

CHANGE DETECTION OF LINEAR MAN-MADE OBJECTS USING FEATURE EXTRACTION TECHNIQUE

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ABSTRACT:

Most of the research in remote sensing is focused on developing well-defined and reliable automated processes for the extraction of information from different types of imagery. In this communication we are dealing with the extraction of linear man-made objects (especially buildings) in urban areas and the determination of changes in these objects using high resolution IKONOS imagery. The modern world needs accurate information about these changes for urban planning and Geospatial Information Systems updating. Our change detection approach is based on feature extraction using interesting points and edges. Linear rectangular features such as buildings can be defined by corner points and edges joining those corner points. We have found that each man-made object formed different groups of corner points and edges, which is useful to classify them. To detect changes between the multi-date IKONOS images, the same man-made objects (i.e. buildings) have been extracted in both images. Using positional information and feature matching techniques the changes have been determined. For the validation and improvement of the results, changes obtained using our technique have been compared with changes obtained from a method using principal component analysis. Limitations and advantages of these two methods for change detection of man-made objects are also discussed.

1. INTRODUCTION

Change detection of man made objects (buildings) using satellite images is one of the important applications of remote sensing. Human can easily detect changes using images, but it is very time consuming and unreliable to depend only on a human operator for complicated work, such as change detection and feature extraction especially in urban areas which are heterogeneous and very complex areas. Therefore the development of automated processes is necessary. There are many issues that need further investigation for the development of fully automated processes. Different approaches for change detection are based on the details of information needed. These approaches can be classified in three groups. The first two approaches are categorized as "Preliminary change Detection" (Forsythe, 2004) and "Detailed change detection" (Huertas *et al.*, 1997) procedures, the third group deals with Change Analysis (Shettigra, 1995).

An operational automated process for change detection and its use for GIS updates should include the following functions.

1. Generation of new version of building layers using feature extraction technique and remotely sensed images.
2. Detection of changes using feature matching technique to identify unchanged, disappeared and newly constructed buildings.
3. Extraction of building layers and detection of changes for GIS updates should include transferring attributes from the old version database to the new version one and organizing both versions in such a way that facilitates efficient spatio-temporal queries and analysis (Zhang and Couloigner, 2003)

An accurate extraction of the objects of interest is very essential for change detection. Almost all methods for feature extraction are based on edge detection. The detection of accurate edges for every feature is a very difficult task. Our newly developed

method is based on feature extraction using multiple edges detected from very high spatial resolution images of an urban area. This paper presents a generic framework for building extraction, change detection using high spatial resolution images and some of our research achievements along this line.

2. FRAMEWORK FOR BUILDING EXTRACTION AND CHANGE DETECTION

The proposed framework of an automated process of change detection is shown in Figure 1. Non linear and linear shaped buildings can be extracted using our new developed method. Feature matching technique is used for detecting changes. Each individual building boundary is identified. Separate identification pixel value is assigned to each building boundary. This is helpful for storing the boundaries of each building in a vector format.

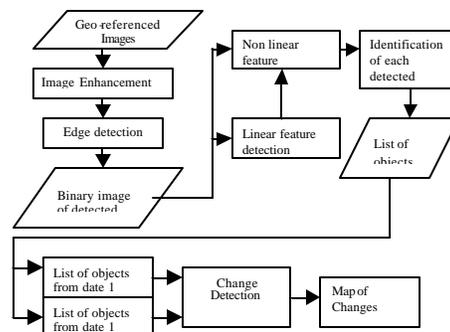


Figure 1. Framework for building extraction and change detection using high resolution image

3. AUTOMATED PROCESS FOR BUILDING EXTRACTION AND ITS CHANGE DETECTION

Orthorectified and perfectly registered IKONOS panchromatic images of the City of Fredericton, New Brunswick, Canada for the year 2001 and 2002 are used to detect changes in man-made objects. This method is divided into the four following steps:

1. Image enhancement and edge detection.
2. Preliminary boundary detection of the buildings
3. Extraction of complete boundaries of buildings
4. Change detection using feature matching

3.1 Image enhancement and edge detection.

Our feature extraction technique is based on the detection of the boundaries (edges) of each building. The results of our algorithm are very much dependent on the clarity of the edge-detected images. Results of edge detection operators are depending on the contrast between the objects, therefore it is necessary to apply some image enhancement. We used the Laplacian type1 and Laplacian type2 operators for the edge detection (Berzins, 1984).

3.1.1 Edge detection: It is well known that each edge detector algorithm has some pros and cons. To obtain complete boundaries of a building, we decided to use multiple edge-detected images. Additional edge-detected images act as a backup to provide information about missing edges in the first edge-detected image. It is not advisable to do simple addition of the edge-detected images resulting from different algorithms. Indeed it will add a lot of noise in the final derived image. As our algorithm is based on a line following technique, we preferred to use less noisy and sharp edge images. Laplacian type1 operator gave us a thin edge-detected image. However the edges were not extracted for some portions of low contrast boundaries. On the other hand the Laplacian type2 operator detected all edges in the image, but those appeared very thick and noisy. Therefore we used the thin edge-detected image for a preliminary boundary detection.

3.2 Preliminary boundary detection of the buildings

The thin edge-detected image is first converted into a binary format. Corner (interesting) points were then extracted using the Forstner operator (Forstner, 1986). We determined the boundaries of the buildings by using template matching at corner points and line following technique. Boundaries of non linear buildings are determined using a line following technique (Zhang *et al.*, 2004). This first stage do not provide complete continuous boundaries of buildings due to missing edges.

3.3 Extraction of complete boundaries of buildings

We determined end points of the preliminary boundaries of the buildings. Some of the end points are joined to fill pixels of discontinuous edges. The direction of the edges and the distance of the gaps were the main criteria for joining the end points. The missing edges were detected from the thick edge-detected image by using positional information of the preliminary edges and matching them with the thick edge-detected image. At this stage we were able to extract complete boundaries of buildings. After the determination of complete boundaries on the basis of pixel connectivity, each boundary was identified as a separate group of pixels. Different pixel value was assigned to each group of pixels in order to obtain an identification value for each building.

3.4 Change detection using feature matching

Based on the positional information of buildings, each extracted building was paired in both images. Using matching technique, match and unmatched pixels were determined for each building. Based on this information, extracted buildings were classified as missing, new or unchanged building

4. CHANGE DETECTION USING PRINCIPLE COMPONENT ANALYSIS METHOD

To obtain changed pixels in temporal images one can use the principle component analysis method (Singh, 1989). The relation between the spectral signal $x_1(T1)$ and $x_1(T2)$ received from a reflecting surface at two times $T1$ and $T2$ is very often modeled approximately as a linear function (Richards 1993, Singh 1989). Based on this linear function, one can plot all pixels along two axes, the first and second principal components. One of the axes represents the unchanged component of the temporal images and the perpendicular one represents the change component.

It is expected that all unchanged pixels will lie in a narrow elongated cluster along the first principal axis (PC1). On the other hand, the pixels which have experienced change in their spectral appearance are expected to lie far away from this axis. The mean of the transformed vectors along the change axis is then computed. By using an optimum threshold, pixels are then classified into change or unchanged pixels.

The magnitude of the second principal component (PC2), *i.e.* the magnitude of the 'change', is given by Equation 1:

$$c_i = e_{2,i}^T (x_i - m_i) \quad (1)$$

where:

$e_{2,i}$ is the second eigenvector of the overall covariance matrix given by Equation 2:

$$C_i = 1/n \sum x(x_i - m_i)(x_i - m_i)^T \quad (2)$$

i is the spectral band number

m_i is the mean of all n pixels in that band (Richards, 1993).

By applying an appropriate threshold, unchanged pixels and noisy pixels are removed from the change image (Phalke and Couloigner, 2004).

5. RESULTS

5.1. Change Detection results using the Principle Component Analysis method

Figure 2 represents the principal component analysis for our 2 IKONOS dataset for two subsets. It shows that most of the unchanged pixels lie along the PC1 axis (which is shown in dark grey) and that changed pixels are diverted from the PC1 axis towards the PC2 (which is shown in light grey) axis.

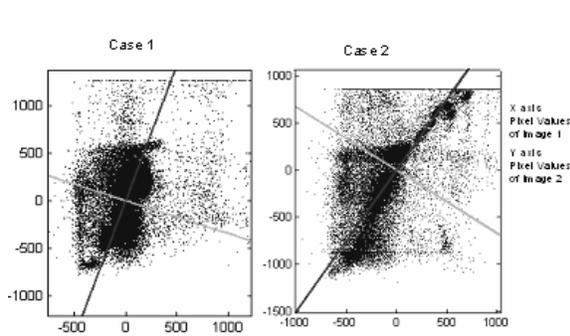


Figure 2. Principal Component Analysis of the 2001 and 2002 IKONOS data.

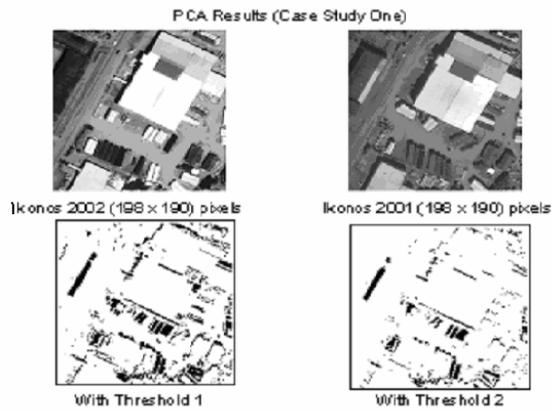


Figure 3. Change Detection using PCA for Case Study One.

Figure 3 and Figure 4 represent the detection of the changes for two thresholds for case one and two respectively. They demonstrate that shadow effects in the images lead to errors in the detected changes. Even sub-pixel misregistration causes error in the derived change image. Man-made objects of size up to 10×10 pixels are very well located in the changed image in both cases. Some relatively small dark objects (containers) located at the bottom of the image disappeared from the 2001 image, but were replaced by other ones in the 2002 image. This change could not be detected completely using the PCA method due to similar spectral response of the objects. It can be clearly observed in Figure 4 that shadow of building located at bottom portion of image appeared as a change. The small objects (containers) located at center portion of the image 2001 are missing in 2002 image. This change is detected in the PCA change image. It is also observed there are lot of small man made objects (cars) in upper portion of image 2002 are missing in image 2001. Even this change is partially observed in PCA results.

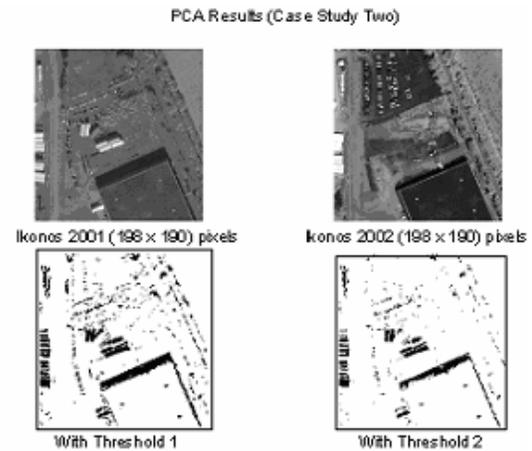


Figure 4. Change Detection using PCA for Case Study Two

5.2. Results of change detection based on automated building extraction process

Figure 5 represents the first stage results from our method for the case study one. The first two images shown in the top row of Figure 5 are the enhanced subset images of our Ikonos panchromatic data set. The bottom row of the figure contains the edge-detected images obtained by the Laplacian type 1 operator for both years.

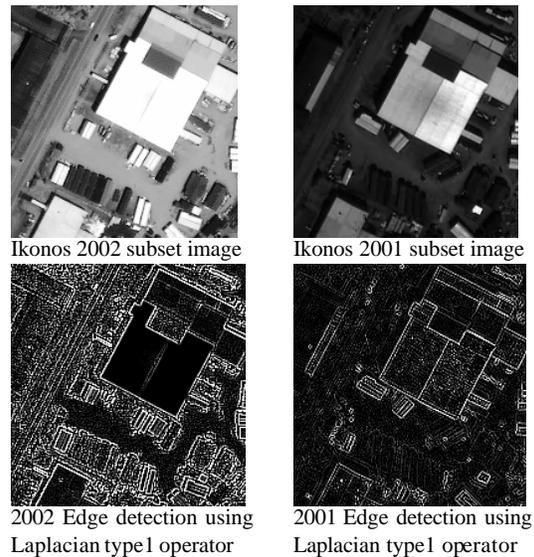


Figure 5. Enhanced subsets of Ikonos Panchromatic images

It can be clearly observed from Figure 5 that the contrast in the 2002 image is better. Therefore most of the detected edges appeared sharper but at the cost of additional noise. The 2001 image is of poor contrast, hence some of edges of some small objects were not detected. However the 2001 edge-detected image contains less noise. One needs to decide an optimum trade-off for the adjustment of contrast.

Figure 6 represents the results from Laplacian type 2 operator (top row of the figure) and the preliminary extracted objects (bottom row).

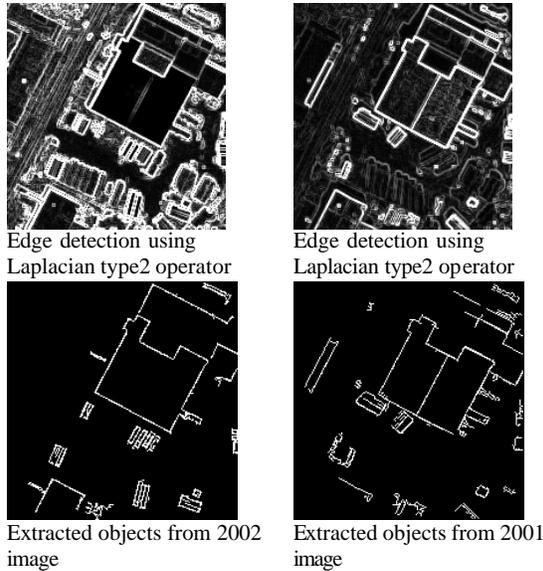


Figure 6. Second stage input images to obtain modified object boundaries

We can see clearly on Figure 6 that there are some missing boundaries in the 2001 image compared to the 2002 image and vice versa. The small dark objects boundaries are not detected by our method.

Figure 7 shows the final output we obtained using our feature extraction based method. The top row of Figure 7 shows the modified extracted objects.

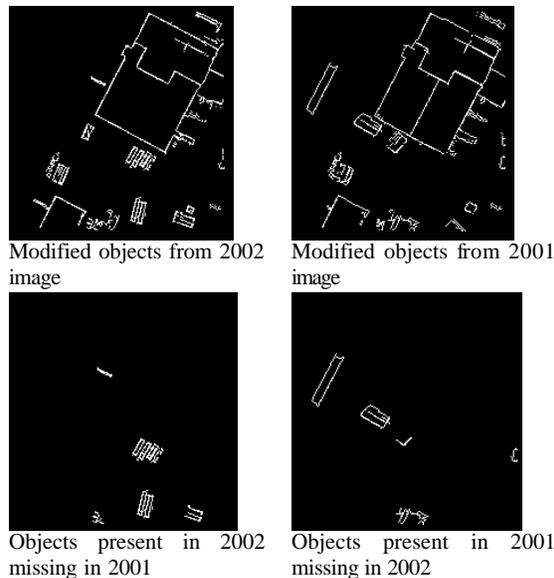


Figure 7. Modified extracted objects and completely changed objects

From Figure 7, it can be clearly seen that some of the edges of objects (top row) not extracted during the first stage appear now. One can even add the unchanged objects boundaries obtained from both images to obtain complete object boundaries. Extraction of a complete object is very essential for GIS update. For GIS update some of the inside edges of the extracted objects need to be eliminated. The bottom row of

Figure 7 contains the changed objects. It is very difficult to identify partially changed objects, because one needs to discriminate between changed and unchanged pixels. It is difficult to find if changed pixels are due to actual changes or due to misregistration, shadow effect or, missing edges for example. However if the change in an object is more than fifty percent, it is easy to identify those objects. Some objects (buildings or containers) are not present in one of the images but are present in the other one (see top row of Figure 5). These changes have been detected by our method (see bottom row of Figure 7).

5.4 Summary

Accurate extraction of buildings and other similar shaped man-made objects depends on the clarity of their edges in the edge-detected image. The small objects that are very close to big objects got connected. Therefore our algorithm considers both objects as one single object. Even in modified objects small portions of the boundaries are discontinuous. However it is still good for change detection. Partial small changes in the objects have been ignored due to the chosen threshold.

6. COMPARISON OF PCA METHOD AND FEATURE EXTRACTION BASED METHOD

The changed image obtained using the PCA method contains more noisy pixels. Shadow effects appeared as change in the PCA results. That is not observed in the results of our method. Sub-pixel misregistration caused errors in the PCA-based change image. This is also not observed in the results of our method. The PCA method just finds out changed pixels but is not able to discriminate between missing objects and new objects. This discrimination is possible with our method. The results obtained by our method are useful for a GIS update. Change detection obtained by both methods depends on image enhancement and radiometric adjustments.

To quantitatively compare the methods, it is necessary to have a information about actual change. This information is obtained using digitization. Some information has been quantified such as total number of pixels in subset portion, number of matched and changed pixels. We calculated accuracy of methods using Equation 3.

$$\text{Accuracy} = (\# \text{Mat. pixels} / \# \text{Ref. Mat. Pixels}) \times 100 \quad (3)$$

The results of this comparison are presented in Table 1. This table shows that our method gives better results, 90 percent of unchanged pixels compared with 82 percent achieved by the PCA.

	# Pixels	#of Matched Pixels	# changed pixels	Accuracy
Digitization (Reference)	21623	19837	1786	100%
PCA Case 1	21623	16433	4390	82.84%
Feature Ext. Case 1	21623	17921	1231	90.34%

Table 1 Comparison of PCA and Feature extraction based method for change detection

7. CONCLUSIONS

The overall accuracy for change detection using the PCA technique and feature extraction based method for change detection in buildings and similar shape objects is 82% and 920% respectively. Our feature extraction based method seems more efficient than the PCA method for man-made object extraction and change detection. However it is difficult to detect partially changed boundary of building using our method. Results obtained from our method can be easily stored in a vector format. Therefore these results are useful for a GIS update. Use of multiple edge-detected images provides improved results. Even though our results are encouraging those are very much dependent on the edge detected input.

8. REFERENCES

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