A Hierarchical Object Oriented Method for Land Cover Classification of SPOT 5 Imagery

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Abstract: - Land cover classification with a high accuracy is necessary, especially in waste dump area, accurate land cover information is very important to eco-environment research, vegetation condition study and soil recovery destination. Funded by the international cooperation project Novel Indicator Technologies for Minesite Rehabilitation and sustainable development, a hierarchical object oriented land cover classification is produced in this study. The ample spectral information, textural information, structure and shape information of high resolution SPOT 5 imagery are used synthetically in this method. There are two steps in object oriented information extraction: image segmentation and classification. First, the image is segmented using chessboard segmentation and multi-resolution segmentation method. Second, NDVI is used to distinguish vegetation and non-vegetation; vegetation is classified as high density vegetation, middling density vegetation and low density vegetation using spectral information, object oriented image texture analysis; non-vegetation is classified as vacant land and main road using length/width. Accuracy assessment indicate that this hierarchical method can be used to do land cover classification in waste dump area, the total accuracy increases to 86.53%, and Kappa coefficient increases to 0.7907.

Key-Words: - hierarchical land cover classification, NDVI, object oriented texture analysis, waste dump opencast coalmine area, SPOT 5

1 Introduction

Remote sensing, especially high spatial resolution multispectral imagery from satellite and aerial sensors(e.g. IKONOS from GeoEye, Inc., QuickBird from DigitalGlobe, Inc., ADS40 from Leica Geosystems, Inc.), is an effective way to acquire large area land use information in a short time, which can be used in land cover classification. In recent years, land cover classification using high resolution remote sensing imagery is a challenging topic due to the complexity of landscapes and such spectrum confusion phenomenon as different spectrum with same object and same spectrum with different object [1-2]. Particularly in waste dump opencast coalmine area where vegetation grow overlap, disorderly and unsystematic and spectrum confusion is very serious, for instance, at a fine resolution, a single vacant land, tree, or grassland may include pixels with many different reflectance values due to differences in materials, shading, or micro-scale site conditions [3]. This complexity reduces the accuracy of classification. Land cover information of waste dump opencast coalmine area serves as an important source of information for both the scientific and government in China, which is the foundation of land consolidation potentiality evaluation, land consolidation planning, land consolidation engineering implementation monitoring and land consolidation Informatization[4-5].

As we all know that, information collecting by manpower is time consuming and hard sledding. Traditional pixel-based land cover classification method only utilizing spectral information for classification, such as parallelepiped, minimum distance from means, and maximum likelihood, and can't consider fine information of high resolution imagery, such as texture, structure, shape and detail etc. [6-7]. There is another serious problem in pixel-based classification, which is the *pepper-and-salt* phenomenon is very serious in classified result which is meaningless for application [8]. In some degree, the improvement of image interpretation falls behind the development of sensor hardware technology out and away. This gap requires the development of new methodologies that will be capable of searching, querying, retrieving, and mining to fully utilize the rich data repositories [9]. Object oriented classification method come into being in this condition [10-11]. A segmented meaningful image object which coincide with 'patches of reality' [8] is the basic unit in object oriented classification method, and the abundant textural, structural, geogramic and detail information can be used adequately in those objects [12]. The experiment results of Lobo A. et al. indicate that the object oriented statistics produces a higher enhancement of discrimination and achieve high land cover classification accuracy [11]. They also conclude that the classification result using object oriented classification method can be interpreted more easily, the internality of polygon is better, and which is the same with the land cover classification of high resolution image.

In the field of object oriented land cover classification research, there are many researches do some meaningful studies. Wharton S.W. develop a prototype expert system to demonstrate the feasibility of classifying multispectral remotely sensed data on the basis of spectral knowledge, which is used in land cover classification in urban area [13]. Their spectral expert achieved an accuracy of 80-percent correct or higher in recognizing 11 spectral categories in TMS data for the Washington, DC, area. In order to solve the problem of object oriented classification of limitation in efficiently applying image segmentation is often represented by the spatial resolution of the image; Geneletti D. proposes a method based on the integrated use of images of Landsat TM data and aerial photographs [14]. In his study, the TM image was used to get a preliminary classification result using the maximum likelihood classifier and additional empirical rules, and the orthophoto was used to get a segmentation result. At last, the classification of the segmented images was performed using as a reference the TM image previously classified. Laliberte A. S. et al. use object oriented image classification to map shrub encroachment from 1937 to 2003 in southern New Mexico [15]. Renaud Mathieu et al. do the research of mapping private gardens in urban areas using object-oriented techniques and very high-resolution satellite imagery, and there are a total of 90.7% of the private gardens were correctly identified in their experiment [16]. Kevin Tansey et al. use object oriented method to classify very high resolution airborne imagery for the extraction of hedgerows and field margin cover in agricultural areas [17].

Texture analysis is another means of integrating spatial information for classifying high resolution remotely sensed imagery. Texture refers to the arrangement and frequency of tonal variation in particular areas of an image. Rough textures would consist of a mottled tone where the grey levels change abruptly in a small area, whereas smooth textures would have very little tonal variation. Smooth textures are most often the result of uniform, even surfaces, such as fields, asphalt, or grasslands [18]. Grey-Level Co-occurrence Matrix (GLCM) is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image[19-20], which has been the workhorse of image texture since they were proposed by Haralick in the 1970s [21]. There are three vital quantify factors in texture analysis: Grey level differences (contrast), Defined size of area where change occurs (window), Directionality or lack of it. And there are many researchers have attempted to improve land cover classification using textural information to describe pixel patterns [22-26].

The texture analysis is regarded as an image feature to be used in hierarchical object oriented land cover classification in this study. The destination of this study is using the ample texture, structure, shape and detail information of high resolution imagery synthetically in order to increase the land cover classification accuracy. Section 2 presents the study area and the data sources used in this study. Section 3 concerns the methods of hierarchical object oriented land cover classification method integrating image texture analysis. The classification results, accuracy assessment and discussion are presented in section 4. At last, the conclusions are presented in section 5.

2 Study area and data source

2.1 Study area

The study area is Haizhou Opencast Coal Mine Dump Area, showen in Fig. 1, which is located in Fu Xin, Liaoning Province, China. This area covers approximately 26.82km^2, extending in 121°40′12″E in longitude and 41°57′36″N in latitude. There are more than 10 topography ladders in sum in the whole area. These ladders come into being in different years, abandoned in about 1955, 1965, 1975, and 1985 respectively. Vegetation conditions in each ladder are different with their different formation ages. Field work indicate that there are 3 species of arbors (*Ulmus pumila*, *Robinia pseucdoacacia*, *Ailanthus altissima*), 1 specie of shrub (*Amorpha fruticosa*) and 7 species of herbage (*Setaria viridis*, *Artemisia argyi*, *Suaeda glauca bunge*, *Eragrostis cilianensis*, *Artemisia scoparia*, *Chenopodium serotinum L*, *Melilotus suaveolens ledeb*) in the whole study area.

2.2 Data source

The remote sensing imagery used in this study is Système Probatoire de l'Observation de la Terre (SPOT) 5 image capured on 2nd September, 2005. There are four multispetrcal bands (i.e. near-infrared

(NIR), red, green, and short waved-length Infrared) with 10-metre spatial resolution and one panchromatic band with 2.5-metre spatial resolution (wavelength ranges from 0.51 to 0.73 um) for SPOT 5 remote sensing image.

In order to get actual radiant value of objects in studied image, radiation correction is done. In the next step, multispectral image and panchromatic image are eo-referenced to a UTM projection and WGS84 spheroid with an RMSE less than 1 pixel. Then, Pansharp method is used to do image merge to get high spatial resolution and fine detail such as texture.

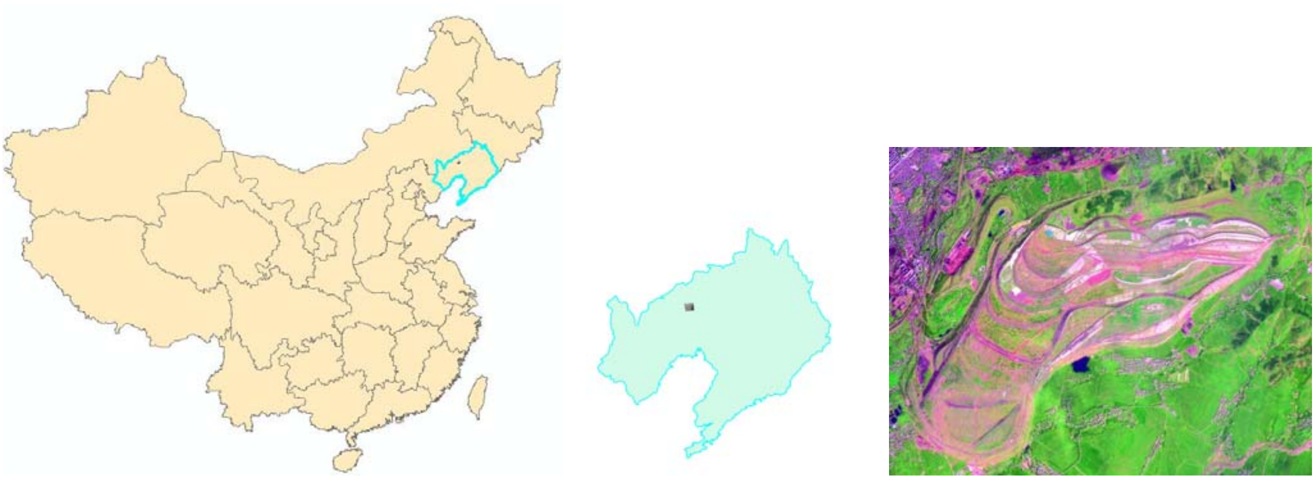


Fig. 1 Study Area (Haizhou Opencast Coal Mine Dump Area, Fu Xin, Liaoning Province, China)

3 Methodology

3.1 Introduction

Object oriented classifications require identifying meaningful objects over the image and labeling them with class attributes. So the proposed method in this study is based on two image segmentation methods (chessboard segmentation and multi-resolution segmentation) and two object oriented fuzzy classifiers (nearest neighbor classifier and membership function classifier). The hierarchical land cover classification steps in this study are described below and graphically in the flowchart (Fig.2). Image segmentation is performed at three scales of the image object hierarchy: the largest scale to classify waste dump area and cropland around, the middle scale to capture all topography ladders and classify vegetation / non-vegetation in every ladder, and the fine scale to classify these five classes: high density vegetation, middling density vegetation, low density vegetation, vacant land, main road (the hierarchical land cover classification system is shown in Table 1). In the sequent classification, there two classifiers used in this study: nearest neighbour classifier (sampling editing → sampling selecting → classify) and membership function fuzzy classifier (right part of Fig. 2).

3.2 Image segmentation

Image segmentation is appealing for remote sensing applications of subdividing the whole image into meaningful objects, which is the foundation of object oriented classification method. So the spectral, textural, shape information within the meaningful objects can be used in classification, enhancing the reparability of those five classes. The image segmentation is done in Definiens 7.0 software, and the bottom-to-up segmentation algorithm is used in this software. There are two segmentation methods are used in this study: chessboard segmentation and multi-resolution segmentation, which are the important two kinds of image segmentation methods. Chessboard Segmentation is splitting the pixel domain or an image object domain into square image objects. Thematic layer used for segmentation will lead to additional splitting of image objects while enabling consistent access to its thematic information. And the results of which are image objects representing proper intersections between the thematic layers. A chessboard size larger than image size is selected to produce image objects based exclusively on thematic layer information. There are two thematic layers used in this study (Table 2): thematic 1 is the border of waste dump area which is used to classify waste dump area and cropland around; thematic 2 are the border of all ladders which is used to separate those ladder areas.

Multi-resolution segmentation is an optimization procedure which locally minimizes the average heterogeneity of image objects for a given resolution. It can be applied on the pixel level or an image object level domain. And the parameters used in multi-resolution segmentation are: scale parameter, color(spectral criteria), shape (including smoothness and compactness). The scale parameter is an abstract term which determines the maximum allowed heterogeneity for the resulting image objects. For heterogeneous data the resulting objects for a given scale parameter will be smaller than in more homogeneous data [27]. Color and shape (smoothness and compactness) are the composition of homogeneity criterion which is used as a synonym for minimized heterogeneity. For most cases the color criterion is the most important for creating meaningful objects, and a certain degree of shape homogeneity often improves the quality of object extraction. The below Fig. 3(a) is the chessboard segmentation result using thematic layer 1 at 100000 scale parameter (level 3), Fig. 3(b) is the chessboard segmentation result using thematic layer 2 at 1000 scale parameter (level 2), and Fig. 3(c) is the multi-resolution segmentation (level 1) result using spectral information, shape, texture, Normal Difference Vegetation Index (NDVI).

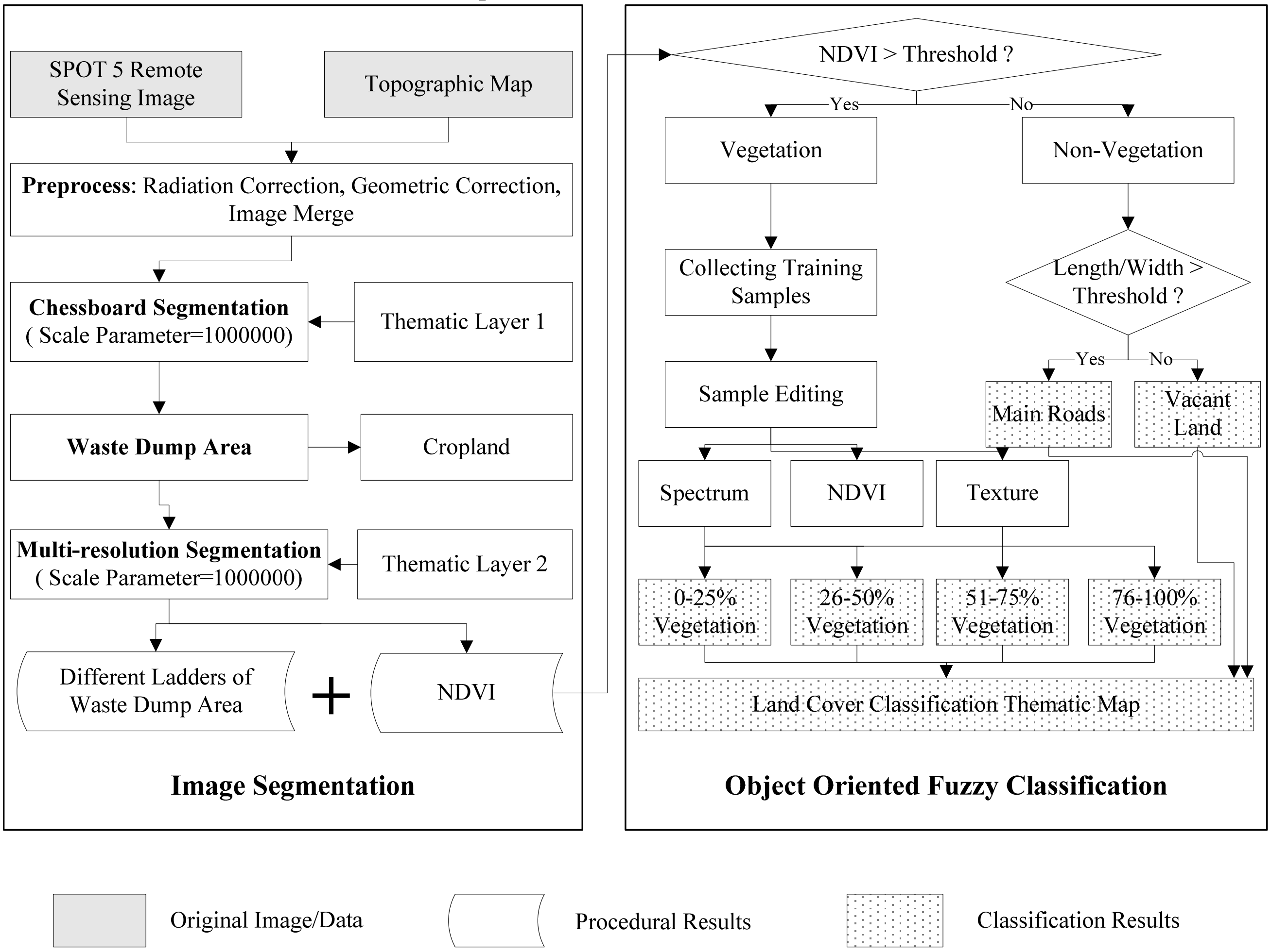


Fig. 2. Workflow of hierarchical object oriented classification

Table 1. Hierarchical land cover classification system

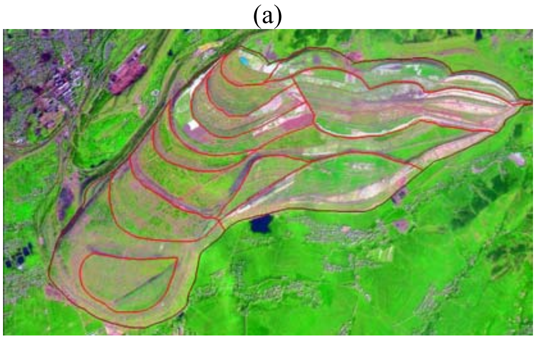
Level 1	Level 2	Level 3
Waste Dump Area	Vegetation	High density vegetation
		Middling density vegetation
		Low density vagetation
	Non-vegetation	Vacant land
		Main road
Cropland		

Table 2. Segmentation parameters

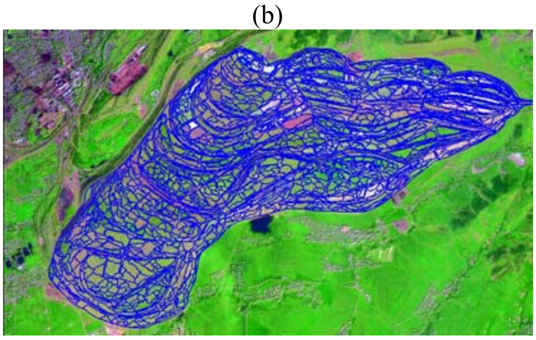
Segmentation Level	Segmentation Method	Scale Parameter	Themetic Layer	Function
Level 1	Multi-resolution Segmentation	25	Not used	Getting meaningful objects
Level 2	Chessboard Segmentation	1000	Used	Dividing different ladders

Level 3	Chessboard Segmentation	100000	Used	Masking study area

(a)



(b)



(c)

Fig. 3 Image multi-resolution segmentation results: (a) is; segmented result on level 3; (b) is segmented result on level 2; (c) is segmented result on level 1.

3.3 Hierarchical fuzzy object oriented classification

The segmented images are classified using these below four features:

(1) Mean brightness value,
(2) Mean difference to neighbors,
(3) Mean NDVI value, and
(4) Mean texture value.

There are two important operations in this hierarchical object oriented classification: the definition of classification rules and hierarchical structure, and the object oriented image texture analysis. There are five land cover types in sum (Table 1): high density vegetation, middling density vegetation, low density vegetation, vacant land, and main road. It is difficult to classify these five classes using spectral information only because there are serious spectrum confusion. Using hierarchical strategy to classify one by one aiming at reducing the spectrum confusion, adding the texture feature and NDVI feature any more in order to increase classification accuracy. The hierarchical structure of this study is as Fig. 4. In the first step, the waste dump area and cropland are separated using large scale chessboard segmentation based on the border of study area (thematic layer 1); next, vegetation and non-vegetation in all ladders is classified using NDVI; at last, high density vegetation, middling density vegetation, low density vegetation, vacant land, and main road are classified at fine scale segmented objects using spectral information, NDVI value, and textural information synthetically.

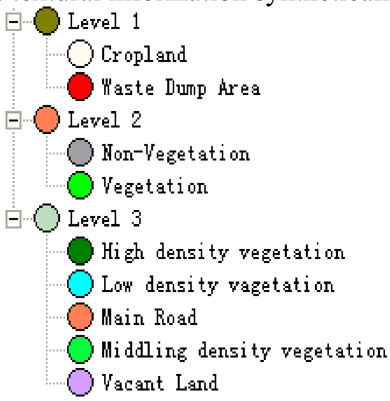


Fig. 4 the hierarchical structure of classification

Object oriented image texture analysis is done to get more detailed difference between high density vegetation class, middling density vegetation class, low density vegetation class, completing spectral information and NDVI. There are three kinds of object oriented texture algorithm in Definiens software: Layer Value Texture Based on Subobjects, Shape Texture Based on Subobjects, Grey Level Co-occurrence Matrix (GLCM) texture after Haralick. Only the GLCM texture after Haralick is used in this study for application activation. And these four texture features such as homogeneity, contrast, entropy, angular 2nd moment in all directions are used in this classification, and the computation algorithm of them are as formula (1) to formula (4). In this step, the Nearest Neighbor classifier is used and the definiens of these features is done by sampling editing. The Nearest Neighbor classifier identify the studied image objects distance to its nearest neighbor training samples in image object's feature space, which is depicted in Fig. 5 (the green image object to be classified should be classified as the nearest red class which is measured in feature distance space).

GLCM homogeneity:

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \qquad (1)$$

GLCM contrast:

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \qquad (2)$$

GLCM entropy:

$$\sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j}) \qquad (3)$$

GLCM Ang. 2nd moment:

$$\sum_{i,j=0}^{N-1} P_{i,j}^{\;2} \qquad (4)$$

Where, i is the row number,

j is the column number,

$P_{i,j}$ is the normalized value in the cell i,j,

N is the number of rows or columns.

There is one detail to be point out, that is: $P_{i,j}$ isn't the digital number of image grey value directly, which a normalized value in matrix. The normalization is as followed:

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}} \qquad (5)$$

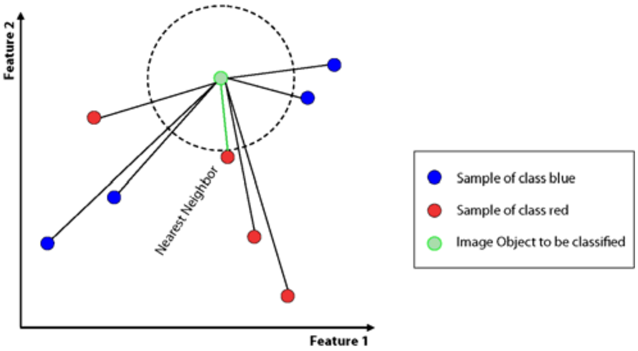
Where, i is the row number,

j is the column number,

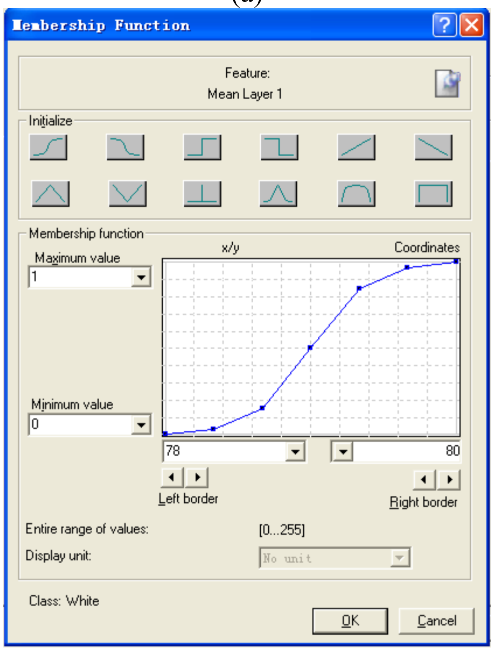
$V_{i,j}$ is the value in the cell i,j of the matrix,

$P_{i,j}$ is the normalized value in the cell i,j,

N is the number of rows or columns.



(a)



(b)

Fig. 5 (a) Principle of the Nearest Neighbor classification, (b) the membership function interface

Notes: the feature space in nearest neighbor classification is composed of Feature 1 and feature 2.

After the classification of vegetation (high density vegetation, middling density vegetation and low density vegetation) using nearest neighborhood classifier, the non-vegetation (vacant land and main road) should be classified in the nest step. The spectral, textural information are similar between these non-vegetation types for their similar composition. So they can't be classified correctly using spectral and textural information only. Fig. 3 indicates that the main road is long and narrow; however, the vacant land is flaky. So the length/width can be used to classify these two classes using membership function (Fig. 5 (b)), which is the implementation manner of fuzzy classification. Membership functions offer a transparent relationship between feature values and the degree of membership to a class, which is defined by its left and right border values in combination with the function slope. There are twelve kinds of membership function: Larger than, Smaller than, Larger than (Boolean, crisp), Smaller than (Boolean, crisp), Larger than (linear), Smaller than (linear), Linear range (triangle), Linear range (triangle inverted), Singleton (exactly one value), Approximate Gaussian, About range, Full range.

3.4 Accuracy assessment

As the application of object oriented classification is innovative, representing a new area of ecological data generation it was important to test for and assess the accuracy of the data being produced [28]. Much effort is devoted to checking how much 'mis-classification' such as omitted classification, error classify A class to B class, are occurring. User's accuracy (ratio of the total area correctly predicted in one class by the total area predicted in this class), producer's accuracy (ratio of the total area correctly predicted in one class by the total area observed in this class), overall accuracy (ratio of the sum of the total area correctly predicted in each class to the total area observed in all classes) are used to quantize accuracy assessment result.

Testing samples are selected randomly to assess the object oriented classification accuracy of land cover classification using SPOT 5 image, which have been validated in field work. All these testing samplings are different from all training samples, which can guarantee the rationality of this accuracy assessment.

4 Results and discussion

4.1 Classification accuracy assessment result

The accuracy assessment results for traditional pixel-based classification and hierarchical object oriented classification are shown in Table 3 and Table 4 respectively. Compared with pixel-based classification method, the total accuracy of hierarchical object oriented classification used in this study increases from 74.53% to 86.53%, Kappa coefficient increases from 0.6054 to 0.7907. More important, there are only four classes (high density vegetation, middling density vegetation, low density vegetation, and vacant land) can be distinguished in pixel-based classification. However, there are five classes can be classified in hierarchical object oriented classification, for the reason of the subclasses (vacant land and main road) of non-vegetation can be extracted using the difference of length/width.

In hierarchical object oriented classification, the producer's accuracy ranged from 41.71% (main road) to 98.31% (low density vegetation) and the user's accuracy ranged from 39.44% (vacant land) to 100% (high density vegetation). The high density vegetation, middling density vegetation and low density vegetation are very well distinguished from non-vegetation. This is expected as both classes mainly consist of these three vegetation classes is usually more heterogeneous. The user accuracy for high density vegetation, middling density vegetation and low density vegetation are only fair to moderate with 100, 93.32% and 83.09, respectively.

Table 3 Accuracy assessment of pixel-based classification

	Ground Truth (Pixels)								
Class	C1	C2	C3	C4	Total	Commission	Omission	Producer Accuracy	User Accuracy
C1	181	23	0	0	204	11.27	27.89	72.11	88.73
C2	70	733	2	0	805	8.94	42.01	57.99	91.06
C3	0	508	882	55	1445	38.96	0.34	99.66	61.04
C4	0	0	1	132	133	0.75	29.41	70.59	99.25

Overall Accuracy = (1928/2587) 74.53%, Kappa Coefficient = 0.6054

Notes: C1: High Density Vegetation, C2: Middle Density Vegetation, C3: Low Density Vegetation, C4: Non-Vegetation

Table 4 Accuracy assessment of hierarchical object oriented classification

	Ground Truth (Pixels)									
Class	C1	C2	C3	C4	C5	Total	Commission	Omission	Producer Accuracy	User Accuracy
C1	170	0	0	0	0	170	0	32.27	67.73	100
C2	81	1132	0	0	0	1213	6.68	10.44	89.56	93.32
C3	0	132	870	22	23	1047	16.91	1.69	98.31	83.09
C4	0	0	0	56	86	142	60.56	28.21	71.79	39.44
C5	0	0	15	0	78	93	16.13	58.29	41.71	83.87

Overall Accuracy = (2306/2665) 86.53%, Kappa Coefficient = 0.7907

Notes: C1: High Density Vegetation, C2: Middle Density Vegetation, C3: Low Density Vegetation, C4: Main Road, C5: Vacant Land

4.2 Classification result map

The classification result map is displayed in Fig. 6. The bottle-green colored areas are high density vegetation, the jade-green ones are middling density vegetation, cyan colored are covered by low density vegetation, red areas are main road and light magenta ones are vacant land. Most area is covered by low density vegetation. Statistical results (Fig. 7 (a)) of classification indicate that most areas are covered by low density vegetation; secondary, vacant land, middling density area; the area high density vegetation is ate least. Fig. 7 (b) indicates that there are more vegetation grown in ladder 6 to ladder 11, which is the result of vegetation naturally recovery and man's action.

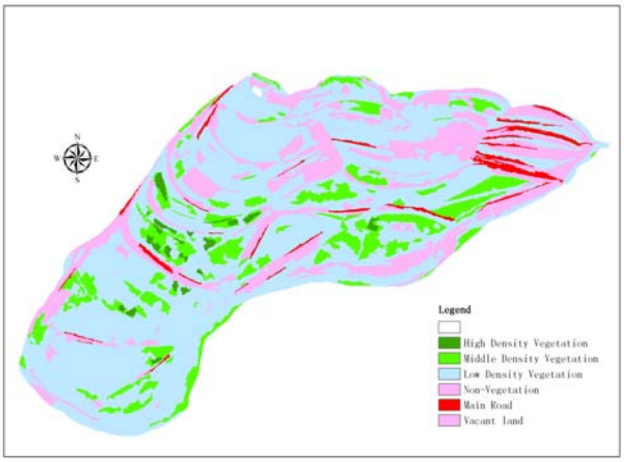
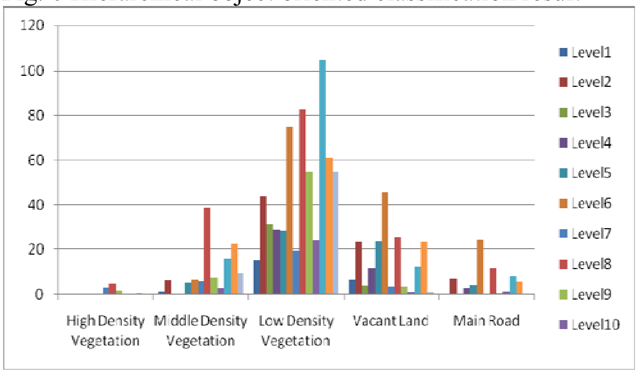
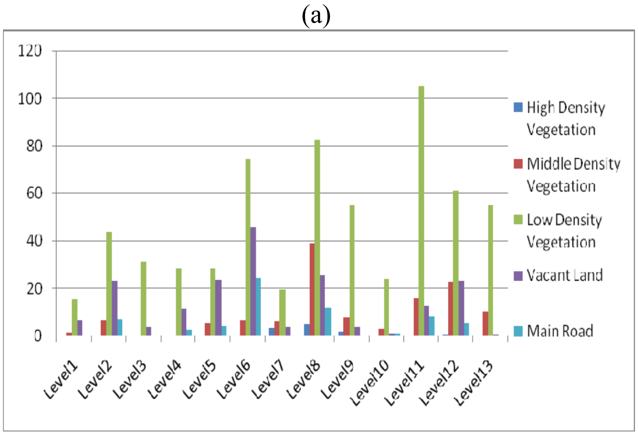


Fig. 6 Hierarchical object oriented classification result



(a)



(b)

Fig. 7 Statistical result of land cover in all ladders

5 Conclusions

Hierarchical object oriented classification is used to do land cover classification of waste dump opencast coalmine area of Haizou, Liaoning province, China. There are some conclusions we can acquire from this study:

(1) Compared with traditional pixel-based classification method, the object oriented classification method has absolute advantages in the information extraction of high resolution image. First, the *pepper and salt effect* is reduced, which approaches the objective world more; second, there is higher classification accuracy, the total accuracy increases from 74.53% to 86.53% compared with pixel-based classification method.

(2) Rational hierarchical strategy is vital to hierarchical classification. Those classes which are easy to distinguish is classified at first, for example, vegetation and non-vegetation in this study; next, those classes which are confused in the first step will be classified whin each classified types. This process can reduce the spectrum confusion in some degree.

(3) The low density vegetation is the dominant land cover type in waste dump opencast coalmine area of Haizou. This states that the vegetation in this area is in a recovery process gradually.

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