OBJECT-BASED IMAGE CLASSIFICATION UTILIZING BACKGROUND KNOWLEDGE: A CASE STUDY OF LAND USE CLASSIFICATION

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ABSTRACT:

Object-based image classification and information extraction approaches are rapidly developing from the beginning of this century, but the automatic procedure for land use mapping are still problematic facing with land use complexity. This paper presents a method of incorporating background knowledge into the object-based image classification procedure, intending to improve the classification accuracy and boundary consistency of land use data. Two forms of knowledge are used in this paper: the expert interpreted land use polygons and the land use change rules. The idea of this paper is tested on the platform of Definiens Developer 7 (trial version). The proposed approach mainly contains three parts: segmentation supported by land-use thematic layer, classification and change detection supported by land-use change rules. The experiment result shows that the proposed procedures have good potential for automatic land use mapping.

1. INTRODUCTION

Object-based remote sensing imagery classification and information extraction approach have been widely tested and proved to be a promising method for automatic image classification and interpretation. The object-based approach has two main advantages over the traditional pixel-based classification method: one is reducing the salt-pepper effect, and the other is utilizing multi features extracted from image objects to improve the classification accuracy. These features include the spectral features, shape features, texture features, spatial relational features and semantic relations multi-level image object hierarchy and class hierarchy.

Many efforts have been endeavoured into the application of object-based approach into image classification and information extraction, including vegetation classification using very high resolution satellite imagery or airborne imagery (Yu *et al.*, 2006; Mathieu *et al.*, 2007; Mallinis *et al.*, 2008), mangrove and tree mortality mapping from IKONOS imagery (Wang *et al.*, 2004; Guo *et al.*, 2007), vehicles detection from high resolution aerial photography (Holt *et al.*, 2009), burn area and fire type mapping from IKONOS imagery and NOAA-AVHRR data (Gitas *et al.*, 2004; Mitri and Gitas, 2006).

In the field of land use and land cover mapping, as the land use and land cover pattern of certain region (like the coastal region) change rapidly and fiercely, it is of great importance to develop automatic procedures to do the time consuming land use and land cover mapping work. The object-based approaches show great potential of automatic land information extraction in imagery, and several attempts have been made for land use mapping and change detection (Walter, 2004; Stow *et al.*, 2007; Rahman and Saha, 2008), but it still has a long way to go before reaching the goal of automatic procedures of land use mapping and change detection.

When using the object-based approach for land use mapping, it is hard to develop a consistent threshold of multi features for certain land use type, and features may be time variant for certain land use type. Take the land use type “cropland” as an example, the spectral features are probably quite different before and after the crop harvested. In addition, land parcel boundaries are generally vague in image, and it is hard to get consistent segmentation result for certain land parcel. Furthermore, the same land parcel may have different boundaries, because of the difference of the radiation characteristics among sensors and the time variation influence.

Intending to improve the object-based image classification result for land use mapping, this paper introduces an idea of incorporating background knowledge into the object-based land use classification procedures. The knowledge presented in this paper mainly refers to two kinds: one is the knowledge persisted by expert in the process of manual interpretation, the other is the land use change pattern knowledge.

Traditionally, land use was mapped through field investigation. With the remote sensing technique developing, land use can be mapped from remotely sensed imagery by the means of manual interpretation by domain experts. Experience shows that the manually interpretation by trained interpreters with field investigation experience can obtain good classification accuracy. There is certain knowledge an interpreter possess for image interpreting, including spectral, texture, shape, spatial relations, semantic relations, and other features unknown. It is justifiable to think that part of the unutterable features and rules remains in the land use data which the interpreter produced. This research is intend to seek for a procedure to utilize the interpreted land use as background knowledge to aid the object-based classification and information extraction, and it is the first kind of knowledge used in this research.

The second kind of knowledge refers to the land use change pattern. Land use types do not change randomly in space, but they change following certain rules in certain regions. For example, “built-up land” is not inclined to change to other land use types in a temporal scale of year. Land use change rules may vary from region to region, and the techniques to extract these rules from data sources are still under development. We employ simple land use change rules in this study, just for the illustration of the procedure and framework of knowledge aided object-based automatic land use mapping.

2. DATASETS

2.1 Study area

The study area is located in west coastal area of Chinese Pearl River Estuary (figure 1). It lies in the west of Hongkong and in the administration zone of Zhongshan city. Rapid urbanization undergoes in this area since the China's reform and opening up.

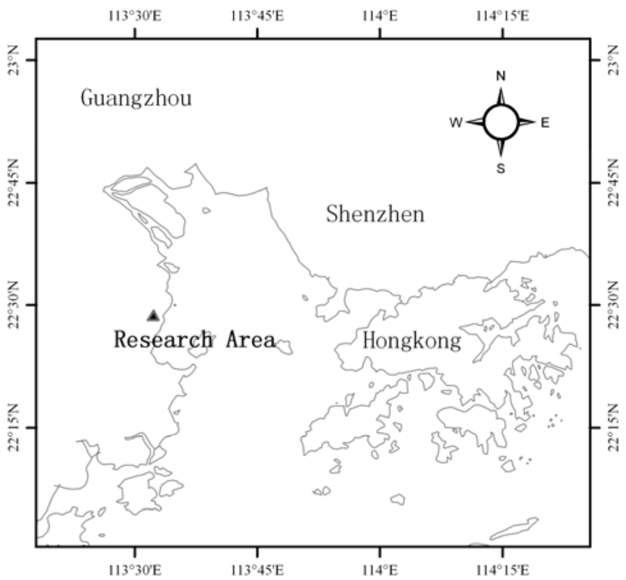


Figure 1. Location of the study area

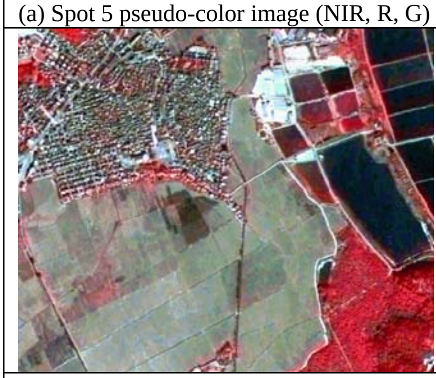
2.2 Imagery

Two image sources are selected for this research: one is the SPOT 5 image and the other is CBERS 02B image. The SPOT 5 image is a fusion image of SPOT 5 panchromatic (2.5m) and multispectral image (10m). The fusion algorithm is Pansharpen implemented in PCI software package, and the final image resolution is 2.5m. Three bands are included in the SPOT 5 fusion image, NIR, Red, and Green. The pseudo colour combined image (NIR, R, and G) is shown in figure 2(a). The imaging time is October 23, 2003, and SPOT image is the source image of the old land use polygon obtained by expert manual interpretation.

The CBERS image is a fusion image of CBERS 02B High Resolution (HR) (2.36m) and multispectral image (20m). The fusion algorithm is also Pansharpen. The final image resolution is 2.5m. Four bands are included in the CBERS fusion image, namely NIR, Red, Greed, and Blue. The combined colour image is shown in figure 2(b, c). The scene date is January 5, 2009. The CBERS imagery is distributed by China Centre for Resources Satellite Data & Application. The CBERS image is used to generate the new land use classification.

By manually interpreting images in figure 2, one can see that SPOT image have better detailed texture information than the CBERS image, one possible reason is that too much resolution difference between the CBERS panchromatic (2.36) and multispectral image (20m). The relatively lower image quality of the CBERS image place some challenges for the effective land use extraction.

(a) Spot 5 pseudo-color image (NIR, R, G)



(b) CBERS 02B pseudo-color image (NIR, R, G)

(c) CBERS 02B true colour image (R, G, B)

Figure 2. Remote sensing imagery of the study area

2.3 Land use polygon data

The land use thematic data is from the Chinese Coast and Island Remote Sensing Investigation Project (Sun, 2008). The land use is mapped through manually image interpretation from SPOT 5 imagery and other ancillary data, the scale is about 1:50 000. The verification result from field investigation shows that this dataset have more than 91% classification accuracy of level 2 land use type. Five land use type appear in the study area, namely cropland, shrub and grassland, forest land, built-up land, and aquaculture (figure 3).

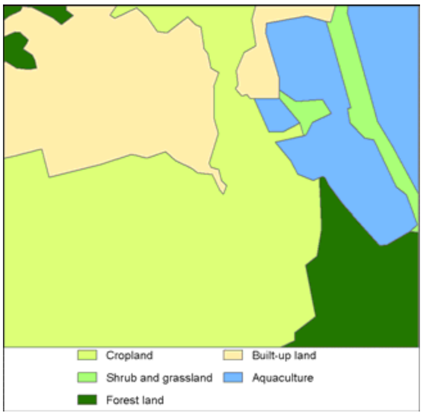


Figure 3. Land use data of the study area

3. METHODS

3.1 Background knowledge aided image segmentation

The knowledge aided image segmentation methods is achieved by incorporating land use thematic layer into image segmentation, and force the segmented image object to have the edge which the land use thematic layer delineated.

This research employs multiresolution segmentation algorithm (Baatz and Schäpe, 2000) implemented by Definiens (Definiens, 2007) to do the segmentation. Through the multiresolution segmentation, individual pixels are perceived as the initial regions, which are sequentially merged pairwise into larger ones with the intent of minimizing the heterogeneity of the resulting objects. The sequence of the merging objects, as well the size and shape of the resulting objects, are empirically determined by the user. Initially, the layers, as well as their weight, the parameters for homogeneity/heterogeneity, and the crucial scale parameters are specified by the analyst (Benz *et al.*, 2004).

The homogeneity criterion is calculated as a weighted combination of color and shape properties of both the initial and the resulting image objects of the intended merging. The color homogeneity is based on the standard deviation of the spectral colors. The shape homogeneity is based on the deviation of a compact or a smooth shape. The computation of homogeneity criterion *f* is illustrated in equation(1):

$$f = (1 - w_1)\sigma_{color} + w_1((1 - w_2)\sigma_{smooth} + w_2\sigma_{compact}) \qquad (1)$$

Where σ_{color} refers to the color homogeneity, σ_{smooth} refers to the smoothness shape homogeneity, and $\sigma_{compact}$ refers to the compactness shape homogeneity.

Segmentation on several scales with different scale parameters can be carried out leading to the formation of a hierarchical network of objects. This procedure is constrained so that spatial shape of objects in one level fits hierarchically into objects of another level enabling consideration of sub-objects and super-objects and their relationships in the classification step.

As in the introduction section explained, expert knowledge is contained in manually interpreted land use data. This research uses the land use polygon data as a thematic layer to help delineate proper land parcels. Detailed procedures are in figure 4. Firstly, image is segmented at a coarse level (level 1) to delineate the old land use type which is indicated by the background thematic layer. Then, based on the coarse level objects, more detailed land parcels at a fine level (level 2) are segmented. Level 2 objects are copied and they make a new level at level 3. Level 3 objects are the sub-objects of level 2 objects, but in fact they hold the same image pixels. In this research, level 3 objects are used for change detection.

The good segmentation result and the definite land use attribute the level 1 objects hold will greatly benefit the classification procedure in section 3.2.

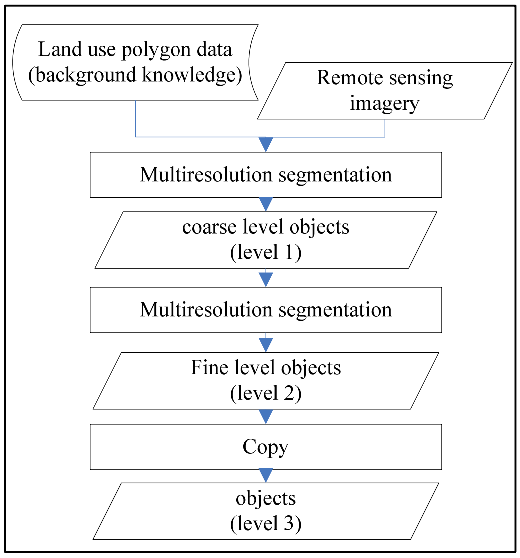


Figure 4. Image segmentation procedure utilizing background knowledge.

3.2 Knowledge aided image classification

In this approach, image objects are classified not only by the traditional multi features, but also by land use change rules.

First, the level 1 image objects land use are classified based on the background land use thematic layer attribute "land use type", and the level 1 image objects classification represents the old land use type. Then, the level 2 image objects are classified with the land use change rules and multi features. The land use change rules used in this research is described in table 1, and the features used for classification is shown in table 2. The feature brightness and vegetation index in table 2 refer to the object mean value.

Table 1. Description of land use change rules.

Old land use	*New land use*	*Condition*
Cropland	Built-up land	BT > 50, VI < 0.1, Entropy >6
	Aquaculture	BT < 45, VI <0.05
	Cropland	Other condition
Shrub and grassland	Built-up land	BT > 50, VI < 0.1, Entropy >6
	Aquaculture	BT < 45, VI <0.05
	Shrub and grassland	Other condition
Forest land	Built-up land	BT > 50, VI < 0.1, Entropy >6
	Aquaculture	BT < 45, VI <0.05
	Forest land	Other condition
Aquaculture	Built-up land	BT > 50, VI < 0.1, Entropy >6
	Shrub and grassland	NDVI > 0.15
	Aquaculture	Other condition
Built-up land	Built-up land	All condition

Table 2. Description of the various object features used in the study.

Abbreviation of the feature	*Name of the feature*	*Computation method (or reference)*
BT	Brightness	(Red + Greed + Blue) / 3
VI	Vegetation index	(Nir – Red) / (Nir + Red)
Entropy	GLCM entropy	Refers to (Definiens, 2007)

3.3 Change detection

Change detection is achieved by comparing the classification of objects at level 1 and that of level 2. Classification at level 1 refers to the Old land use, and classification at level 2 refers to the new land use. If the land use type of a level 2 object is different with the land use type of its super object at level 1, then the sub-object at level 3 of this image object is classified as "changed", otherwise, the sub-object at level 3 is classified as "unchanged".

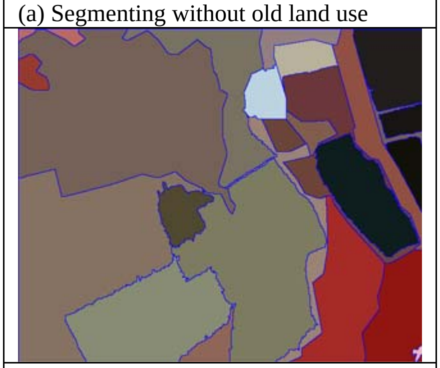
4. EXPERIMENTS AND RESULTS

4.1 Knowledge aided image segmentation

4.1.1 Comparison of segmentations without and with land use polygons

To demonstrate the effect of segmentation method supported by land use thematic layer, a test is conducted to compare the segmenting result with or without the old land use polygons. Segmentations are performed at CBERS layer 1-4, with scale parameter 100. Result is shown in figure 5. The segmentation result without land use delineate land parcels too fine boundaries, and it does not in consistent with the map generalization rule; but the segmentation result supported by land use polygon preserves the old land parcel boundaries very well, and some possible type changed land parcel are delineated as well without conflicting with the old land boundary.

(a) Segmenting without old land use



(b) Segmenting with land use aided

Figure 5. Comparison of segmenting result of CBERS image without and with land use polygons.

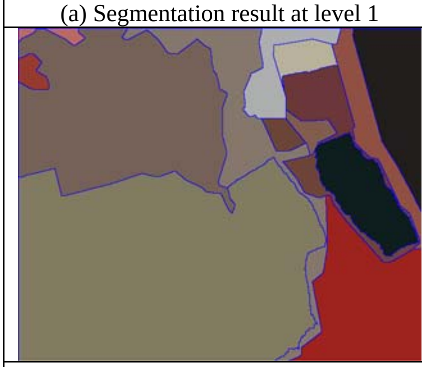
4.1.2 Segmentation result at multi level

As described in the method section 3.1, the coarse level objects (level 1) are segmented first, then based on the old land use polygon, fine level objects (level 2) are segmented. Level 3 objects are used for change detection, and they are copied from level 2 objects. The detailed parameters used for segmentation is shown in table 3. The segmentation result is shown in figure 6. The boundaries of level 1 object are consistent with the land use map shown in figure 3.

Table 3. Parameters used for segmenting four image layer of the multi-scale object

level	**scale**	**bands**	**thematic**	**shape**	**compactness**
Level 1	500	Band 1-4	yes	0.1	0.5
Level 2	200	Band 1-4	no	0.1	0.5
Level 3	200	Band 1-4	no	0.1	0.5

(a) Segmentation result at level 1



(b) Segmentation result at level 2

Figure 6. Segmentation result at level 1 and level 2.

4.2 Knowledge aided image classification

Land use change rules are employed in the process of classification. Objects on level 2 are classified according to the rules described in table 2. The features used for classification are described in table 1. Take the classification procedure of land use type "aquaculture" for example, the detailed classification tree is shown in figure 7. Classification procedure of other land use types is about the same of type "aquaculture", only the land use change rules varied. The final classification result is shown in figure 8.

4.3 Change detection

By comparing the land use type of level 2 objects (new land use) with the land use type of their super-object (old land use), the land use change status for each land parcel in level 3 are defined. The final result is as figure 9 shows, one land parcel changed the land use type.

By manually interpreting the image in figure 1, the spectral feature of land use type "cropland" in the CBERS image is quite different from that in the SPOT image. Generally used object-based change detection approaches are hard to tell this kind of difference, normally they result in false change detection in this research condition. The pixel-based change detection approach are not suitable for this condition, because the radioactive characteristics of the sensors (SPOT 5 and CBERS 02B) are quite different.

The result of the automatic procedure of our approach is quite consistent with manual interpretation. As described in section 2, the image quality of SPOT 5 image is better than that of CBERS 02B image, but high price of SPOT image limit the access of research community for such data. The procedure proposed in this paper also shows good potential for classification and change detection for less quality images.

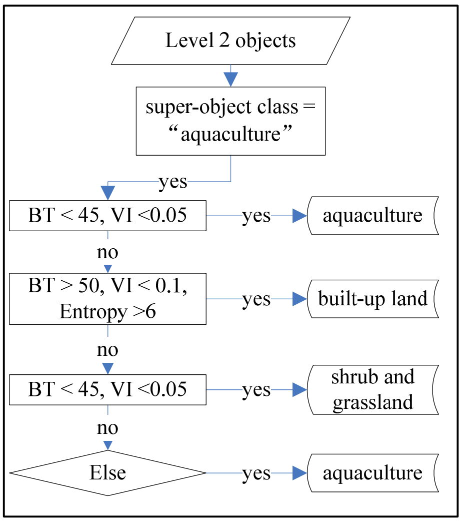


Figure 7. Classification tree for land use type "aquaculture".

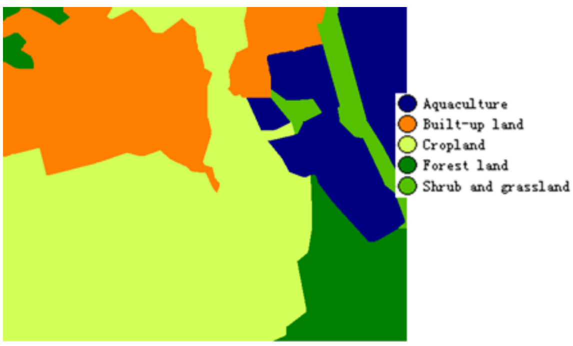


Figure 8. Classification result for level 2 objects.

Figure 9. Change detection result.

5. CONCLUSION

Object-based approaches are promising for automatic land mapping, but there is still a long way to go to reach the goal automatic. This paper introduced an object-based approach for land mapping and change detection by utilizing background knowledge. In the case study, the old manually interpreted land use thematic layer and user defined expert land change rules are employed as background knowledge, and aiding the segmentation, classification, and change detection in the proposed procedures. The experiment result shows that there is good potential for the proposed knowledge aided object-based classification approach to become automatic procedure for land mapping.

However, it has to acknowledge that the framework proposed in this paper is only a prototype, and the exact knowledge used in this paper is problematic when applying for other regions. Further work has to be done to reach full automatic procedure for land mapping by knowledge aided object-based approach. Firstly, proper knowledge discovering techniques have to be developed to extract effective knowledge, either in the form of rules or patterns, which can be used for automatic land classification. Secondly, the optimal feature space for the classification of certain land type need to be discovered. Thirdly, knowledge and feature variation among different regions need to be considered for further automatic procedure for large area (regional) land mapping.

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