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Object oriented land cover classification using ALS and GeoEye imagery over mining area

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Abstract: An object oriented coal mining land cover classification method based on semantically meaningful image segmentation and image combination of GeoEye imagery and airborne laser scanning (ALS) data was presented. First, DEM, DSM and nDSM (normalized Digital Surface Model, nDSM) were extracted from ALS data. The GeoEye imagery and DSM data were combined to create segmented objects based on neighbor regions merge method. Then 10 kinds of objects were extracted. Different kinds of vegetation objects, including crop, grass, shrub and tree, can be extracted by using NDVI and height value of nDSM. Water and coal pile field was extracted by using NDWI and the standard deviation of DSM method. Height differences also can be used to distinguish buildings from road and vacant land, and accurate building contour information can be extracted by using relationship of neighbor objects and morphological method. The test result shows that the total classification accuracy of the presented method is 90.78% and the kappa coefficient is 0.891 4.

Key words: airborne laser scanning; GeoEye; nDSM; object oriented classification; mining areas

1 Introduction

With the development and utilization of mine resources, the landscape pattern of mining area has changed and the ecological damage to the environment is serious. Fast and accurate land cover information extraction of mining area is essential for mine environmental impact assessment. Because of various object types and complex environment of mining area, the classification accuracy of traditional remote sensing imagery is poor. Recently, emerging ALS (airborne laser scanning) is proved to be an adequate technique to deliver highly (spacing is less than 2 m) accurate 3D mass points of the ground objects. High-resolution digital elevation models (DEMs) and digital surface models (DSMs) derived by ALS can be used for developing models to extract the man-made features in a complex environment [1−3].

In this paper, an object oriented coal mining land cover classification method is presented based on semantically meaningful image segmentation and image combination of GeoEye imagery and ALS data. ALS and GeoEye imagery each have particular advantages and disadvantages in horizontal and vertical positioning accuracy. Compared with GeoEye imagery, ALS generally provides more accurate height information but less accurate boundary lines. GeoEye imagery can provide extensive 2D information such as high-resolution texture and spectral information [4]. This method can take advantage of these two images. The concurrent use of these two kinds of imageries can improve land cover classification accuracy. ALS data can be used to distinguish objects covered with the same material or similar spectral characteristics at a different height, such as concrete buildings and road, water and coal pile, different kinds of vegetation [5]. GeoEye imagery can provide accurate objects boundaries and vegetation information. Integrating GeoEye imagery and ALS data can give better characterization of the mining area studied.

2 Experimental

2.1 Study area

The study area is situated in Hebi, China, with mountainous terrain at the edge of the Shanxi plateau in northern Henan Province, China. Hebi is a densely

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populated area with industries based on coal mines. The distribution information of land cover is essential for coal mining management and environmental monitoring. The study area is situated at No.5 coal mine of Hebi, China. Figure 1 shows the GeoEye data of study area. Figure 2 shows the shaded view of the DSM extracted from ALS data.

Fig. 1 GeoEye image of study area

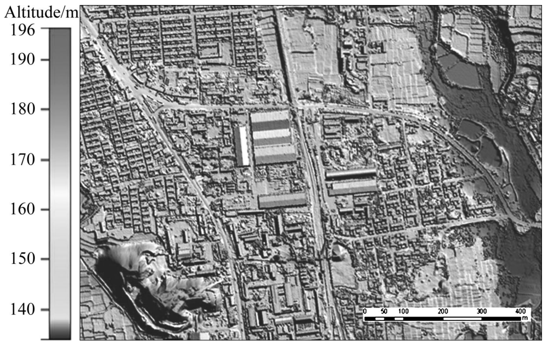

Fig. 2 Shaded view of DSM extracted from ALS data

2.2 Data

Within the framework of the National Basic Research Program of China on geologic disasters and environment in mining area, ALS data were acquired in April 20th, 2009 with Leica ALS50 scanner over Hebi mining area in China. A subset of this dataset was selected for classification test, covering 0.95 km^2 of complex mining area. Acquisition date of GeoEye data was July 12th, 2009. Surveyed features include residential houses, mining buildings, single trees, forest, farmland, roads, coal pile field, coal gangue pile and water. Data of two different dates are more favorable for distinguishing different types of vegetation.

ALS point clouds have been processed as follows. DEM was generated from ALS data. After data acquisition, using the simultaneously obtained GPS and IMU observations, the determination of 3D coordinates for every pulse measurement is established. Subsequently, systematic and gross measurement errors must be detected and removed. Then, an adaptive TIN (ATIN) filtering is conducted to classify ground and off-ground points [6]. Finally, the DTM is generated using Kriging interpolation method. At the same time, the digital surface model (the 1st return surface) is also generated. The subtraction of DTM from DEM results in the absolute height values of the objects and the model representing such heights is called as normalized digital surface model (nDSM). For the purpose of land cover objects extraction, nDSM is calculated to eliminate the influence of terrain. The spatial resolution of the nDSM is 1 m.

3 Methodology

The preprocessing of the data includes geometric and radiometric processing. The images are orthorectified using the DSM and the ground control points. The rectified images are essentially co-registered with the ALS data. In the process of object oriented image analysis, the steps followed are image segmentation and land covers information extraction based on object features.

3.1 Image segmentation

In our example, the image segmentation method followed the object-oriented classification method available in eCognition. This method identifies geographical features using scale and homogeneity parameters obtained from the spectral reflectance of GeoEye image and the elevation values in the DSM [7].

Scale relates to the minimum size required to identify a particular object, which depends on the resolution of the images. Higher image resolutions require larger scale parameters to identify a particular object. In our case, the value of the scale parameter was determined empirically, using a trial–error process that minimized the aggregation of buildings.

Homogeneity f is described by a mutually exclusive interaction between color (Δh_{color}) and shape (Δh_{shape}). Color refers to the spectral response of the objects, whereas shape conveys information about the semantic consistency of the objects. The weight parameters ($w_{\text{color,}}$ w_{shape}) allow adapting the heterogeneity definition to the application. Shape is divided into two equally exclusive properties: smoothness and compactness that, respectively, define the boundaries of the objects and their transition to others (see Ref. [7]). In our study, the weight parameters of shape and smoothness are 0.3 and 0.5, respectively. The segmented result of GeoEye image is shown in Fig. 3.

$$f = w_{\text{color}} \times \Delta h_{\text{color}} + w_{\text{shape}} \times \Delta h_{\text{shape}} \tag{1}$$

Fig. 3 Segmented result of GeoEye image

3.2 Land covers information extraction

3.2.1 Vegetation extraction

The normalized difference vegetation index (NDVI) is calculated from the calibrated GeoEye image to extract vegetation. Equation (2) shows the formula of NDVI.

$$\mathrm{NDVI}=\frac{B_{\mathrm{Nir}}-B_{\mathrm{R}}}{B_{\mathrm{Nir}}+B_{\mathrm{R}}} \tag{2}$$

where B_{Nir} is the near-infrared band of GeoEye data, and B_{R} is the red band.

Using histogram analysis, the threshold of vegetation and non-vegetation in NDVI is set to be 0.57. The height difference information can be used to distinguish tree, shrub from crop and grass because shrub is high above the ground but crop is near the ground in April. Membership function is used to define the height difference of nDSM. The height thresholds for shrub and tree are 0.5 m and 1 m, respectively.

3.2.2 Building extraction

After vegetation has been extracted, building candidates are obtained based on a certain height threshold of segmented objects of nDSM. The threshold is set as a lower value to ensure the integrity of the building. In our study area, the rural residential buildings are very low, so we set the threshold to be 1 m.

Shadows are close to the building and may be classified to building. But the brightness of shadows is very low and the roof of building is usually high, so we use the brightness of pan band of the GeoEye to remove shadows from building candidates. The threshold of brightness of pan for shadow is set to be 350 in our study.

ALS generally provides more accurate height information but less accurate boundary lines, while the high-resolution GeoEye imagery has more accurate boundary lines. So we use the spectral information to refine the edge of the building, which is implemented by classifying spectrally similar neighbors to the class of building in high steep area.

If the partial derivatives of elevation (H) along the east (x) and the north (y) direction are known, then slope is computed from Burrough [8].

$$\mathrm{Slope}=\sqrt{\left(\frac{\mathrm{d}H}{\mathrm{d}x}\right)^2+\left(\frac{\mathrm{d}H}{\mathrm{d}y}\right)^2} \tag{3}$$

The study of both the slope image and the slope frequency histogram combined by a trial and error procedure for selecting slope cut-off values, through experiment, assisted by that the criteria are defined as slope values in the interval of the results, indicating [40°, 90°].

The spectral similarity of the adjacent objects for classification needs to be analyzed. As roofs have a high variety in color, the spectral similarity for all channels, red, green, blue and near-infrared has to be evaluated at once. The easiest way to do this is to refer to the brightness of an object. But this is not enough, the brightness has to be linked to the neighboring ‘Building’ objects. This can be expressed by comparing the differences in brightness to neighboring ‘Building’ objects. With the customized relational features, we can define the search range in which objects are evaluated according to their similarity. Only those objects within a certain distance are compared to a ‘Building’ object. Here in our case, a distance of 20 pixels is sufficient. The spectral similarity used here is mean absolute brightness difference of the compared objects. The difference is set to be 30 here.

At last, two types of morphological operations are applied to the building objects. Firstly, a filling operation is employed to fill the small internal holes whose size is smaller than a specified threshold value. Secondly, a closing operation, which consists of a dilation operation immediately followed by an erosion operation, is used to effectively smooth the rough boundaries and close small gaps in the building objects. The structure element adopted in this study is a 5×5 square. After eliminating the spurious objects and smoothing object boundaries through morphology operations, a set of reliable and clean building objects are obtained. Rural residential building can be distinguished from mine building by the height threshold of nDSM. Here we set the height threshold as 6.5 m.

3.2.3 Water and coal pile field extraction

Water bodies and coal pile fields appear differently on ALS data and GeoEye imagery. There is no back scatter on the ALS data but in the GeoEye imagery, and there is an obvious absorption in the near infrared band. ZHAN et al [9] extracted water surface from ALS data and labeled the non-signal area of ALS data as water area. We find two issues with this application. Firstly, the resolution of ALS data (1 m) is coarser than that of GeoEye imagery (0.5 m). Secondly, airborne ALS system may receive signal returns in some shallow and turbid water areas. Therefore, we use the normalized difference water index (NDWI) and the standard deviation of DSM method to extract water surface from GeoEye imagery.

NDWI was used to extract open water features [10]. NDWI is here calculated using the near-infrared band (B_{Nir}) and the green band (B_{G}) as follows:

$$\mathrm{NDWI}=\frac{B_{\mathrm{Nir}}-B_{\mathrm{G}}}{B_{\mathrm{Nir}}+B_{\mathrm{G}}} \tag{4}$$

Unfortunately, the value of water and coal pile field is similar in the NDWI image, as shown in Fig. 4.

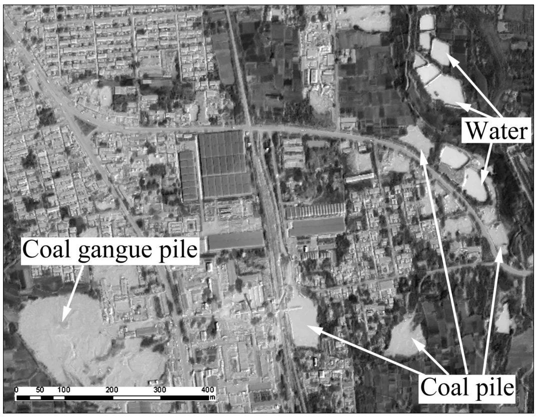

Fig. 4 Coal pile and water body looking similar in NDWI image

We use NDWI to mask black body (water and coal pile field). In the next step, we develop the standard deviation of DSM (σ) to distinguish water from the coal pile field. The water area usually has lower standard deviation than other objects. σ is computed as below [11]:

$$\sigma_m=\sqrt{\frac{1}{n}\left(\sum_{(i,j)\in P_m} f^2(i,j)-\frac{1}{n}\sum_{(i,j)\in P_m} f(i,j)\sum_{(i,j)\in P_m} f(i,j)\right)} \tag{5}$$

where σ_m is the standard deviation of DSM of all pixels (n) forming an image object m; P_m is set of pixels of an image object m; $f(i, j)$ is DSM value at pixel (i, j). In this study, the threshold of the standard deviation of DSM for separating water from coal pile field is 0.26. Coal gangue pile is usually bigger than coal pile field, and the area threshold can be used to classify coal gangue pile.

3.2.4 Road and vacant land extraction

After water, coal pile field, vegetation and building are extracted, only the road and the vacant land remain to be classified. However, it is difficult to classify them properly by spectral features and elevation because these two classes are very similar in terms of the spectral information and the elevation. Functionally, the compactness can be used to separate the vacant land and the road by using the eCognition software, which is expressed as [11]:

$$c=\frac{ab}{n} \tag{6}$$

where c is the compactness; a is the width of an object; b is the length; and n is the number of its inner pixels.

Usually, roads are linked together and have long length. So, the minimum merged object length is set to be 600 pixels for road.

4 Results and discussion

Ground truths ROIs (Regions of interest), which are generated randomly from GeoEye imagery by visual interpretation, are used to perform the classification assessment. Table 1 illustrates the classification accuracy as a result of the object oriented classification of coal mine area. There are ten kinds of land covers types which can be classified correctly. These are water, coal pile field, coal gangue pile, shrub, crop and grassland, rural buildings, mine building, roads, vacant land, and tree. The extracted results of these objects are shown in Fig. 5. The blue objects are water, and the black objects are coal pile field, which are discriminated from the water body by using the standard deviation of DSM. The dark green objects are trees and the light green is crop, grassland and shrub. These are extracted from the vegetation mask using the height difference information.

The object oriented classification method represented in this work improves the information extraction accuracy to 90.78%. In the extracted result with the standard deviation of DSM method, almost all shadow and water (93%−100%) can be classified correctly.

The nDSM is the height model of the objects above ground, including shrub, tree, crop and buildings above the ground. NDVI is used to clip crop, shrub and trees, and the remaining objects above the ground are buildings.

Height differences distinguish buildings from road and vacant land. The length/width and compactness distinguish the buildings, roads and vacant lands. Using height information, rural buildings and mine buildings are distinguished. Moreover, the classification accuracy of these land cover types is high: the accuracy of mine building, residential building, road, and vacant land are 99.97%, 97.19%, 86.48%, and 63.61%, respectively. The classification result of all land cover classes are shown in Fig. 5.

Table 1 Classification accuracy result

Class	Area/m^2									
	Water	Coal pile field	Residential building	Mine building	Shrub	Road	Vacant land	Coal gangue pile	Crop & grass	Tree
Water	10141	0	0	0	0	0	0	0	0	0
Coal pile field	0	9755	0	0	0	706	0	0	0	0
Residential building	0	0	13565	0	0	46	269	0	0	77
Mine building	0	0	0	25542	0	7	0	0	0	0
Shrub	2	41	62	1	3231	190	22	0	743	2617
Road	18	164	5	177	0	13760	1280	4	497	7
Vacant land	2	244	187	359	67	276	2792	69	357	36
Coal gangue pile	0	0	0	0	0	0	0	21535	0	0
Crop & grass	15	178	6	0	1416	298	366	0	44647	3717
Tree	0	33	115	170	510	126	4	0	276	10 154
Total	10178	10415	13940	26249	5224	15409	4733	21608	46520	16608
User acc/%	100	93.25	97.19	99.97	46.77	86.48	63.61	100	88.16	89.16
Prod. acc/%	99.64	93.66	97.31	97.31	61.85	89.3	58.99	99.66	95.97	61.14

Total accuracy: 90.78%; kappa coefficient: 0.891 4.

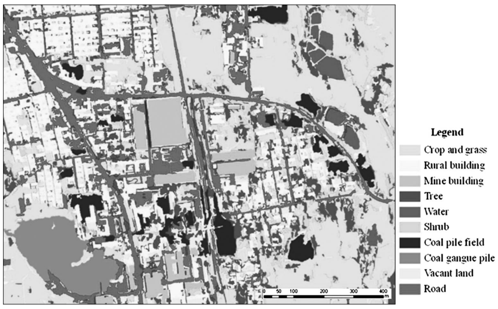

Fig. 5 Coal mine area lands cover information extraction result

5 Conclusions

An object oriented classification method which integrates GeoEye imagery and ALS data is proposed. The study area is a representative coal mine area—No. 5 mine of Hebi in China. The object oriented classification method produces ideal classification results which better represents the real world. The pepper–salt phenomenon can be solved with this method. The improvement of this method is summarized as follows:

1) The combination of multi-spectral GeoEye imagery and ALS data can improve coal-mine land cover classification accuracy. The object oriented classification method improves the total accuracy to 90.78%. Height information can be used to solve the heterogeneous spectrum of buildings. More detailed land cover classes can be extracted. For example, the buildings can be subdivided into mine buildings and rural buildings and the crop can be distinguished from the forest.

2) The standard deviation of nDSM can be used to extract water body and coal-pile field exhibiting the similar spectral representation in high resolution GeoEye imagery.

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