Chapter 9
An Object-Level Approach Improved by Quadtree to Dynamic Monitoring of Mining Area Expansion

Liang Huang, Yuanmin Fang, Xiaoqing Zuo and Xueqin Yu

Abstract An object-level approach improved by quadtree to dynamic monitoring of mining area expansion is proposed. In order to improve the efficiency and quality of objects acquired from high spatial resolution remote sensing image, multi-scale segmentation combined with quadtree segmentation is used to obtain objects of multitemporal remote sensing images; Then object-oriented image analysis method which takes into account the spatial relationship between ground objects is used in multitemporal remote sensing images to extract mining information respectively; Finally, overlay is use in mining areas extraction respectively, and Inter-erase operation is used to obtain result of mining expansion. Experiments are carried out in remote sensing images from a certain phosphate area of Anning, and the results prove that method was proposed in this paper is feasible and effective.

9.1 Introduction

The mineral resources are important natural resources; it is an essential material basis for the development of social production. Mineral resources belong to the non-renewable resources, and reserves are limited. Over the years, the development

L. Huang (✉) · Y. Fang (✉) · X. Zuo · X. Yu
Faculty of Land Resource Engineering, Kunming University of Science and Technology, 68 Wenchang Road, 12.1 Street, 650093 Kunming, Yunnan, China
e-mail: kmhuangliang@163.com

Y. Fang
e-mail: fangyuanmin@126.com

and utilization of mineral resources in China is relatively extensive, some unreasonable exploitations and utilizations, illegal disordered mining and neglect of the mining area ecological environment are serious. These lead to not only the loss of mineral resources, waste and destruction, but pollution of ecological environment around mining and huge life and production losses of the surrounding folks.

There are two main methods to dynamic monitoring the mining development and expansion: (1) field survey; (2) mining expansion dynamic monitoring based on multitemporal remote sensing images. The field survey method can get high accurate monitoring results, but it needs a lot of manpower, especially for complex terrain and large areas of mining. Because remote sensing have many characteristics, such as macroscopic, dynamic, fast and objective, it provides a new technical method for monitoring the change of mine environmental [1]. There are three ways for dynamic monitoring the mining expansion in multitemporal remote sensing images: (1) visual interpretation; (2) pixel-based change detection method; (3) object-level change detection method. Although visual interpretation method can obtain higher monitoring accuracy, but it relies on the expertise and interpret experience of interpretation personnel, and it takes a lot of time and energy, so the timeliness of the information can not be guaranteed. In the past, the low or middle resolution remote sensing images are main image data sources of dynamic monitoring of mining area expansion. Pixel-based change detection method is the main method of change detection based on low or middle resolution remote sensing images; changes are identified by comparing two images that are acquired on the same geographical area at two different times pixel by pixel. Such pixel-based change detection technique is usually divided into three main technological processes: (1) pre-processing; (2) generating a different image by comparing two registered and corrected images pixel by pixel. (3) Analyzing the different image to divide the pixel points into change points or no change points [2]. There are several methods to obtain the difference image, such as image difference method, image ratio method, CVA (Change Vector Analysis) [3–5] and difference method used after transforming the Multitemporal images by PCA (Principle Component Analysis), ICA (Independent Component Analysis) and KICA (Kernel Independent Component Analysis) [6]. Unsupervised change detection on remote sensing images based on Bayesian theory [7] or MRF (Markov Random Field) [8] are the main methods for processing the difference image. With the successful launch of a new generation of high spatial resolution remote sensing satellite, the space structure and surface texture of target ground objects can be more clearly expressed, more sophisticated internal composition of ground objects can be distinguished, the edge information of the ground objects can be seen clearly in the high spatial resolution remote sensing images, so the high spatial resolution remote sensing image becomes the condition and basis of effective mining area expansion dynamic monitoring. It is limited to use pixel-based change detection method to dynamic monitor mining area expansion on high spatial resolution remote sensing image, because there are low separability of each class, huge computation and ambiguity of "change" [9]. In order to solve the problems, the object-level change detection method came into being and widely used. Walter (2004) proposed a

remote sensing image change detection methods based on object-oriented classification. The method classifies objects instead of pixels [10]; Jovanović et al. [11] presented a new method which used object-oriented image analysis techniques for land cover change detection; Bovolo [12] presented a novel multilevel parcel-based approach to detect change in very high resolution multitemporal images; YOU [13] proposed a multi-scale optimization of SAR change detection method, the method used multi-scale segmentation to generate parcels of two images, then cross-entropy was used to calculate the degree of difference between the parcels and obtain the change region. Objects are as units in object-level change detection method, so the intrinsic object size and shape characteristics can be used fully, the separability between the change domain and no change domain can be improved, and so do separability between different ground objects. But acquisition of the objects becomes the difficulty. Now lake of an universal and high precision segmentation algorithm for high spatial resolution remote sensing image is the bottleneck. Comprehensive consideration of the pros and cons of the above methods, An object-level approach improved by quadtree to dynamic monitoring of mining area expansion is proposed. It takes advantage of flexible blocking and high compression ratio of quadtree segmentation [14], it combined with the multi-scale segmentation is used to generate the image objects; Then object-oriented image analysis method which takes into account the spatial relationship between ground objects is used in multitemporal remote sensing images to extract and classify mining information respectively, and the results can be obtained; Finally the mining expansion results can be got by compare the classification results.

9.2 Dynamic Monitoring of Mining Area Expansion

9.2.1 Proposed Method Scheme

With the continuous improvement of spatial resolution, difficulty in high spatial resolution remote sensing image automatic disposal increases. Mass data and complex details not only make pixel-based change detection inapplicable, but increase difficulty of object-level change detection. Because traditional image segmentation can hardly be used in high spatial resolution remote sensing images directly. In order to solve the problem, an object-level change detection approach improved by quadtree is proposed in this paper. First, preprocessing (radiation correction, geometry correction, image filtering and image registration) is used in two remote sensing images (T1 and T2) acquired on the same geographical area at different times; Second, quadtree segmentation is used in T1 and T2 respectively to obtain original objects, on that basis, multi-scale segmentation is used in T1 and T2 respectively to obtain final image objects; Then, object-oriented image analysis method which takes account the spatial relationship between ground objects is used respectively for image objects classification, meanwhile mining and other

ground object classes can be extracted; finally, results of mining area expansion are obtained through comparing and analyzing results of classification and extraction. The specific process is shown in Fig. 9.1.

9.2.2 Data Source

Two remote sensing images from a certain phosphate area and surrounding areas of Anning are used as date source in experiments. One image (T1) with a spatial resolution of 2.5 m is acquired by the SPOT-5 satellite in 2005, shown as Fig. 9.3a, another (T2) with a spatial resolution of 0.1 m is acquired by photo plane in 2011, shown as Fig. 9.4a. Quality of data is good, and radiation correction and geometric precision correction were carried out in images.

9.2.3 Object-Level Change Detection Method

Remote sensing image classification, thematic information extraction and target recognition are main researches of object-level remote sensing image analysis method, but there is very little research on remote sensing image change detection. With continuous improvement of resolution of remote sensing image, object-level change detection has become one of main development trends in the remote sensing image change detection [15]. Image segmentation and change regions extraction are key technologies of object-level change detection method.

Fig. 9.1 General scheme of the proposed approach
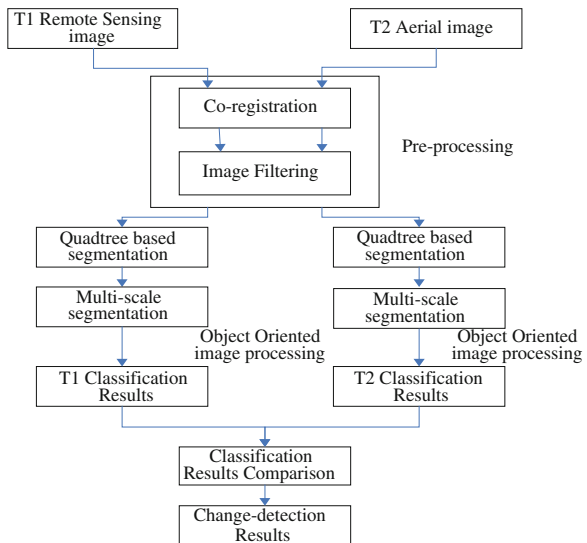
9.2.3.1 Image Segmentation

Image segmentation means that specific regions of interest are extracted from remote sensing image, and it is the basis of automatically extracting ground objects with computer, expressing and measuring ground objects. So, Image segmentation becomes one of main research contents of object-level change detection method. At present, multi-scale segmentation algorithm developed in eCognition by Definiens in Germany is the most widely used segmentation algorithm. The algorithm has advantage of that it can reduce average heterogeneity and also increase object homogeneous in more image objects. But it also has some short-comings, for example, original objects are formed slowly, this can affect overall segmentation efficiency, and inappropriate segmentation scale can cause broken segmentation and over-segmentation. To solve problem of efficiency, quadtree segmentation in remote sensing image is introduced as pre-segmentation in this paper. Quadtree segmentation method is image segmentation algorithm based on uniformity detection. In the algorithm image is expressed as a quadtree, and the original image is expressed as root. In the tree, each tree node has 4 child nodes except leaf nodes, the 4 child nodes mean subblocks in 4 quadrant of original image or image block. The basic idea behind it that an image is subdivided into 4 regions, if a region meets consistency standard, segmentation should be stopped in it; else segmentation is done until each sub-region meets consistency standard. The advantage of this method is high flexibility and fast computation speed [16].

In the paper, quadtree segmentation was first used in image to obtain original objects, then multi-scale segmentation was used after the first segmentation, and finally image objects were obtained. To compare efficiencies and qualities of multi-scale segmentation algorithm combined with quadtree segmentation and traditional multi-scale segmentation algorithm, experiments were carried out in local image (Fig. 9.2a). In experiments, segmentation scale was chosen as 100. The run time of multi-scale segmentation algorithm combined with quadtree segmentation was 1067.124 s, run times of quadtree segmentation and multi-scale segmentation were 42.282 s and 1024.842 s; but run time of traditional multi-scale segmentation algorithm was 1665.208 s. Results of multi-scale segmentation algorithm combined with quadtree segmentation and multi-scale segmentation algorithm were shown respectively in Fig. 9.2b, c. The results of experiments proved that efficiency of multi-scale segmentation algorithm combined with quadtree segmentation was improved and segmentation quality could meet requirement of subsequent change regions detection.

9.2.3.2 Change Region Extraction

There are two change region extraction methods: one is post-classification comparison; another is extracting after direct comparison between objects. Because of different data source and huge data, direct computing can not be implemented effectively between region objects using current algorithms. Post-classification
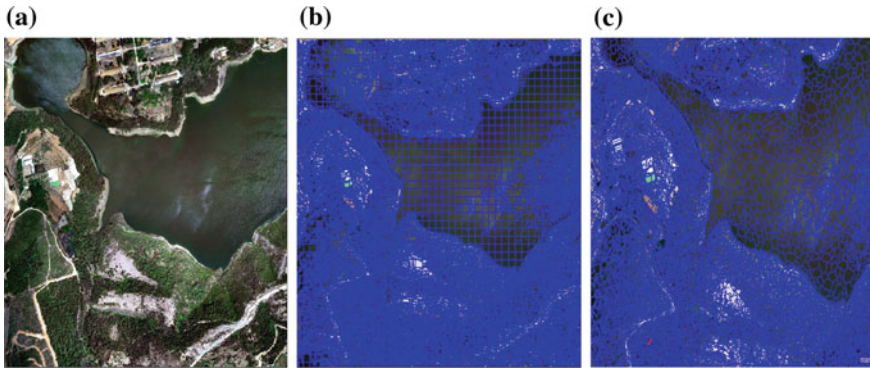
Fig. 9.2 Image segmentation: **a** original image; **b** results of multi-scale segmentation algorithm combined with quadtree segmentation; **c** results of multi-scale segmentation

comparison depends on high-precision classification results, however high-precision classification results are often difficult to obtain. So, now efficiency of post-classification comparison is still much higher than efficiency of direct comparison between mass objects. To obtain high-precision classification results, object-oriented image analysis method which takes into account the spatial relationship between ground objects is used in T1 and T2 for images classification. The results are shown in Figs. 9.3 and 9.4, Figs. 9.3a and 9.4a are the results including mining, vegetation and water. The following classification strategies were carried out in two different temporal images:

(1) Vegetation and water: First of all, NDVI was used to differentiate vegetation areas and nonvegetated areas, in this step water was recognized as vegetation; and then, Mean Blue was used to separate water from vegetation areas through spectrum difference between vegetation and water. For example, NDVI was chosen as (−0.9, 0) to differentiate vegetation areas (include water) and nonvegetated areas, Mean Blue > 100 was set to separate water from vegetation areas.
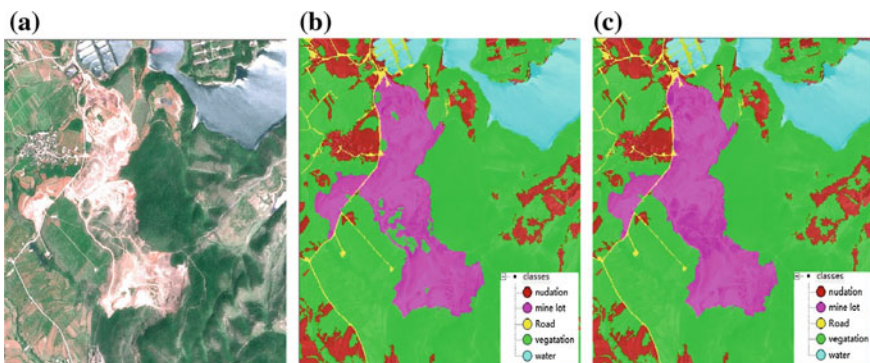

Fig. 9.3 Classification results of T1 image: **a** T1 image; **b** mine include vegetation; **c** mine
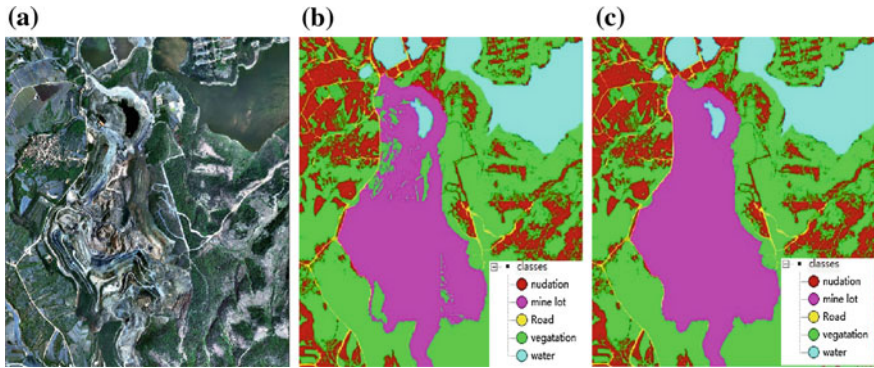
Fig. 9.4 Classification results of T2 image: **a** T2 image; **b** mine include vegetation and water; **c** mine

(2) Road network: Part of roads was difficult to extract in remote sensing image T1 for that resolutions of remote sensing images T1 and T2 are different, so only the main roads would be extracted in images (T1 and T2). In order to best use the road long/width ratio, and taking into account that the spectral characteristics of the roads, bare ground and mining are similar, firstly the roads segmented were merged artificially, and then road network was extracted by road long/width ratio.

(3) Bare land and mining area: Because the spectrum, shape and texture of bare land and some mining areas were extremely similar, mining areas were difficult to extract only by spectrum, texture and geometric feature. In the paper, the spatial relationship between ground objects was introduced to mining extraction. Mean Red, Mean Green and Mean blue of greater than 230 were set to extract some mining areas for that Mean Red, Mean Green and Mean Blue of phosphorite were greater than 230; relationship with adjacent objects of mining was used to separate from areas, in which spectrum of mining and bare land were similar. For example, according to distance relations in "Relations to Neighbor Objects", Distance to Mine lot of greater than 30 pixels was set to extract mining in T1 through classification. Semi-automatic or human-interactive method was used to extract through classification in mining areas, whose spectrum, shape and texture were similar to them of bare land. The relationship of coincidence boundary in all directions of vegetation or water and mining was used to extract vegetation and mineral bath from mining areas. For example, mineral bath and vegetation in mining areas were extracted as mining by border relationship in "Relations to Neighbor Objects" through setting Border to Mine lot of greater than 0 pixel and Border to Vegetation/ Water of less than 0 pixel.

After the classification results of T1 and T2 were obtained, overlay (Fig. 9.5a) was implemented in the output mining areas of T1 and T2 using Arcgis9.3. Then results (Fig. 9.5b) of mining area expansion were acquired through inter-erase.
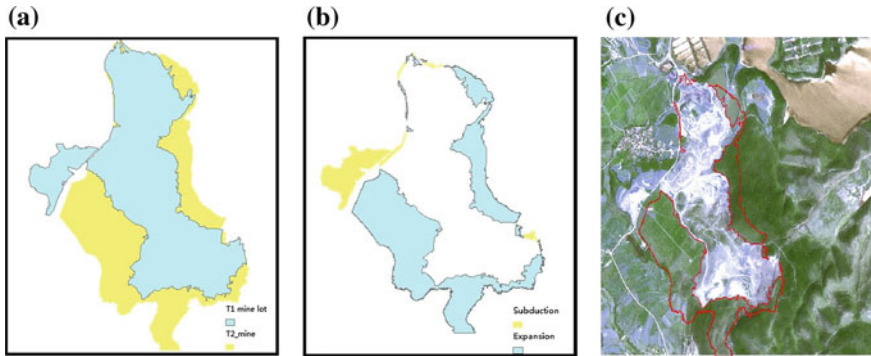
Fig. 9.5 Change analysis: **a** mining area overlay of T1 image and T2 image; **b** mining area expansion and subduction; **c** expansion area overlay of T1 image

9.2.3.3 Results Analysis

Mining areas are acquired through analyzing the results of mining information extraction in T1 and T2 respectively. There are two mining areas in research area of 2005, and areas of them are 69078.125 m^2 and 673218.750 m^2. Mining of 2011 has an area of 1114850.481 m^2. Expansion area of 455341.964 m^2 is acquired from 2005 to 2011 through inter-erase, two mining areas of 2005 reduce 69078.125 m^2 and 13710.230 m^2 respectively (Fig. 9.5b). As Fig. 9.5c shows, expansion area is main forest in 2005, and mining area expansion destroys local forest. However, mining reduction area is forest, which was mining before; Figs. 9.3b and 9.4b show that exploited mining are gradually transformed into vegetation.

9.3 Conclusion

Greatly improve the efficiency of the high spatial resolution remote sensing image segmentation by quadtree segmentation combined with multi-scale segmentation methods. The object-oriented image analysis method which takes into account the spatial relationship between ground objects can take full advantage of various kind of spatial relationship has greatly improved the accuracy of the mining classification and extraction. In the basis of the two, mining information were separately extracted, then the mine information of multitemporal remote sensing images were processed by inter-erase, and finally the mining expansion results were obtained. The expansion results prove that method was proposed in this paper is feasible and effective. Because of different objects with same spectrum, the capability of applying remote sensing images on mining classification is reduced. Due to interference of different objects with same spectrum, part of the misclassification

occurred. But correct the misclassification is difficult to achieve a fully automated, partially corrected using a semi-automatic way, and thus how to better automatic extract the mining information need to be further study.

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