

OBJECT-ORIENTED CHANGE DETECTION FOR HIGH-RESOLUTION IMAGERY USING A GENETIC ALGORITHM

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Commission VIII, WG VIII/8

KEY WORDS: change detection, high-resolution imagery, Object-oriented, genetic algorithm

ABSTRACT:

In this paper, we propose a novel method of change detection for high-resolution remote sensing imagery. The method has three primary processes: image segmentation, image difference and change detection. The pre-processed multi-temporal images are segmented into objects by a multi-resolution segmentation algorithm. Then a difference image is generated according to the pair of segmented maps with an interval. Each object is represented by the mean value of some spectral absolute-valued differences, which are calculated for each pixel in it. Finally, by defining the iterative degree, a genetic algorithm (GA) was employed to search the optimal binary change detection map. In the searching procedure, the crossover and mutation was applied to produce new individuals. According to our experiments using the QuickBird imagery, the Overall Errors of the proposed method decreased by more than 2500 pixels compared with the pixel-based change detection using a GA. Meanwhile, it decreased by more than 1000 pixels compared with the object-oriented change vector analysis (CVA).

1. INTRODUCTION

With the development of human society, the human activity brings a number of complicated influences to the global environment. Timely and precisely detecting the land-cover/use changes is a crucial way to find out the human influence toward the earth. Up to now, change detection has been one of the most important applications in remote sensing. Many researches focus on it. According to the characteristics of change detection methods, they could be categorized into supervised methods and unsupervised methods. Generally, a supervised change detection method requires some prior knowledge about the changes occurred in the imagery whereas an unsupervised method doesn't need it. It is problem-dependent whether using a supervised change detection method or an unsupervised one.

However, with the development of high spatial resolution remote sensing satellites, the amount of image information has increased dramatically. The information presents the details of ground objects in the visual field. The conventional change detection methods, which are appropriate to the low-/middle-resolution images, could not model the high-resolution imagery very well. The improved spatial resolution has not brought about better detecting capability. The reason is that the autocorrelation is no longer easy to approximate by a pulse function in high-resolution imagery. With high spatial resolution, the pixels are not spatially independent, resulting in the conventional change detection techniques becoming ineffective (Bovolo, 2009).

There have been some techniques that conform to the increase in spatial resolution. The object-oriented technique is one of the most typical methods. It has been proved to be suitable for high-resolution imagery. The principle of the object-oriented technique is to process of a set of pixels as a

unit, which is called an object. These pixels involved in the same object are spatially adjacent, and spectrally similar to each other. They would be processed as a homogeneous entity. In this way, various kinds of information contained in the images can be fully used, such as spatial and spectral information. In addition, processing an object as a unit can remove redundant details resulting from the increase in spatial resolution. These characteristics all perfectly meet the needs of high-resolution imagery processing. In other words, the object-oriented technique can reduce the local spectral variation and suppress the salt-pepper effect in high-resolution imagery. Bruzzone and Prieto (2000) applied the object-oriented technique to change detection, which effectively improved the change detection result of high-resolution imagery. But it was just utilized with single-scale, which could not conform to the various sizes of ground objects in reality. Walter (2003) introduced the object-oriented technique to post-classification comparison. It still did not settle the problem of single-scale. In addition, the object-oriented post-classification comparison brought about attached errors that resulted from classification. Bovolo (2009) applied an object-oriented technique with multi-scale to the change vector analysis (CVA). It resolved the shortcomings of single-scale and post-classification comparison, but it did not dispose of the limitations of CVA that is highly dependent on the spectral feature. It only considers the spectral values of pixels to construct the change vectors. Particularly, in this method, the pixel values used to build the change vectors were the mean values of pixels in each object. These deviate greatly from the real ones, which could result in considerable errors.

This paper introduces a novel method of object-oriented change detection in multi-temporal high-resolution images. As these images are taken with time differences of several years

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and in different seasonal and lighting conditions, some pre-processes are indispensable, such as registration and radiometric correction. They can remove the unnecessary differences between the multi-temporal images. After the segmentation of multi-temporal images with the Fractal Net Evolution Approach (FNEA) (Batz and Schape, 2000), the sets of pixels in each object are confirmed. According to the absolute-valued difference of each pair of pixels, in the process of image difference, the object would be presented as the mean value of these absolute-valued differences contained in it. Then a genetic algorithm (GA) is employed for searching the optimal binary change detection map by considering each object in the differenced segmented map. The iterative searching procedure would continue until the number of generations comes to the predefined iterative degree. Therefore, the proposed method is a supervised change detection method. The obtained results were compared to the results of pixel-based change detection using a GA (Celik, 2010) and the object-oriented CVA (Bovolo, 2009). It could be concluded that the proposed method can make better use of information in the high-resolution images than the pixel-based method. It also can effectively avoid the limitation of CVA. Moreover, the errors resulting from classification in the method of post-classification comparison can be averted as well.

2. METHODOLOGY

2.1 Segmentation using the Fractal Net Evolution Approach (FNEA)

In the proposed method, the Fractal Net Evolution Approach (FNEA) is employed to segment the high-resolution images. It adopts the individual pixel value and its neighbourhood to compute the colour criterion (h_{color}) and the shape or spatial criterion (h_{shape}). According to these criteria, the image can be segmented into an object map by reviewing the heterogeneity (S_f) of every pair of neighbouring objects. This heterogeneity is a weighed sum of the colour criterion and the shape or spatial criterion (equation (1)). Each of the objects in the resulting map includes the relatively homogeneous pixels neighbouring each other:

$$S_f = \omega_{color} h_{color} + (1 - \omega_{color}) h_{shape} \tag{1}$$

where $0 \leq \omega_{color} \leq 1$ is the user defined weight of spectrum. It is relative to the weight of shape. If the spectral feature is to be emphasized, the value of ω_{color} should be larger. Conversely, when the spatial feature is more important, the value of $(1 - \omega_{color})$, which is the weight of shape or space, should be larger.

In equation (1), the colour criterion (h_{color}) is a weighted mean of the change in standard deviation on the k th band of the image:

$$h_{color} = \sum_{k=1}^m \omega_k \left[n_{mg} \sigma_k^{mg} - (n_{ob1} \sigma_k^{ob1} + n_{ob2} \sigma_k^{ob2}) \right] \tag{2}$$

where ω_k is the weight of the k th band, n_{mg} is the number of pixels in the object after merging, σ_k^{mg} is the standard deviation of spectral values in the object after merging, n_{ob1} and n_{ob2} are the numbers of pixels in the objects before merging, and σ_k^{ob1} and σ_k^{ob2} are the standard deviations of spectral values in the objects before merging.

On the other hand, the shape or spatial criterion (h_{shape}) is a weighted sum of two parts, which are compactness and smoothness:

$$h_{shape} = \omega_{cpt} h_{cpt} + (1 - \omega_{cpt}) h_{smooth} \tag{3}$$

where $0 \leq \omega_{cpt} \leq 1$ is the user defined weight of compactness.

This equation estimates the value of the shape criterion through every merge by calculating the weighted sum of the compactness and smoothness criteria. Equations (4) and (5) show the formulae for the compactness and smoothness criteria separately:

$$h_{cpt} = n_{mg} \frac{l_{mg}}{\sqrt{n_{mg}}} - \left[n_{ob1} \frac{l_{ob1}}{\sqrt{n_{ob1}}} + n_{ob2} \frac{l_{ob2}}{\sqrt{n_{ob2}}} \right] \tag{4}$$

$$h_{smooth} = n_{mg} \frac{l_{mg}}{b_{mg}} - \left(n_{ob1} \frac{l_{ob1}}{b_{ob1}} + n_{ob2} \frac{l_{ob2}}{b_{ob2}} \right) \tag{5}$$

where l_{mg} is the pixel perimeter length of the object after merging, l_{ob1} and l_{ob2} are the pixel perimeter lengths of the neighboring objects before merging; b_{mg} is the pixel perimeter length of the minimum enclosing rectangle of the object after merging, and b_{ob1} and b_{ob2} are the pixel perimeter lengths of the minimum enclosing rectangle of the neighboring objects before merging.

At the beginning of segmentation, every pixel is regarded as an individual object. After calculating the heterogeneity (S_f) of each pair of neighbouring objects, they are compared to the user defined value of scale, which can be regarded as the threshold of heterogeneity. If the value of S_f is lower than the scale, this pair of objects would be merged, otherwise they would be preserved as two individual objects. These procedures are repeated until no pair of objects remains that could be merged. Then the object map can finally be obtained. From the above, the selection of scale, the weights of spectrum and compactness are critical to the segmentation result. Especially to the scale, it decides the size of objects in the object map.

2.2 The genetic algorithms (GA)

The genetic algorithms (GA), categorized as global search heuristics, are a sort of search techniques used in computing to find exact or approximate solutions to optimization and search problems. They are a particular kind of evolutionary algorithms (EA) that use techniques inspired by evolutionary biology, such as inheritance, mutation, selection and crossover.

When a GA is implemented in an evolving procedure to get the optimal solution of problem, every candidate solution called individual is abstractly represented as a string of codes, which is called chromosomes or the genotype of the genome. A standard representation is an array of bits. The evolution usually starts from a set of randomly selected individuals. In each generation, the fitness of each individual is evaluated with a criterion, which measures the quality of the represented individual. Some individuals would be selected randomly and modified by some predefined rules of evolutionary biology, such as crossover and mutation. With some filtering strategies, the new set of individuals would be then generated and used in the next iteration as the next generation of individuals. The common termination conditions can be various, such as finding a solution with the minimum criterion or reaching a fixed number of generations. In the proposed method, we use the latter one.

2.3 Object-oriented change detection using a genetic algorithm (GA)

In this paper, a genetic algorithm was employed to resolve the change detection in high-resolution remote sensing imagery.

After pre-processing of the initial images, the FNEA is used to segment the pair of multi-temporal images simultaneously with the same parameters. These parameters include the value of scale, the weight of spectrum and compactness. In this way, it can be ensured that the two sets of objects in the pair of segmented maps have the same number, and each pair of objects have the same pixels as well. By this time, the pixels in the pair of images are still represented by the spectral values in the initial images.

The next step is the image difference to the pair of multi-temporal segmented maps. The absolute-valued differences of each pair of pixels would be calculated firstly. Then a difference segmented map would be generated. In this map, the pixel is presented as the mean value of all absolute-valued differences of pixels in the same object.

With the difference segmented map, a genetic algorithm is subsequently employed to detect the changed objects covered by the multi-temporal images. According to the ground reference data, the approximate ratio of changed areas (P_{ch}) could be estimated, which is the prior knowledge in the proposed change detection method. It can also be adjusted according to the required detecting degree of changes, which is usually user defined. Meanwhile, it is required to define the number of individuals in every generation (K), the iterative degree (G_{max}), the ratios of individuals to do the crossover (P_c) and mutation (P_m). Then the procedure of change detection could be start.

First of all, K individuals are randomly selected as the parent individuals of the first generation. An array of bits is produced for each of these individuals. In the arrays, the number of 0 on the n th bit means the n th object is changed in the corresponding individual, while 1 meaning the object is unchanged. The ratios of changed objects are calculated and recorded for each of these arrays.

According to the ratio of individuals to do the crossover (P_c), $K * P_c / 2$ pairs of parent individuals would be selected randomly to do the crossover. To each pair of them, the start bit (c_{bit}) is randomly produced as well. In the crossover process, each pair of bit would be exchanged after the start bit (c_{bit}). It is worth to noting that the decimal value of K has to be changed as long as the K th individual has done the crossover.

In the same way, according to the ratio of individuals to do the mutation (P_m), $K * P_m$ individuals would be randomly selected to do the mutation, while the bit of mutation (m_{bit}) is also randomly selected for each of these individuals. Different from the crossover, the individuals to do the mutation only change the value on the m_{bit} th bit to the opposite one. It is also worth to noting that the decimal value of K has to be changed as long as the K th individual has done the mutation. As the crossover and mutation have finished, the new set of K individuals is regarded as the offspring individuals. According to the array of bits for each offspring individual, the ratio of changed objects would be calculated and recorded as well.

Combining the parent individuals and the offspring individuals, the ratio of changed objects (r_{ch}) would be sorted. Then a set of K individuals, whose values of r_{ch} are nearest to the value of P_{ch} , would be get as the new set of parent individuals for the next generation.

The processes of crossover, mutation and generating new sets of parent individuals for the next generation would repeat until the number of generations reach to the value of G_{max} . Then the individual with r_{ch} nearest to the value of P_{ch} is regarded as the optimal results of change detection. To each object in the difference segmented map, whether it was changed or unchanged is accorded to the value of corresponding bit in this optimal individual.

The specific flow of the proposed method is shown in the Figure 1.

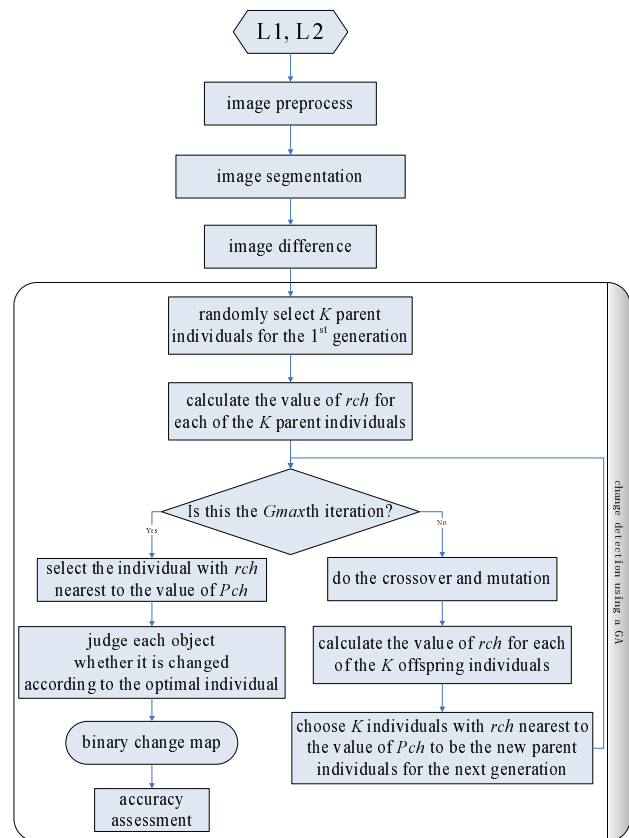


Figure 1. Flow of the proposed method

3. EXPERIMENT

3.1 Study areas

In the experiment, a pair of multi-temporal high-resolution images was investigated. They were acquired by the QuickBird satellite separately in April 2002 and April 2005. The multi-temporal images covered a similar area of Wuhan in the central of China. In order to preserve the spectral information as much as possible, the multispectral images were used in the experiments. Each of the images had four spectral bands, namely, the red band (0.45–0.52 μm), the green band (0.52–0.60 μm), the blue band (0.63–0.69 μm) and the near infrared band (0.76–0.90 μm).

The study area was around the campus of Wuhan University (Figure 2) in Wuhan City. It covered an area of 400×400 pixels, with a spatial resolution of 2.4 m. The ground objects contained the roofs, vegetation (grass and trees), water (swimming pool and pond), bare land, rubber ground (playgrounds), roads and shadows. The changes to be detected were the anthropogenic changes that can reflect city development, such as the appearance or disappearance of man-made green areas, and the construction or reconstruction of buildings.

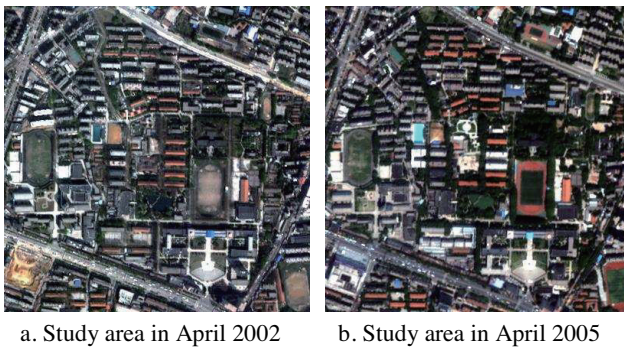


Figure 2. Study areas in the multi-temporal images

A good pre-processing could remove some valueless difference information in the initial multi-temporal images and improve the result of change detection. In the experiment, the 2002 image was taken as the reference one and the 2005 image was processed based on it. Firstly, registration was performed using the software of Envi 4.6 (ITT, Westchester Avenue, New York, America). As they were recorded on different dates of the year and also at different times of the day, the two images were received in considerably different illumination conditions. Therefore, a relative radiometric correction to the image of 2005 was performed on the basis of the one of 2002. As the aim of detecting the anthropogenic changes reflecting the development of this area, the changes resulting from vegetation growth and shadow covering would affect this work. The areas covered by vegetation or shadow were masked in both images for each study site. Lastly, a median filter was applied to each image to reduce the redundant details.

3.2 Statistical Evaluation

To evaluate the proposed method roundly, we did three sets of experiments from different aspects. In addition, the obtained results were compared to the pixel-based change detection using a GA (Celik, 2010) and the object-oriented CVA (Bovolo, 2009).

According to the reference data of ground truth, the ratio of changed areas is approximately 20% in the study area. The ratios of individuals to do the crossover (P_c) and mutation (P_m) were both 50%. In this way, it is convenient to assess the obtained results by varying a certain parameter, such as the segmenting scale, the number of individuals in every generation (K) or the iterative degree (G_{\max}).

Firstly, it was investigated how the varying scale would affect to the results of the proposed method. Ranging from 10 to 100, ten scales were selected with equal intervals. After the process of segmentation with different scales, the image difference and change detection processed with same parameters. The number of individuals in every generation (K) was fixed as 140 individuals while the iterative degree (G_{\max}) was always 100,000 iterations. As different scales bringing on different sizes of objects, the results of the proposed method were various. The Overall Errors, which included False Alarms and Missed Alarms, were used to assessing the accuracy of change detection. It means the number of pixels wrongly or missed detected as the changed ones in the totally 160,000 pixels in each of the multi-temporal images. According to the first and second rows of Table 1, the optimal scale of the proposed method in this study area was about 20.

scale	Overall Errors (the proposed method)	Overall Errors (the object-oriented CVA)
10	8052	9070
20	7617	8657
30	8251	10231
40	8593	9788
50	9062	10143
60	9328	10447
70	9574	10935
80	9537	10265
90	9758	12376
100	10143	11572

Table 1. Comparison of Overall Errors between the proposed method and the object-oriented CVA

Besides above, we did the experiments with different numbers of individuals in every generation (K) to analyze its infection in the proposed method. The segmenting scale was invariably 50 while the iterative degree (G_{\max}) was 100,000 iterations at all time. The Figure 3 shows the Overall Errors with different values of K varying from 20 to 200 individuals. With the increasing value of K , it was hard to summarize the changing pattern of Overall Errors. The relatively superior value of K in this range was around 140 individuals with the least Overall Errors of approximately 9500 pixels. Thereby, we could conclude that the increasing number of individuals in every generation could not apparently improve the result of change detection based on a GA.

Additionally, we did a set of experiments to evaluate the role of the iterative degree (G_{\max}), which represented the total number of generations in the process of inheritance. The segmenting scale was kept as 50 while the number of individuals in every generation (K) being fixed as 140 individuals. The iterative degree (G_{\max}) changed from 10,000 to 100,000 generations. According to the obtained results, different values of G_{\max} resulted in different number of Overall

Errors (Figure 4). Moreover, the Overall Errors decreased persistently with the increasing value of G_{max} . Therefore, the total number the generations in the iteratively genetic procedure could directly affect the results of genetic algorithm (GA). The results would be more superior if the iterative degree (G_{max}) increases.

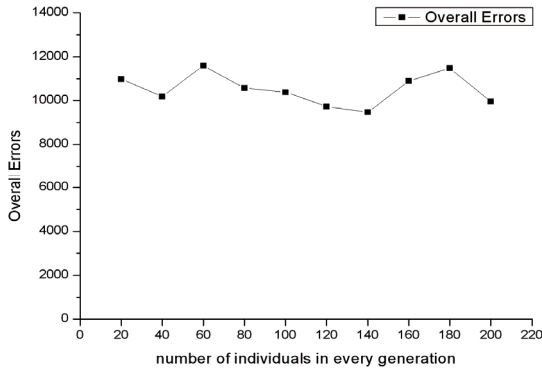


Figure 3. Overall Errors with different value of the number of individuals in every generation (K)

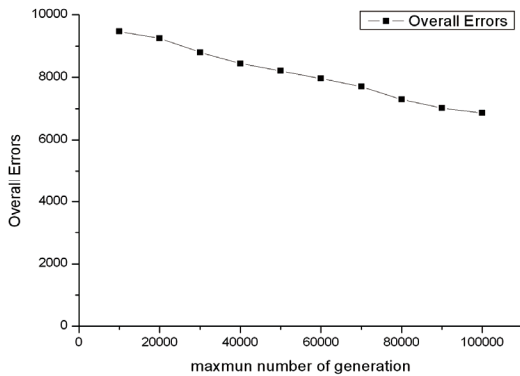


Figure 4. Overall Errors with different value of the maximum number of iteration (G_{max})

To prove the superiority of object-based method, the proposed method was compared to a pixel-based change detection method using a GA (Celik, 2010). In these two method, the number of individuals in every generation (K) was fixed as 140 individuals, while the iterative degree (G_{max}) changing from 20,000 to 100,000 iterations. The segmenting scale was kept as 50 in the proposed method. Table 2 shows the Overall Errors and elapsed times between these two methods. With same value of G_{max} , the Overall Errors of the pixel-based method increased more than 2500 pixels from the Overall Errors of the proposed object-oriented method. Furthermore, the pixel-based method needed a dramatically longer time than the object-oriented one. These could both verify the predominance of the proposed object-oriented change detection method with respect to the conventional pixel-based one.

In addition, in order to prove the effectiveness applying the genetic algorithms (GAs) into the object-oriented change detection, the results of the proposed method were compared to the object-oriented CVA (Bovolo, 2009) (Table 1). The Overall Errors of our method decreased by more than 1,000 pixels from the object-oriented CVA. Therefore, it could be conclude that the genetic algorithm used in the proposed method is suitable for searching the binary change detection map.

G_{max}	the proposed method		the pixel-based method	
	Overall Errors	elapsed time (min)	Overall Errors	elapsed time (min)
20,000	9253	20	11863	115
40,000	8446	38	11036	241
60,000	7963	55	10752	356
80,000	7298	76	9846	472
100,000	6862	98	9472	618

Table 2. Comparison of Overall Errors and elapsed time between the proposed method and the pixel-based change detection using a genetic algorithm (GA)

3.3 Visual inspection

Synthetically analyzing our experiments, the currently optimal result was obtained when the scale was 50, the values of K was 140 individuals and the value of G_{max} was 100,000 iterations. The binary change detection map is shown in Figure 5(a), in which white objects present the change regions, and black objects indicate the unchanged areas. Figures 5(b) shows the best results of the pixel-based change detection using a GA (Celik, 2010). The salt-pepper effect was serious in the result of pixel-based method, while the local spectral variation was effectively depressed by the proposed method. This proved the superiority of the object-oriented techniques in the change detection of high-resolution remote sensing imagery. Additionally, the optimal result of the proposed method could be also compared with the best results of the object-oriented CVA (Bovolo, 2009) with scale 20 and threshold 2 (figure 5(c)). The False Alarms of the proposed method was obviously less than the object-oriented CVA.

It was seen that the binary change detection map of the proposed method was approximately the same as the reference one (figure 5(d)), which presented the virtual changes in the observed field. However, there were some inevitable errors. The False Alarms were mainly due to the relatively larger objects covering over the edges between the changed and unchanged areas. On the other hand, the Missed Alarms primarily result from the relatively small objects in the changed areas. As the size of objects was less than the area that really changed, some of these pairs of objects were more similar than the others. Therefore, it was likely that these similar pairs of objects would be detected as unchanged.

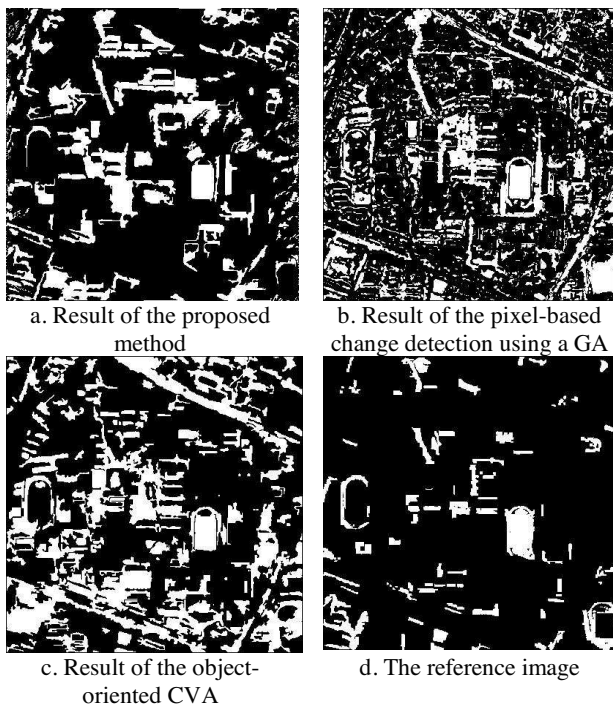


Figure 5. Visual comparison of the results

4. CONCLUSION

In this paper, we proposed a novel method of change detection for the high-resolution imagery. The object-oriented technique is employed by segmenting the pre-processed multi-temporal images into the same sets of objects. In the process of image difference, an absolute-valued difference is firstly calculated for each pixel in a same object according to the spectral information in each pair of the initial multi-temporal images. Then these pixels are presented as the mean value of these differences, which would be seen as the spectral value of the corresponding object. The process of change detection is specific to the sets of objects in the differenced segmented map. As the degree of changed areas in the study area is known as a priori knowledge, a GA is employed to search the optimal binary change detection map. For all the objects in the map, every probability about their changing condition is considered as an individual in this genetic iterative search. The evolutionary biology of crossover and mutation would be occurred in each of the iterations. The termination condition of search is the degree of genetic iteration, which is user-defined. According to the optimal individual gotten in the end of search, the changing condition of every object could be confirmed, from which the final binary change detection map would be generated.

Compared with the pixel-based method, the superiority of the object-oriented method lies in processing the multi-temporal images with unit of an object rather than a pixel. In this way, the spatial and spectral information of images can be fully used. On the other hand, it is effective in reducing the local spectral invariance and avoids the salt-pepper effect for the high-resolution images. Compared with the object-oriented CVA, in the process of image difference, the proposed method uses the initial spectral values of pixels to generate the difference segmented map, instead of mean values of objects. Comparing the mean value of absolute-valued difference with the absolute-valued difference of mean values, the former used in

the proposed method has a minor variance than the later one. This can avoid from loss of some useful information and the limitation of CVA. In addition, the global searching characteristic of a GA is suitable to find the optimal binary change detection map in the existing condition.

According to the results of experiments, the proposed method has proved to be an improvement on the current methods. However, there are still some problems worthy to be improved. We will focus our work on the automation and fitness criteria of the GA used in the object-oriented change detection.

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