Polygon Change Detection for SPOT5 Color Image Using Multi-Feature-Clustering-Analysis

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***Abstract*—This paper applies the multi-feature clustering analysis for SPOT5 color remote sensing images change detection based on image subtraction method and solves the problem of misjudge polygons. Subtraction chart is constructed by computing gray difference between pixels with a quite low threshold; Then, multi-feature-clustering-analysis is utilized to subtraction chart to delete misjudge polygons; Lastly, median filter and morphology algorithm are applied to remove noises caused by image registration and pixel-to-pixel-calculation. Experimental results on SPOT5 images are given to show the validity and advantages of the proposed approach.**

Keywords-change detection; multi-feature-clustering;SPOT5 color image

I. INTRODUCTION

Change detection is an important part of remote sensing applications. Two main approaches to the change detection problem have been proposed: directly compare algorithm and post-classification comparison algorithm. The former is based on significantly difference between the images of the same scene taken at different times. Image subtraction belongs to this type of method. Because it is easy to understand and utilize, image subtraction is the most appealing approach in the city land use change detection[1][2][3]. A key issue is that the change also contains "unimportant" or "nuisance" forms, such as those induced by camera motion, sensor noise, illumination variation, or atmospheric absorption[4]. The "unimportant" and "nuisance" change, leading to many misjudge change polygons, sometimes makes it difficult to apply directly compare algorithms in change detection. The latter performs change detection by comparing classification labels after segmenting or classifying, which usually requires tools tailored to a particular application. Although the post-classification comparison method exhibits some advantages over the directly compare algorithms (e.g. capability to recognize the kinds of land cover transitions, robustness to the different atmospheric and light conditions at the two acquisition times, etc), the accuracy of it is usually quite low. Multi-feature-clustering-analysis belongs to post classification comparison method, the accuracy of which is depended on the accuracy of classification approach for each image.

In this paper, we focus on one of the most widely used change detection technique: image subtraction. And then, due to the ability of providing classification information, multi-feature-clustering-analysis can be utilized to subtraction chart to delete misjudge polygons caused by the "unimportant" and "nuisance" change. Lastly, Median filter and morphology algorithm are applied to remove noise caused by image registration and pixel-to-pixel-calculation. All the algorithms applied in this paper provide a method for polygons change detection of SPOT5 color images automatically.

II. POLYGONS EXTRACTION BASED ON IMAGE SUBTRACTION METHOD

Image subtraction method based on radicalization change of images is implemented after channel selection and threshold value decision. For SPOT5 color images, more information is concluded in gray images than in color channels images(channel red, channel blue or channel green), therefore, the subtraction image is gained through gray value subtraction of corresponding pixels. The change and unchanged polygons are determined by the subtraction threshold value. A high threshold value will cause many missed polygons, and a low threshold value will cause many void polygons. Other facets, such as brightness difference of multi-temporal images, season difference and so on, also should be taken account into threshold selection[3].

However, owing to multi-feature-clustering-analysis utilized in the next step, the decision of subtraction threshold is not a big problem in this paper. A quite low threshold is required to ensure that all the change polygons can be extracted, and then void polygon will be removed after multi-feature-clustering-analysis.

III. CHANGE POLYGONS REMOVED BASED ON MULTI-FEATURE-CLUSTERING-ANALYSIS

Multi-feature-clustering-analysis as an unsupervised clustering algorithm is applied to identify land use classes of change polygons for SPOT5 color images. In the city land use change detection, all the objects are divided into three main categories: water(including river, lake, reservoir, sea

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etc), construction(including building, street, industrial sites, bare land etc) and greenland(including forest, pasture, farmland, orchard etc). The first step of clustering analysis is choosing feature space in which the three categories can be represented as a set of separate regions; then, the K-means clustering algorithm is utilized to obtain the feature clustering attributes of change polygons; lastly, all the feature clustering attributes are integrated to identify the land use classes of change polygons according to cluster-to-class-rule, and change polygons with the same class label in both image from two dates will be removed.

A. Feature Chosen and Analysis For Spot5 Color Images

Most of the attempt to color image segmentation used color feature and texture feature[3][5][6][7], the former one describes the local color composition, and the latter one describes the spatial characteristics of the grayscale component of the texture[5]. For SPOT5 color images, these features are first developed independently, and then combined to obtain an overall segmentation.

As an important cue for visual discrimination ability for human being, color can be used as feature to extract object or object classification. There are a number of color spaces to quantize color information, e.g. RGB, HSV, Lab, CMYK and so on. RGB and HSV are two commonly used color spaces, However, colors in the HSV space are more appropriate to be used as features, because each component in RGB color space often has high correlation and HSV color space shows very consistency to human vision systems[7].

Segmentation of images with texture is a difficult task, the main difficulty of which is finding proper features to represents textures. We use edge density as a simple but effective characterization of spatial texture. The key reason to chose this feature is that edge density image has little correlation with the intensity image. To prove this important characteristic, ten SPOT images(all about 2644×1938) have been applied into experiment. As shown in Figure1, values of correlation between intensity image and edge density image are around 9×10^{-8} and it is safe to think little inter-feature relationship is contained between these two features.

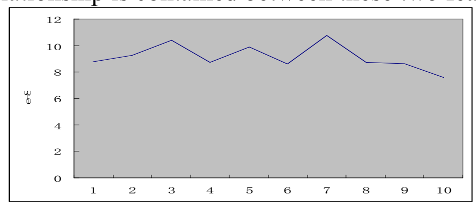


Figure 1. Value of correlation between intensity image and edge density image

For SPOT5 color images, each pixel is represented by a collection of feature vector in the four-dimensional space: three features in color feature space(hue, saturation, value of intensity) and one feature in texture feature space(edge density). Sample areas of water, construction, greenland are carefully selected by using the available sources of data including the existing land use maps, visual interpretation of the SPOT5 color image and field checking. For all the samples pixels(1.5×10^{6} pixels of construction, 2.8×10^{5} pixels of water and 2.6×10^{6} pixels of greenland), the corresponding feature value are calculated and the resulting histogram plots are shown in Figure2. The horizontal axis represents the feature value, while the vertical axis indicates the counts for the appearances of each value.

The segmentation algorithm then combines the color and spatial texture features to obtain uniform result using multi-feature-clustering-analysis in the next section.

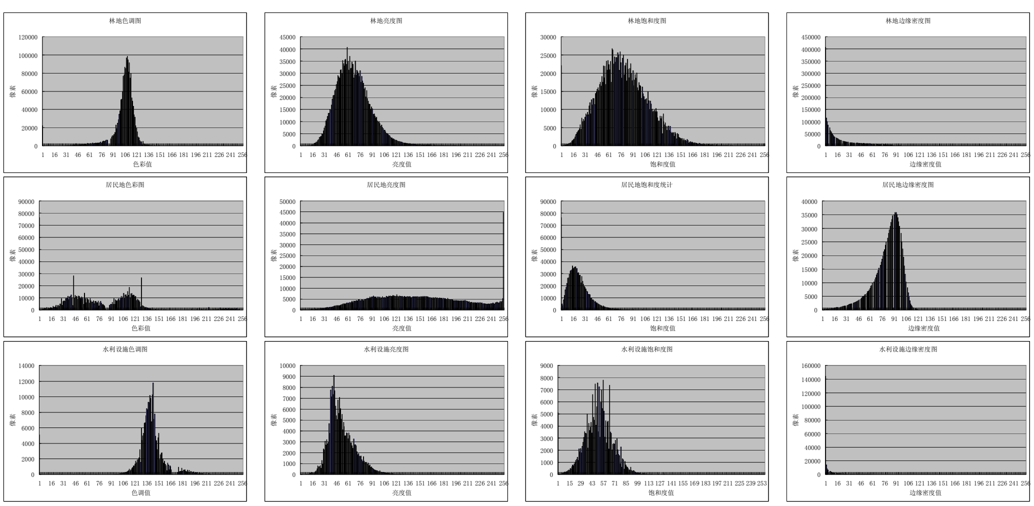


Figure 2. Hisgrams of the samples feature: greenland samples in the first row, construction samples in the second row, water samples in the third row; hue feature in the first column, saturation in the second column, idensity feature in the third column, edge density feature in the forth column

B. Feature Combination and Analysis For SPOT5 Color Images based on Multi-feature-clustering-analysis algorithm

As feature hisgrams of samples shown in Figure2, the three land use classes have their own characteristics in the four feature spaces, the next problem is how to combine these features to obtain segmentation result. An common way to use a feature space of more than 3 dimensions for segmentation is multi-dimensional clustering. It is found that, when we calculate the difference between two four-dimension feature vector as a whole, the differences between each kind of feature are confused. In this paper, instead of using the multi-dimensional clustering, we base the decision on a combination of sole feature clustering using the cluster-to-class rule drawn from feature analysis of samples.

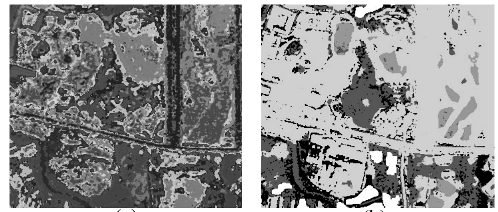
K-means clustering algorithm, which relies on individual image statistics, is applied to segment every feature image into clusters, so that each cluster provides essentially the same characteristics. It was noted that the number of clusters should be specified and the initial cluster centroids should be given. The number of clusters, corresponding to the application in this paper, is set to 5, which is proved to be appropriate by experiments. Our initial cluster centroids are calculated as formula (1) :

$$m_i = M + \sigma * [\frac{2(i-1)}{k-1} - 1] \; i = 1,...,k \tag{1}$$

where m_i represents the initial centroid of the i-th cluster, M and σ represent the mean and various of the feature space respectively, k represents the number of clusters(5 in the approach).

After all the four feature images have been segmented and all the clusters have been generated, the cluster-to-class rule drawn from feature analysis of samples is applied for classification, and all the change polygons are classified independently in images from two dates according to the rule.

The same image is segmented using both multi-dimensional clustering and multi-feature-clustering-analysis for comparison. Figure3.(a) is the result of multi-dimensional clustering using K-mean method, the number of clusters is 10. It can be seen that the segmental region is discontinuity and the multi-feature-clustering method fails to differentiate construction and greenland(with 75% accuracy rate only) because of its inability to recognize the difference in edge density feature space. The result will be worse if we set the number of cluster to 3. The segmental result of the same region based on the multi-feature-clustering-analysis is shown in Figure3.(b), in which all the objects have been classified into three main categories and background(represented in dark). Using multi-feature-clustering-analysis however enables to differentiate each kind of feature for class and leads to an accurate segmentation result (shown in Figure3(b), always over 85%).



(a) (b)

Figure 3. Segmental results

The multi-feature-clustering-analysis provides land use class labels for change polygons and the comparison of classification labels permits the identification of particular change classes so that void polygons with the same class in both image can be removed. Finally, median filter and morphology algorithm are applied to remove noise caused by image registration and pixel-to-pixel-calculation.

IV. EXPERIMENT RESULT

We run the algorithm on several SPOT5 color images. In Figure3.(a) and (b), we have been considering two SPOT5 color images(860×604) of the same region in Guangzhou, China from different time, including building, cropland, wide river, lake, reservoir and cropland.

Preliminary result of change detection using image subtraction alone is shown in Figure4.(c). The total detection accuracy is 32.77% with threshold of 25. It can be seen that the subtraction chart including most change areas , "unimportant" change areas, such as region A in Figure4.(a) and region B in Figure4.(b), which represent different surfaces but have the same land use class label(construction for both region A and B), and noise caused by image registration and pixel-to-pixel-calculation.

For the sake of comparison, we have implemented post-classification comparison based on the multi-feature-clustering-analysis. The classified images based on multi-feature-clustering-analysis are displayed in Figure4.(d) and Figure4.(e), where construction is displayed as white, greenland is displayed as light gray, water is displayed as dark gray and object difficult to recognize is displayed as black. Clearly, three main classes have been identified generally. Although parts of water and greenland are confused, the accuracy is still over 85% each. However, as shown in Figure4.(f), the accuracy of post classification comparison approach based on the classification results of Figure4.(d) and Figure4.(e) is quite low, only about 48.67% according to manual interpretation.

When multi-feature-clustering-analysis is adopted to remove misjudge change polygons in Figure4.(c), 59.43% of change polygons have been removed because their class labels unchanged. The result are shown in Figure4.(g), only the change polygons required and some noise are remained.

Then median filter and morphology algorithm are applied to remove noise caused by image registration and pixel-to-pixel-calculation. The result is shown in Figure4.(h), with the accuracy of over 90%. In comparison with traditional directly compare algorithm using image subtraction alone, the demonstrated method achieves more accurate result. The differences in accuracy between those change detection results are tested using over twenty pairs of

SPOT5 images in Guangdong province, with the same subtraction threshold, number of clusters and same cluster -to-class rule, without any human interference, to confirm the significance in detection accuracy improvements.

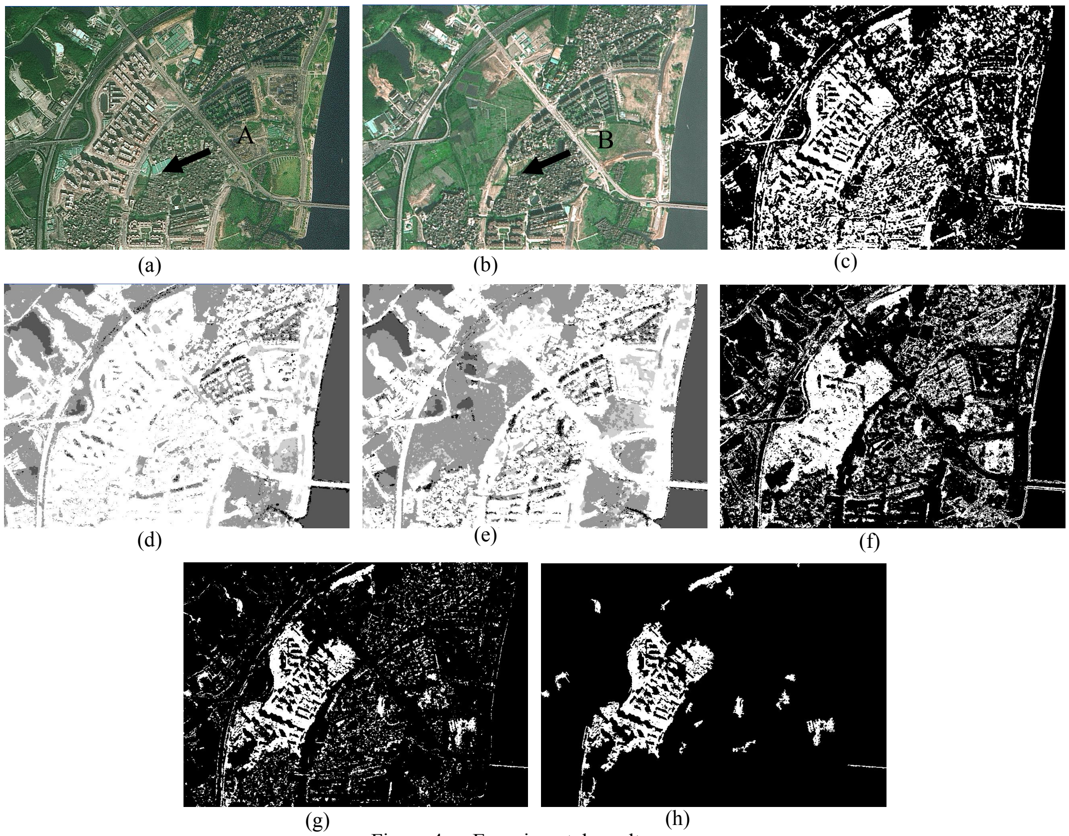


Figure 4. Experimental results

V. CONCLUSION

In this study, we show the improvement in change detection accuracy by adding multi-feature-clustering-analysis and morphology algorithm into the differencing chart. The results reveal that, compared to the use of image subtraction or post-classification comparison based on multi-feature-clustering-analysis alone, higher levels of accuracy can be obtained. Twenty pairs of SPOT5 color images of different regions from the year 2006 and 2007 have been implemented into experiment, using the same subtraction threshold, number of clusters and cluster -to-class rule. Experimental results show the validity and advantages of the proposed approach. However, the approach based on multi-feature-analysis of samples is only applied for SPOT5 color images and the three main land use classes. Due to the feature difference of images and classes, the approach should be improved for other remote sensing resource and application, which may draw our attention in future study.

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