BUILDING CHANGE DETECTION BASED ON OBJECT EXTRACTION IN DENSE URBAN AREAS

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Commission VI, WG VII/5

KEY WORDS: Aerial, Object, Extraction, Segmentation, Building, Change Detection, Urban

ABSTRACT:

This study presents a novel approach for building change detection from digital surface models (DSMs), which are generated from the images acquired by a multi-line digital airborne sensor ADS40. Our approach is based on building extraction, which is one of the most challenging research fields. A scheme is proposed that allows efficient integration of a local surface normal angle transform (LSNAT) method and a marker controlled watershed segmentation (MCWS) method for building extraction in dense urban areas mainly from DSMs, and subsequently, performs change detection based on the results of building extraction and the height difference of DSMs. The merits are that really changed buildings are detected, and false-detection can be decreased considerably compared to some other change detection methods. The proposed approach presents wonderful results for building extraction and acceptable results for change detection.

1. INTRODUCTION

Change detection of man-made objects in dense urban areas using high-resolution aerial images is one of the most attractive and challenging research fields in remote sensing. One of the important practical applications is to solve the common needs of assessors, property inspectors and some other government entities responsible for creating, maintaining and updating building description lists to grasp the new physical characteristics resulting from new construction or other property alterations (Carroll, 2001). It is not easy to track all of the building changes within a metropolitan environment with potentially millions of buildings. However, the availability of high resolution aerial imagery can provide a high quality temporal record of building changes over a short-term or long-term duration. The challenge is to develop a reliable change detection approach by comparing previous records to the new imagery. Many studies have contributed to change detection from high-resolution images (Murakami et al., 1999; Agouris et al., 2000). However, it has proved to be quite difficult due to the complexity of urban environments and the redundant information in the images. Most change detection approaches focus on performing pixel-level or feature-level comparison of past and present images. However, too much false-detection, i.e. over-detection and miss-detection is still an avoidable problem, and these approaches are far from being useful in practice. Thus, there is a great demand for development of corresponding new strategies to detect building changes.

In order to solve the problem to detect really changed buildings correctly, and at the meantime, to avoid too much false-detection, a two-stage approach is applied in this study. In the first stage, buildings are extracted by two novel methods, the LSNAT method and the MCWS method, respectively. The results of the two methods are combined together for the next change detection stage. In the second stage, change detection is performed based on the height difference of past and present DSMs, and the results of building extraction which are used as mask data to identify really changed buildings and decrease false-detection.

2. BUILDING EXTRACTION

In this study, building extraction is implemented by following three steps. The first step is to generate a normalized DSM (NDSM). DTM is derived from DSM by morphological filtering. Morphological operators are used to remove aboveground features. A low pass filter is used to smooth the DTM in order to remove step effects. Then, the NDSM can be generated by subtracting DTM from DSM. The second step is to perform building extraction by the LSNAT method and the MCWS method. The LSNAT method uses a hierarchical strategy to extract huge buildings and small gabled buildings, respectively. Huge buildings are extracted by thresholding the NDSM and morphologically processed in order to separate the objects connected and remove some small areas. After the extraction of huge buildings, the extraction of small buildings with gabled roofs is implemented through the extraction of roof plane. Since some small buildings with very small areas, low heights and plane roofs are easily miss-detected, the MCWS method is applied. The MCWS is an improved method based on general watershed segmentation to avoid over-segmentation. The aboveground objects are assigned foreground markers, and the ground of the NDSM is taken as the background and is assigned background markers. The final results of building

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extraction are derived by merging the results of the MCWS method together with that of the LSNAT method.

2.1 Normalized DSM Generation

Morphological operators are used to remove aboveground features, like buildings, trees, cars, and other objects since they are proved to be suitable for such shape processing of the objects. A morphological filter performs first a close operation to fill the pits in the DSM. A close operator dilates the DSM first and erodes it then. After that, the morphological filter performs an open operation to remove surface obtrusions such as buildings, trees and cars. The size of morphological element is decided by the size of the maximum object to be removed. Since removing aboveground features with a large-scale element will cause step effects in the DTM, a low pass filter is used to smooth the DTM.

Then, the NDSM can be generated by subtracting DTM from DSM. The NDSM refers to the surface that suppresses the terrain height to an equal level. It gives the real heights of the objects above the ground and can be segmented according to a certain height threshold.

2.2 Local Surface Normal Angle Transform

From the NDSM, it is found that that some buildings are quite small. If a low threshold is used to binary them, there will be large non-zero regions composed of several connecting buildings. If on the contrary, most buildings can simply be segmented but the small ones will be lost. Therefore, roof plane extraction by local surface normal analysis is used.

There are several methods for obtaining local surface normal from range data. The basic approach is to fit a continuous differentiable function to data and compute its derivatives analytically. In this study, a local quadratic surface least squares method is used to obtain normal vectors. When estimating normal vectors, the idea is to choose a local neighborhood, and determine the planes that fit to the points in the neighborhood. The normal of the plane is obtained as the normalized coefficients of the fitted local plane.

Now the NDSM can be transformed into two normal angles α and β at each grid. They represent the normal vector by directions. Figure 1 illustrates local surface normal angle transformation.

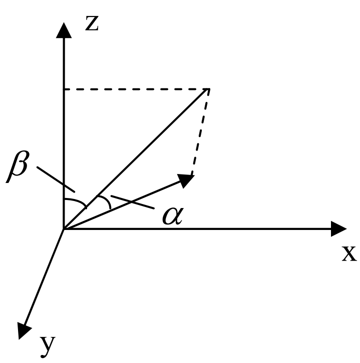

Figure 1. Local surface normal angle transform

Then a 2D histogram of the angles can be generated. The peaks will correspond to the directions of concentrated normal vector directions. The roof grids with the same normal direction will generate a peak in the histogram, and so do other roof grids and ground grids, etc. By extracting the grids corresponding to some peaks, the planes corresponding to some roofs can be detected. Figure 2 shows the histogram of two angles of the LSNAT.

Figure 2. Histogram of two angles of the LSNAT

It is obvious that the 2D histogram generates approximately three main peaks. Among the three peaks, the maximum value occurs at the center. It implies that the directions of the normal mostly go upward. They represent the pixels of the ground and horizontal roofs. The other two peaks locate at the arcs symmetrically. They represent the grids of the gabled roofs, respectively.

If a building has a gabled roof, it should show at least a pair of plane. Thus, the following approach is applied to detect small buildings. The numbers of grids corresponding to the upper left circle and lower right circle of the 2D histogram are counted within a watershed region. The ones with grids greater than a certain value are taken as a building.

Here, if we extract the plane first and detect buildings, the plane will be too much and disordered. Thus we decide to detect huge buildings and small buildings separately. Before plane extraction, huge buildings are segmented in advance to make the roof detection easier. For the remained buildings, the LSNAT is performed and the gabled buildings are extracted.

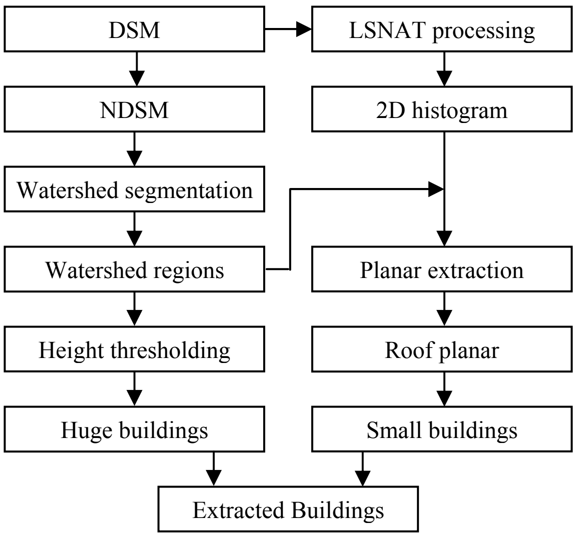

Figure 3. Flow chart of building extraction using the LSNAT

Figure 3 shows the flow chart of building extraction using the LSNAT method. In this study, the huge buildings are extracted by the following steps: 1) Threshold the NDSM. Then the huge buildings and trees will be segmented as large regions. There will also be some regions corresponding to small buildings but generally not the whole of them; 2) Erode the thresholded NDSM to separate the objects connected, removing the small area again, and dilate the remained regions to the same extend; 3) Detect the edges within the regions of the LSNAT over a certain intension, and calculate the edge density. The huge buildings are detected by an edge density threshold.

Comparing with the watershed segmentation, it is found that by watershed, a huge building may be segmented in several parts. While by NDSM thresholding, it maintains the correct contour. It is also found that by thresholding, some small buildings connected each other are always segmented as a large region, but by edge density limitation, this kind of region can be excluded. Since the large regions generated by watershed are either huge buildings or masses of trees, thus, the huge buildings are detected, and the remaining large regions are tree mass and are excluded from building extraction.

The small building extraction is implemented through roof plane extraction. However, we have not extracted the plane roofs corresponding to the greatest peak, the center of the circle in the histogram. They represent the normal up-straight, or, the plane roofs. Here, the grid with this normal angle are not extracted as the roofs, because the area including higher ground or somewhere within a mass of trees or a circle of walls in NDSM are also plane and corresponding to this angle.

2.3 Marker Controlled Watershed Segmentation

Watershed to gray level image is suitable for the gray level images to separate the objects each others. But it will not give the actual boundaries of each object. The boundary between two objects by watershed just locate somewhere between them, not exactly the object contours.

Watershed to gradient image can resolve this problem and give the real contour of the object. If we apply the watershed to the gradient image, the catchment basins will be the dark regions of the gradient image, which should theoretically correspond to the homogeneous grey level regions. Then the watershed will stop at the contours of the dark objects in the gray level image.

However, in practice, this transform produces an important over-segmentation due to noise or local irregularities in the gradient image. To avoid the over-segmentation, a marker controlled watershed is introduced (Gao *et al*. 2001, Salembier *et al*. 1994). Here, the watershed segmentation is implemented to the gradient of NDSM (GNDSM). A marker is an area which is the initial of a catchment basin. By giving each object and the background a marker, and making them the catchment bases, the desired objects can be segmented from the background.

Figure 4 shows the flow chart of building extraction using the MCWS method. When using the MCWS method for building extraction, large regions need to be segmented from NDSM firstly to avoid multi-marker of woods and huge buildings. If not, there will be several catchment bases detected for a huge building and therefore it will be taken as several objects.

Buildings, trees, and other off-terrain objects are taken as the foreground objects and are assigned the foreground markers. A foreground marker is a spot. If it is the catchment basin for the gradient then the marker will grow to an object. There will be as many objects as foreground markers.

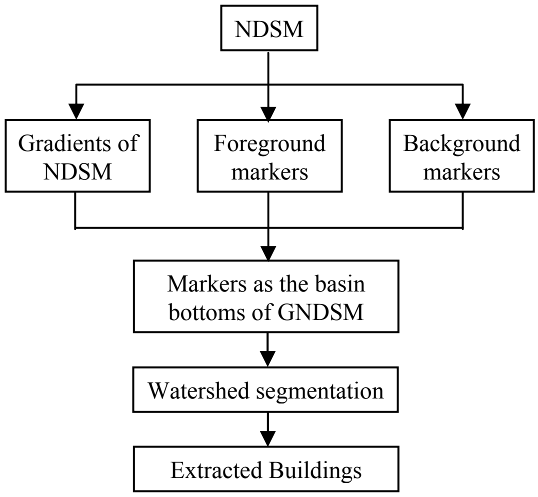

Figure 4. Flow chart of building extraction using the MCWS

The foreground marker is detected by local maxima. The local maximum of an object may be a spot with certain area as a marker. For the buildings with flat roofs, all the pixels in the roofs will be detected as the local maximums in the ideal case. In practice, most pixels of the roof, especially in the center, will be detected as the marker spot. For some objects, because they have more than one obstruction in the roof, there will be several markers detected and consequently they will be segmented as several objects. This disadvantage can be avoided by merging the large regions with the foreground markers.

The ground of NDSM is taken as the background and is assigned the background marker. Because the watershed of the segmentation of the NDSM generally locates between objects, it is initially taken as the marker of the background. Sometimes the background marker crosses large regions so that these objects will grow to the background. A refined procedure is implemented to maintain these foreground markers.

The building extraction results by the MCWS method are merged together with that of the LSNAT method, then, the orthoimages are used to identify the trees and shrub areas, and the final results of building extraction can be obtained.

3. CHNAGE DETECTION

For building change detection, the height difference of the past and the present DSM are calculated first. Then, a height thresholding and a morphological spatial processing are performed in order to remove noises and extract the areas which have a real change in height. However, there still exists a lot of false-detection due to the unavoidable problem of the DSM quality. Our strategy is that the change detection will be limited within the area where the buildings have been extracted. The extracted buildings are taken as the mask to the DSMs. For a building in the past, it is checked to see if the height has any change within its contour by subtracting the DSM of present from the DSM of past. The same procedure is carried out to a building in the present. Finally, the change detection results from these two procedures are merged together. This strategy allows that the really changed buildings are detected, and false-detection be decreased considerably compared to some other change detection methods. Figure 5 shows the flow chart of the change detection algorithm.

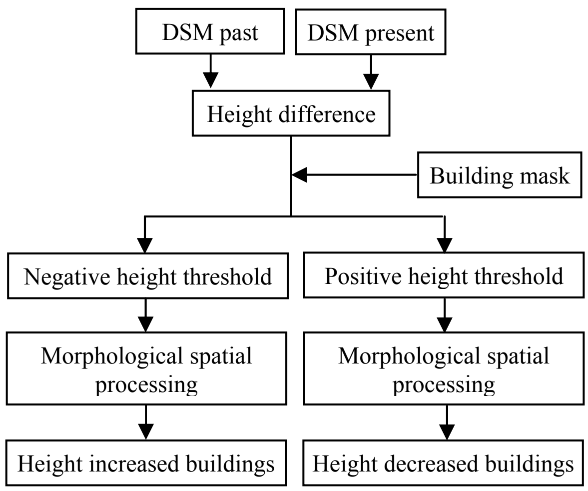

Figure 5. Flow chart of the change detection algorithm

4. RESULTS

In this study, DSMs and aerial orthoimages of Yokohama and Sapporo, Japan, are used to assess the performance of the proposed approach for building extraction and change detection. The past and present data of Yokohama are acquired in January 2003 and January 2006, and that of Sapporo are acquired in June 2005 and June 2006, respectively. All these data are obtained by the multi-line digital airborne sensor ADS40 and are processed by the Pixel Factory system of Infoterra France. The resolution of DSMs is 1m and that of RGB orthoimages is 0.2m. Table 1 shows the results of building extraction in Yokohama and Sapporo.

	Yokohama region			Sapporo region	
	Area 1	Area 2	Area 3	Past	Present
Building number	1108	957	1531	6912	6946
Building extracted	1090	950	1523	6817	6747
Building missed	18	7	8	95	200
Extracted Accuracy (%)	98.4	99.3	99.5	98.6	97.1

Table 1. Building extraction results of Yokohama and Sapporo

The performance of building extraction is assessed by comparing the buildings extracted from the DSMs with that observed from the orthoimages. A building extraction rate is defined as the ratio of the extracted buildings with respect to all the buildings. If there is a building observed in the image at the location of the extracted building from DSM, it is taken as detected. The building extraction results of three test sites of Yokohama region show high building extraction rate that are greater than 98%. In Sapporo region, the results of the past and present data also present building extraction rate greater than 97%. These results suggest that the performance of building extraction by the proposed approach is satisfying. It can be further improved using a near infrared band to remove the influence of vegetation.

The performance of change detection is assessed by comparing the results obtained by the proposed approach to the reference data acquired from field survey and image interpretation. Almost all newly built and vanished buildings are detected except some very small ones. Most enlarged buildings are also detected. The false-detection are decreased considerably compared to that of some other change detection methods. There is a little difficulty for detection of re-built buildings that have almost the same height in the past and present DSMs. However, the proposed approach can be further improved by using DSMs combined with images.

5. CONCLUSIONS

This study presents a novel approach for building change detection based on building extraction in dense urban areas. A scheme is proposed that allows efficient integration of a local surface normal angle transform method and a marker controlled watershed segmentation method for building extraction mainly from DSM data. This procedure ensures a high degree of building extraction. The change detection approach can detect most really changed buildings, and is effective to reduce the problems of false-detection. The proposed approach presents wonderful results of building extraction and acceptable results of change detection in the experiments for performance assessment. It can be further improved by employment of images to make the performance more reliable for practical use.

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