OBJECT-LEVEL CHANGE DETECTION FOR MULTI-TEMEPORAL HIGH-RESOLUTION REMOTE SENSING IMAGERY

Mu H. Wang[a,b], Ji.X Zhang[a], Hai T. Li[a], Hua L.Xu[a,b]

[a]China Academy of Surveying and Mapping,Beijing,100039,China-(zhangjx, lhtao)@casm.ac.cn
[b]Liaoning Technical University ,School of Geomaticas,Fuxin,123000,China- amudc@126.com, hualong_0795@163.com

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ABSTRACT:

A new object-level change detection(OLCD) approach, combining object analysis with change detection process is proposed for land surface monitoring. The object analysis is consisting of Mean Shift(MS)&Region Grow(RG) multiscale segmentation, Support Vector Machine(SVM) classification and object footprint. Change detection process is composed of object overlay analysis(OOA),class attributes comparison and accuracy assessement.Depending on this approach,we can detect the change type of objects according to classification label. Furthermore,object boundaries are extracted assisted on the vector tool, and the detection result in the form of vector data can be used to update GIS database in the land use/cover(LUCC) change. The OLCD approach performances were assessed using multisource SPOT-5 and IKNOS reference data in Jiaxing, and were compared to a pixel-based method using post classification comparison in CASMImgeInfo3.5.High overall accuracy(>85%) was achieved by object-level method.The experiment result illustrated the approach could make full use of contextual information of objects and effectively detect object changes.

1. INTRODUCTION

Remote sensing technique has been widely used in the field of change detection because of the advantage of macroscopy,high speed and short interval of acquiring resources,ample information and effective usability(Massonnet et al.,1993).In the history of remote sensing applications, many change detection techniques have been developed.They can broadly grouped into four categories: visual interpretation approaches,pixel-level change detection(PLCD),feature-level change detection(FLCD)and object-level change detection(OLCD).

Specifically,visual interpretation requires human experience(computer-assisted or not) to label zones that are considered as changed,which can make full use of analysts’experience and knowledge but is time-consuming(Mu H. Wang et al.,2007).

PLCD approaches extract spectral information of pixels to describe the geography pattern,and the spatial or contextural information between proximate pixels is most often ignored(Atkinson et al.,2000, Townshend et al.,2000).With the improvement of imagery resolution,the single pixel can’t represent a region or object but a part.Espectially for urban areas, the phenomenas that are different object with the same spetra characteristics and different spetra characteristics with the same object are severe because of the materials,furthermore,the effect of projection and shade must be taken into accounted.All of those make it noninteresting to analysize object change in the manner of pixel-level methods(Shackelford A.K.，Davis,C.H，2003；Wang Jianmei et al.，2005). Image analysis aims to interpret, quantize and describe landscape,while the basic unit of landscape is spatially homogeneous parcel,which composes multiscale interestint objects.The differences between parcels are spectra,texture,shape and spatial layout information,which can’t be provided by a single pixel.

FLCD methods extracted many kinds of features from images by means of some information extraction techniques such as Principal component analysis(PCA),texture analysis,shape analysis,vegetation index,wavelet analysis and so on.And then we compared those features to decide whether change or not.Though FLCD has advantages in feature attributes comparison,while it can introduce other errors in the process of information extraction.

Recently, pursuers pay more attention on object level image analysis technique which is similar to visual interpretation. Instead of analysing pixels independently of their location, similar contiguous pixels are grouped into objects.The interest for OLCD methods has increased with the improvements in image segmentation techniques. The main advantage of object-based methods is the incorporation of contextual information in the change analysis (Flanders et al.,2003). Moreover, the segmentation reduces the local spectral variation inducing better discrimination between land cover types (Lobo, 1997). However, although the object delineation remains crucial, a limitation is the definition of a Minimum Mapping Unit (MMU). Therefore,the final result is largely determined by objects delineation(Baudouin Desclee et al.,2006).

This research aims to develop a new OLCD methods to detect land cover and land use change in Jiaxing,Zhejiang Province, taking advantage of Mean Shift & Region Grow(MS&RG) multiscale segmentation,Support Vector Machine(SVM)classification,Object Overlay Analysis(OOA). This study also aims to test this new approach on a multitemporal SPOT-5 and IKONOS data set and to compare its performances to the pixel-level method using the post classification comparison technique.

2. STUDY SITE AND DATA

The city of Jiaxing covers 5282km^2 and is located in the southern of Changjiang Delta of China.There are various of land use type,including agriculture,water body,

Mu H.Wang :Phone : 86 10 88217730; Fax: 86 10 68211420; http:// www.casm.ac.cn

forest,building,mountanious region and so on.In the recent years,land cover changes are more frequent because of activities of human beings in Jiaxing. Four cloud-free panchromatic and multispectral SPOT5 and IKONOS images were acquired over four years and are considered as our multidate data set.The acquisition date of these images were July 17th 2002(SPOT-5 pan),August 24th 2002(SPOT-5 multispectral), August 10th 2006(IKONOS pan) and July 18th 2006(IKNONS multispectral).The spatial resolutions of above images are different,2.5m for SPOT-5 pan,5m for SPOT-5 multispectral,1m for IKONOS pan and 4m for IKONOS multispectral,respectively.

Two preprocessing steps were required for a meaningful comparison of the satellite images. First, coregistration and fusion operations between the panchromatic and multispectral images of the same date were carried out. And then images from different sensors were registrated to each other with high precision to avoid misregistration errors inducing false change alerts.Depending on the satellite image, a set of 49GCPs spread over the whole study area were selected from satellite images.

Figure 1. Fused images left:SPOT-5(2.5m) right:IKONOS(1m)

3. OBJECT-LEVEL METHODOLOGY

OLCD is based on object-oriented analysis technique,the principle of which is post classification comparison method.Firstly, Image segmentation partitions an image into groups of pixels, hereafter named as objects that are spectrally similar and spatially adjacent, by minimizing the within-object variability compared to the between-object variability.Secondly, we classify those objects to thematic map and outline the polygon objects(vector data format).And lastly,we apply overlay analysis to objects and estimate whether change or not and further change type according to the object class attributes.

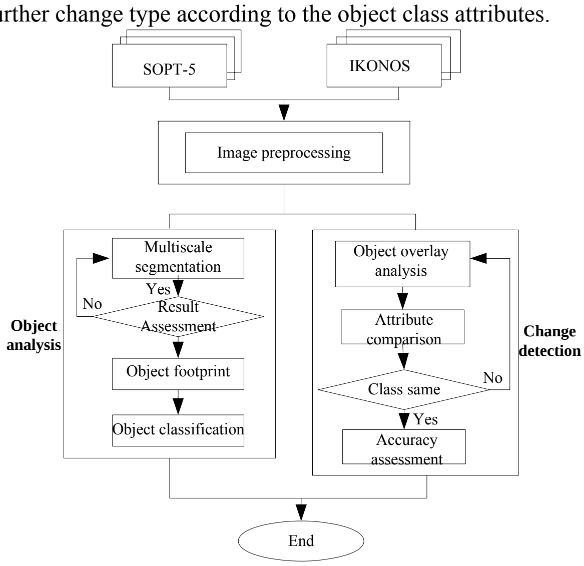


Figure 2. The flowchart of OLCD based on MS&RG,SVM and OOA

3.1 MEAN SHIFT& REGION GROWMULTISCALE SEGMENTATION

Objects of interest typically appear on different scales in an image simultaneously. The extraction of meaningful image objects needs to take into account the scale of the problem to be solved. Therefore the scale of resulting image objects should be free adaptable to the scale of task.Multiscale segmentation aims to analysize objects in different scale levels.Generally speaking,in this algorithm,we firstly operate MS procedure on the images which is the density estimation-based non-parametric clustering approach.In subsequent steps, region grow technique merged smaller image objects which acquired from MS procedure into bigger ones. Throughout this iteractive clustering process, the underlying optimization procedure minimizes the weighted heterogeneities (*hs*, *hr* and *M*) of resulting image objects.

The multiscale segmentation algorithm(Fig.3) as follows:

Given x_i, z_i(i=1,2,……,n)are d-dimentional space input and filtered image pixels in spectral and spatial domain,L_i is the ith labeled pixel after segmentation,and h_s, h_r and M are bandwidth in spatial and spectral domain and minimum merging region.

(1) Input image data set and transform color space from RGB to LUV,
(2) Carry out MS procedure in LUV color space and store all convergent data points to z_i,
(3) Describe the clustering $\{Cp\}$ $p=1,2,\ldots\ldots m$,connect all of the z_i which are smaller than h_s and h_r in spectral and spatial domain,
(4) $L_i=\{p,z_i\in C_p\}$,for i=1,2,……n,
(5) Merge adjacent objects according to the parameter M and obtain segmented images.

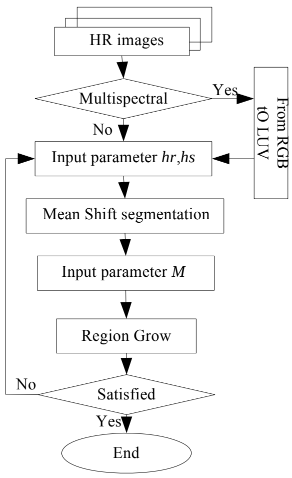


Figure 3. The flowchart of multiscale segmentation algorithm

3.2 SUPPORT VECTOR MACHINE CLASSIFICATION

SVM is a useful technique for data classification,which aims at seperating classes with an optimal hyperplane to maximize the margin among them (see Fig. 4).It is based on Vapnik-Chervonenkis (VC) dimension theory and Structural Risk Minimization (SRM) rule, which solves sparse sampling, non-linear, high-dimensional data, and global optimum problems.Its performance has been proved as good as or significantly better than that of other competing methods in most cases. The SVM method separates the classes with a hyperplane surface to maximize the margin among them (see Fig. 4), and m is the distance between $H1$ and $H2$, and H is the optimum separation plane which is defined as:

$$w \cdot x + b = 0, \quad (1)$$

where *x* is a point on the hyperplane, *w* is a n-dimensional vector perpendicular to the hyperplane, and *b* is the distance of the closest point on the hyperplane to the origin. It can be found as:

$$w \cdot x_i + b \le -1, \text{ for } y_i = -1 \quad (2)$$

$$w \cdot x_i + b \ge 1, \quad \text{for} \quad y_i = +1$$

(3)

These two inequalities can be combined into:

$$y_i[(w \cdot \mathbf{x}_i) + b] - 1 \ge 0 \quad \forall i. \quad (4)$$

The SVM attempts to find a hyperplane (1) with minimum $\| w \|^2$ that is subject to constraint (4).

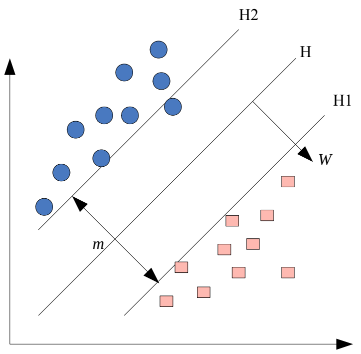


Figure 4. Optimum separation plane.

The processing of finding optimum hyperplane is equivalent to solve quadratic programming problems:

$$\min \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{l} \xi_i$$

$$s.t. \; y_i[w \cdot \phi(x_i) + b] \ge 1 - \xi_i \quad (5)$$

$$\xi_i \ge 0, i = 1,2,...,l$$

where *C* is penalty parameter, which is used to control the edge balance of the error ξ. Again, using the technique of Lagrange Multipliers, the optimization problem becomes:

$$\min \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, y_j) - \sum_{i=1}^{l} \alpha_i$$

$$s.t. \; \sum_{i=1}^{l} y_i \alpha_i = 0$$

$$0 \le \alpha_i \le C, i = 1,2,...,l \quad (6)$$

where $K(x_i, y_j) = \phi(x_i) \cdot \phi(y_j)$ is kernel function. There are three major kernel functions including Gaussian Radius Basis Function (RBF), Polynomial, and Sigmoid function. The optimum classification plane is solved through chunking, Osuna, and SMO algorithms, and then we will only need to compute $K(x_i, y_j)$ in the training process. The final decision function is:

$$f(x) = \operatorname{sgn}(\sum_{sv} y_i \alpha_i K(x, x_i) + b) \quad (7)$$

When multi-class SVM is concerned, three basic methods are available to solve the classification: One-Against-All (OAA), One-Against-One (OAO), and Directed-Acyclic-Graph (DAG).

3.3 OBJECT OVERLAY ANALYSIS(OOA)

OOA namely polygon overlay analysis creates new features and attribute relations by overlaying the features from two input layers. Features from each input layer are combined to create new output features. Attributes of each input feature are combined from the two input layers to describe each new output feature, thus creating new attribute relationships.

Boolean Algebra is useful for performing operations on the attributes attached to object entities in the format of vector data. Boolean algebra uses the logical operators **AND**, **OR**,**NOT** to determine whether a particular condition is true or false. The **AND** operator is the intersection of two sets - for example those object entities that belong to both set A and set B. The **OR** operator is the union of two sets - for example those entities that belong to either set A or to set B. The **NOT** operator is the difference operator identifying those object entities that belong to A but not B.

OOA is analogous to the boolean logical operator OR, where all elements from both input layers will be present in the output layer,which is illustrated in the following example.

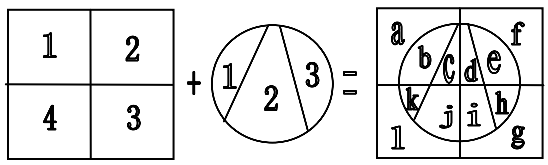


Figure 5. OOA sketch map.For areas a,f,g,l,the attributes are 1,2,3,4 from the first layer.And areas b,d,h are unchanged since the attributes from two layers are the same, and reverse for the rest areas.

4. TEST CASE

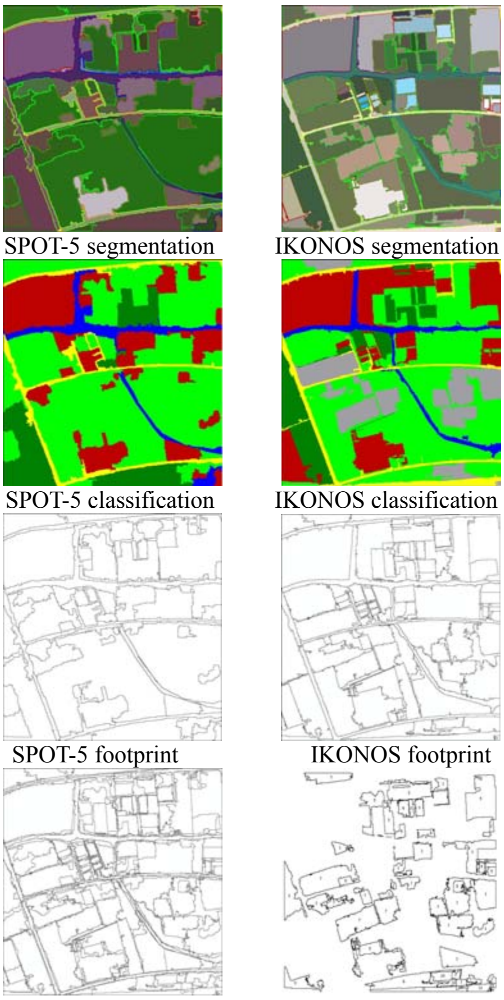
The proposed OLCD methodology was tested on the SPOT-5 and IKONOS images in order to assess its performance.The result was compared to a robust pixel-level post-classification comparison method.

4.1 Object-level change detections

The multidate segmentation was carried out from multisource HR images using MS&RG multiscale segmentation methodology. The segmentation parameters *hs*, *hr* were both set at 50,20 for the before and after event image,according to the "Try&Error" strategy. The parameter *M* was separately set at 250 and 300 to obtain segmented image with a minimum object size.

After the segmentation, we selected spectra(mean) and texture(contrast) characteristic of several objects from each class as the training samples, taking advantage of statistic methods and Gray Level Co-occurrence Matrix (GLCM) filtering.During the classification processing, firstly, we scaled the training samples and the testing samples before applying SVM. Secondly, we chose RBF kernel, which is more suitable to land use and land cover classification. Thirdly, we used cross-validation and grid-search method to get the best parameters of RBF. The highest overall accuracy on the multi-source image information was obtained with γ=0.3,0.25 and *C*=100, 130,respectively,where γ is the width of the kernel function, and *C* is the penalty parameter. At last, the training

samples were used to train the support vector machine, and the result model was used to classify the multidate images to get the preliminary classification result which is perhaps not the best one. So we selected samples and refined those classes that were unsatisfying.
OOA were carried out for all the objects. According to class attributes,change occurred if different class attributes existed for an object. The iterative OOA procedure was applied to each image object and the analytical results was shown in Fig.6.



In classification map: Building Forest Agriculture Water Body Road Unused
Figure 6. OLCD results: the multitemporal image segmentation results were overlaid with object footprint illustrated as the first two map.

In the above change type map,labels in each object denoted change type referring to Tab.2.

Labels	Change Type
0	No Change
1	From Building to Agriculture
2	From Road to Forest
3	From Agriculture to Forest
4	From Road to Building
5	From Agriculture to Building
6	From Forest to Agriculture
7	From Agriculture to Unused Area
8	From Building to Unused Area
9	From Forest to Building
10	From Forest to Unused Area
11	From Forest to Road
12	From Agriculture to Road

Tabel 2. Change Type Reference

4.2 Pixel-level change detections

Besides all the preprocessing procedures mentioned in Section 2, multidate fused images,namely SPOT-5 and IKONOS were resampled to the same spatial resolution(1m)because of the essent characteristic of PLCD.The sequent steps,including sample selection,SVM classification,post-classification comparison were carried out by CASMImageInfo3.5.Firstly,we edited signature for all classes and applied pixel-level SVM classification to multitemporal images.And then we adopted post classification comparison based on pixel-to-pixel to obtain the change type map.

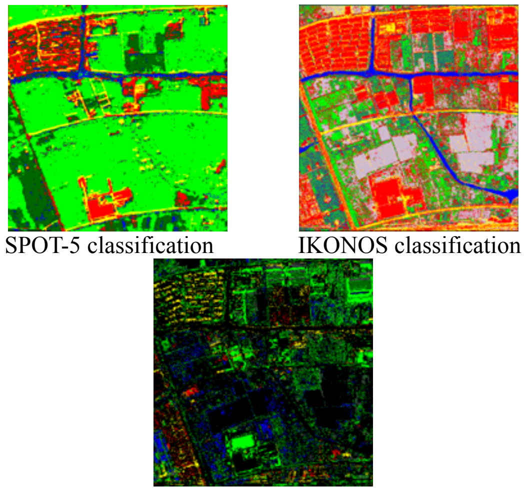


Figure 7. PLCD results.In change map,the colors represent change type.

4.3 Accuracy assessment

Accuracy assessment is a way to estimate the effectiveness of change detection methods.There are two aspects: (1) attribute accuracy,detecting change/no change and change type,(2) geometric accuracy,spatial detection error.Attribute accuracy is assessed in the form of confusion matrix,while geometric accuracy is estimated by the consistency of area and shape. According to Zhan et al. (2002), 4 accuracy indices derived from this confusion matrix are required to compare these change detection methods. The overall accuracy is the proportion of changed and unchanged elements (objects or pixels) that are correctly classified by the method. The detection accuracy is the proportion of correctly detected changed elements. The omission error is the proportion of omitted changed elements, while the commission error is the proportion of falsely detected unchanged elements. Kappa analysis (Cohen, 1960) uses the overall Kappa and the per-class Kappa statistic, which is a measure of accuracy or agreement based on the difference between the confusion matrix and chance agreement (Rosenfield & Fitzpatrick-Lins,1986). In this research we took advantage of the above accuracy assessment methods and compared the performance of object-level post classification comparison(OL-PCC) method and pixel-level post classification comparison (PL-PCC)approach.

Change detection approach	OL-PCC	PL-PCC
Detection accuracy (%)	67.3	52.6
Overall accuracy (%)	85.4	68.9
Omission error (%)	32.7	48.4
Commission error (%)	15.7	25.2
Overall kappa	0.74	0.54

Table 3. Change detection accuracy of OL-PCC and PL-PCC

5. RESULT DISCUSSION

As outlined above, the proposed OL-PCC method combinng MS&RG multiscale image segmentation, SVM and OOA was proved to have advantages against PL-PCC methodology.Besides the low detection precision,it is worthing noting that the phenomenon of "Salt and pepper" is severe in the change map based on PL-PCC.

Through the OLCD, the initial multiscale image segmentation process insures the quality of the multispectral data to be submitted to SVM classification. Indeed, the object delineation combined the spectral, spatial and contextual information to create consistent units of interest. The segmentation is also less sensitive to misregistration errors than traditional pixel-level analysis methods(Mäkelä & Pekkarinen, 2001)between multidate images and reduces the change detection processing time given that there are much fewer objects than pixels. Based on these objects,OLCD method breakes the constraint of sensor characteristics and spatial resolution in multisource satellite images and the change detection performances are increased.Moreover, the object boundaries derived directly from the segmented images are more convenient to update GIS database in land surface monitoring and map updating.

6. SUMMARY AND RECOMMENDATIONS

The object-level change detection method proposed here proved to be very efficient to identify land use and land cover changes of HR satellite images.A detection accuracy higher than 85% and an overall kappa higher than 0.7 were achieved using a SPOT5 and IKONOS multitemporal data set covering a 4-years time span. This technique can be considered scene-independent in the sense that OOA determines whether change or not according to class attributes of each object ,instead of predefined change threshold of the multidate image.

Whereas this research focused mainly on the whole technique workflow and final detection accuaracy,igoring the influence of segmentation precison.If the aim is to obtain accurate and quantitative assessments about the change area,this approach needs further theoretical developments.

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