzy set theory and the ARTMAP's advantages of adaptive resonance and automatic search of optimal solution from feature space. Compared to Back propagation neural network, Fuzzy ARTMAP's characteristics of self-organized resonance, incremental learning, and highly complex mapping make it more similar to the function of human perception system, which make it more suitable for classification of high dimensional and complicated data.

During the process of Fuzzy ARTMAP, if there are M bands in classification samples and L land cover categories after classification, we can assume that there are M nodes in F0, M nodes in F1 and N nodes in F2 of

ARTa. In the samples vector $x=[x_1,\Lambda\ ,x_M]$ x_i is the spectral reflectivity of pixels in every band, $x_i \in [0，1]$. Vector $\mathbf{z}_j$ indicates the connection weight vector between F1 and F2. There is L nodes in F0, L nodes in F1 and K nodes in F2 of ARTb. b is desired output vector of L-dimension. $0 \le \rho \le 1$ is system vigilance criterion and $0 \le \eta \le 1$ is the learning rate of system.

The basic learning steps are as follows:

x is classified according to the comparability between x and zj which is the original vector of all kinds of units stored in F2. For each input x and F_2 node j, the choice function T_j is defined by

$$T_j(x)=\frac{|\mathbf{x}\wedge z_j|}{\beta+|z_j|} \qquad (1)$$

Where β>0 is the choice parameter. Where the fuzzy AND operator $\wedge$ is defined by

$$(\mathbf{p}\wedge\mathbf{q})_i \equiv \min(p_i,q_i) \qquad (2)$$

And the city-block norm $|\cdot|$ is defined in Eq(3):

$$|\mathbf{p}| \equiv \sum_{i=1}^{M} p_i \qquad (3)$$

F_2 node J is chosen in the network and the index J denotes the chosen category, where

$$T_J=\max\{T_j : j=1,2,\Lambda\ ,N\} \qquad (4)$$

Then $\mathbf{x}\wedge z_J$ become the activity vector in F_1 and obtain the match function $\boldsymbol{k}$ by comparing with the current input vector **x**, and $\boldsymbol{k}$ is defined by

$$k=\frac{|\mathbf{x}\wedge\mathbf{z_J}|}{|\mathbf{x}|} \qquad (5)$$

Compared with the vigilance criterion ρ, if the matched function $k \ge \rho$, then the category is given to F_2 node J, the original vector is updated according to the following equation:

$$z_J^{(new)}=\eta(x\wedge z_J^{(old)})+(1-\eta)z_J^{(old)} \qquad (6)$$

where $z_J^{(new)}$ is the updated weight vector, η is the learning rate. The first item in right equation (6) indicates the contribution of new input vector to updated weight vector, the bigger η is, and the bigger its contribution is. The bigger $\boldsymbol{k}$ is, the smaller contribution is, which indicates the samples with large resemblity have low attention; on the contrary, the smaller k is , the bigger contribution is, which indicates samples with small resemblity have high attention. The second item of equation (6) shows the contribution of unadjusted weight vector to the updated weight vector.

If $k<\rho$, then in the left nodes a new F2 node will be created according to equation (4), and the network training continues until a node in F2 is found to meet $k \ge \rho$.

When the expected training accuracy can't be reached under the current system vigilance criterion, ARTb will automatically add the vigilance ρ through F^{ab} and Match Tracking technology so that new nodes in ARTa F2 can be created to meet the expected accuracy of

ARTb.

5. Result and discussion

In this study there are three types of supervised classifiers: Maximum Likelihood classifier, BP neutral network classifier and Fuzzy ARTMAP neutral network classifier, adopted to classify the preprocesses CBERS-1 image. In order to have a comparison among different classifiers, same training areas are selected as samples to train the three classifiers. After the training area were selected, we began to classify the image in Shihezi using the above three classifiers.

We randomly chose 500 pixels from the three classified land cover maps to assess classification accuracy. We compared these pixels with visual interpretation and the results are showed in Table 1.

Table 1 Accuracy of three types of classifiers

Land use types	MLC	BP	ARTMAP
Desert and resident	85.67%	89.75%	92.27%
Water	75.01%	87.63%	95.32%
Wheat	69.41%	71.72%	83.33%
Cotton	55.56%	67.67%	81.33%
Salinity	81.88%	90.21%	95%
Irrigated land	64.44%	80.56%	86.78%
Average classification accuracy	78.84%	82.69%	89.53%
Kappa coefficient	0.735	0.782	0.824

From the table 1 we can see that classification accuracy of Fuzzy ARTMAP is the most high among three classifier, classification accuracy increases by 10.69% and 6.84% respectively compared with maximum likelihood classifier and BP classifier.

In order to evaluate the performance of three classifiers more scientifically, Kappa coefficient was adopted to compare them. Kappa statistic possesses the more strong capability of differentiation and analysis for the evaluation on classification accuracy of different classifiers. From the last line in table 2 we can see that the comparison result by Kappa coefficient is same to that by classification accuracy.

6. Conclusion

（1） In this study the CBERS-1 image in Shihezi was used as data source and the land cover classification in Shihezi was conducted. From the classification result we can see that CBERS-1 image not only can be used in land use surveys, but also can obtain ideal classification result.

（2） In order to find a classification method with fairly well accuracy in arid and semi-arid areas, integrated with GIS, land cover classification in Shihezi was employed by using maximum likelihood classifier, BP neural network classifier and Fuzzy- ARTMAP neural network classifier in this paper. The classification result showed that the accuracy of Fuzzy- ARTMAP was the highest among three classifiers, secondly is BP network and then Maximum likelihood classifier. The accuracy of Fuzzy ARTMAP increased by 10.69% and 6.84% than

Maximum likelihood and BP neural network.

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