BUILDING CHANGE DETECTION USING 3-D TEXTURE MODEL

Masafumi NAKAGAWA [a, *], Ryosuke SHIBASAKI [b]

[a] National Institute of Advanced Industrial Science and Technology, 1-1-1, Umezono, Tukuba-city, Ibaraki, Japan - m.nakagawa@aist.go.jp

[b] Center for Spatial Information Science, University of Tokyo5-1-5, Kashiwanoha, Kashiwa-city, Chiba, Japan - shiba@csis.u-tokyo.ac.jp

Commission Ⅲ, WG Ⅲ/4

ABSTRACT:

Texture models are potentially very useful for automated urban data revision. We propose a 'model-based change detection algorithm' using three-dimensional urban data. In this algorithm, temporal images are projected on a common three-dimensional geometry model and the latest textures are compared with previous textures to detect an object's change accurately. In addition, a shadow simulation with three-dimensional data can improve the accuracy of image comparison. Consequentially, the authors show that this algorithm is more reliable than an existing image-based change detection algorithm. Experimentally, using observed environmental temporal data, the authors confirmed that their algorithm could achieve reliable change detection with close to a 100% success rate.

1. INTRODUCTION

1.1 Background

Various forms of 3-D urban data have been proposed and fresh maps may provide a reliable geographic information system (GIS) service and accurate results of environment analyses. It is necessary to revise data quickly in order to keep maps fresh. However, maintenance services for 3-D data, such as patch file downloads, are not currently available due to the high cost of 3-D data construction. Therefore, 3-D data revision techniques are required as well as 3-D data reconstruction techniques. A technique that detects changed fields in an urban area with high precision can produce the latest urban information in a time, and update urban data efficiently. This will make it possible to revise 3-D data at a low cost. Thus, change detection is one of essential keywords in the urban data revision.

Buildings, roads, street trees and movers are features to be modeled in the GIS data of an urban area. In terms of numbers, building features are dominant. Thus, if building changes are recognized automatically, the cost performance measure should be considerably improved. "Newly built", "demolition", "replacement" and "extension and remodeling" are counted as a definition of individual building object changes or behaviors. The following three methodologies have been developed to recognize these building changes in urban change detection topics.

(1) Raster-based change detection (detection of feature or segment changes in temporal images [1], [2], [3])
(2) Vector-based change detection (detection of horizontal shape changes in temporal GIS maps [4])
(3) Height-based change detection (detection of temporal objects' volumes [5] [6] [7] [8])

However, especially in urban dense areas, each approach cannot provide flawless and reliable results alone. A limiting factor is the spatial resolution of input data such as general GIS maps and aerial images, which is insufficient to recognize details of individual buildings and makes small building changes with limited data points difficult to recognize.
Moreover, methods 1 and 3 are area change detection approaches, that is, they do not recognize individual object changes. Therefore, even if a changed area is detected, it is uncertain whether the changed area is a building or something else and it is difficult to detect the changed object's attributes.

1.2 Objective

Even in a dense urban area, the authors believe that building change detection can provide more reliable results through a combination of change parameters, such as colors, horizontal shapes and the height of buildings. Here, precise 3-D building data [9][10], which have ultra-high texture resolution as shown in Figure 1, are used as reference information to observe each change parameter of buildings.

Figure 1. Precise 3-D urban data using three-line sensor images

A target of this research is to develop a building change detection algorithm, which detects "demolition", "replacement" and "extension and remodeling" of buildings in a dense urban area.

2. METHODOLOGY

2.1 Model-based change detection

When a 3-D surface in an object space is projected onto a 2-D region in an image space, the 2-D region can be remapped to the 3-D surface as a texture. Moreover, textures taken from the images can be superposed on the 3-D surface in the object space.

Here an image taken from old images is defined as "a reference image" and an image taken from new images is defined as "a comparison image". When detailed 3-D data with textures are prepared, the textures can be used as "reference textures" directly. When there are color changes, horizontal shape changes or height changes of buildings, some differences should exist between the texture of the reference image and that of the comparison image. Based on this, the building change detection process is the motivation for this research, but the accurate orientation of images is as a precondition.

When a building is obtained from image-based model processing, the position and shape of the building are given in the reference image and the object space. Therefore, 3-D reference textures can be produced from the reference image. Next, the 3-D shapes of these reference textures are projected onto the comparison image to detect the position and shape of the same building in the comparison image. Then, the 3-D comparison textures can be produced from the comparison image by projection processing. Then, change detection between the 3-D reference textures and 3-D comparison textures is performed.

It is possible to apply various methods, such as image subtraction or cross-correlation calculation function, to evaluate texture similarity. Therefore, a major part of this change detection algorithm is image subtraction processing. However, the algorithm is substantively based on 3-D geometric constraints, which reconcile the image space and the object space. Therefore, the authors call this algorithm a "model-based change detection methodology" (see, Figures. 2 and 3).
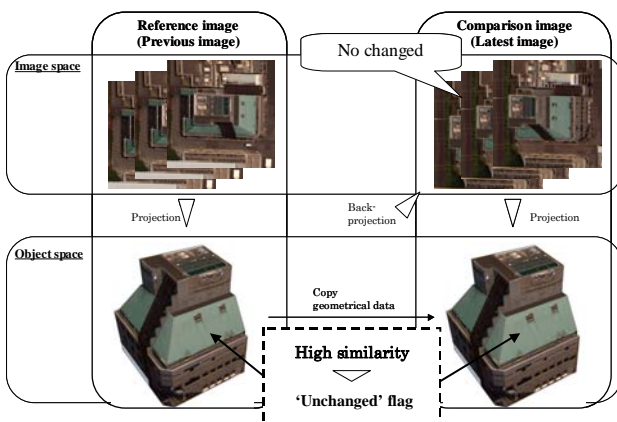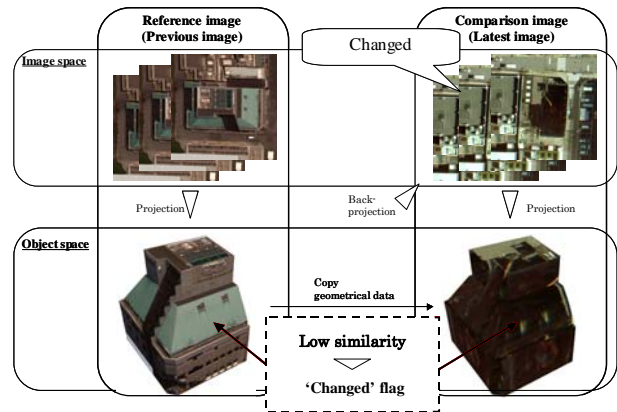

Figure 3. Example of model-based change detection processing (case of change)

Model-based change detection can give a more precise image superposition than 2-D-based image processing. In general, the images can be superposed approximately using 2-D-based image processing, such as the affine-transformation algorithm but, in the case of close-range photos, such as aerial photographs taken from low altitude, images cannot be superposed completely due to the center projection camera model. Accordingly, in image superposition based on the 2-D model these errors are manifested as noise in the image comparison. On the other hand, with the 3-D geometrical restriction the images can be superposed completely. Therefore, highly reliable evaluation of texture similarity can be achieved through the model-based change detection methodology. In the case of vacant lots, after preparation of a 3-D vacant lot database as building objects, "newly built" area detection is possible using the same form of processing. (In particular, as well as roof surfaces, vertical surfaces are visible in three-line sensor imagery. To achieve greater precision, changes can be detected by calculations using both roof surfaces and wall surfaces.)

However, some problems remain with subtraction processing of images observed at different times. For example, shadows, which are caused by nearby buildings and some objects (see, Figure 4), reduce the reliability of object change recognition.

Figure 2. Example of mode-based change detection processing (case of invariance)
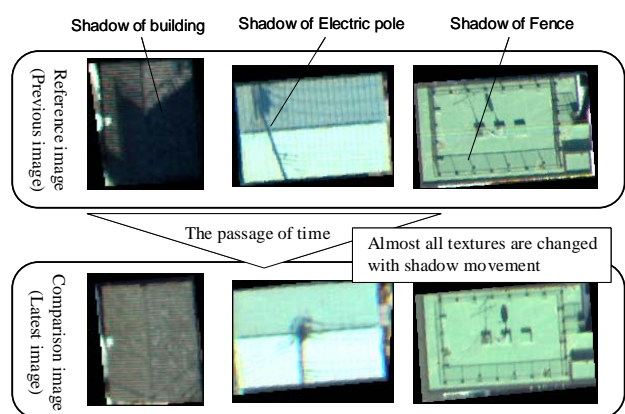

Figure 4. Shadow is a factor in decreasing the recognition rate of object changes

2.2 Model-based change detection with shadow area specification

If shadows in an image are detected beforehand, an unshadowed image can be generated using an image enhancement of the detected area [11][12]. However, it is difficult to decide the parameters of brightness control to smooth the boundaries of the bright and shadowed areas to produce the unshadowed images. Pixel values of the shadow and bright areas in the same features should be sampled to preset the image enhancing model parameters. Usually, this sampling task requires manual operation to provide reliable results.

Here, considering an automated procedure, we tried to improve the success rate of the change detection algorithm without the unshadowed image generation. Only bright regions or shadow regions in the images are extracted and used for model-based change detection processing. Figure 5 shows the processing flow of model-based change detection with additional shadow area detection processing. Shadow area detection is one of the key points in this processing. There have been many studies of shadow area detection. Generally, geometrical detection approaches using a 3-D model or an image segmentation approach are used in existing techniques. Both approaches are applied to the shadow detection in this research.
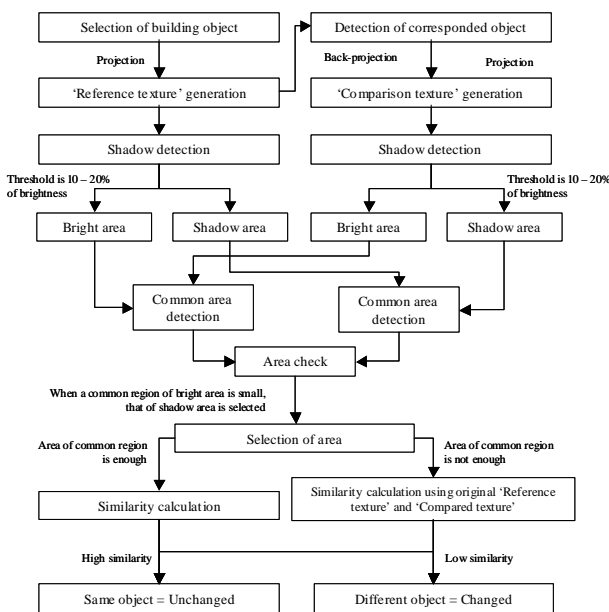

Figure 5. Processing flow of model-based change detection

2.2.1 Geometrical detection approach

The elevation and azimuth of a sunray produce the shadow area in the object space correctly, as shown in Figure 6. Moreover, when the detected shadow area is back-projected onto the images, the shadow area in the image space can be detected automatically. The elevation and the azimuth of the sunray can be calculated with a time stamp of the image acquisition and sun orbital information [13]. In addition, the elevation and the azimuth can also be obtained by stereo measurement of shadow features in the images.

Detected shadow area

(The elevation and azimuth of a sunray produce the shadow area in the object space correctly.)
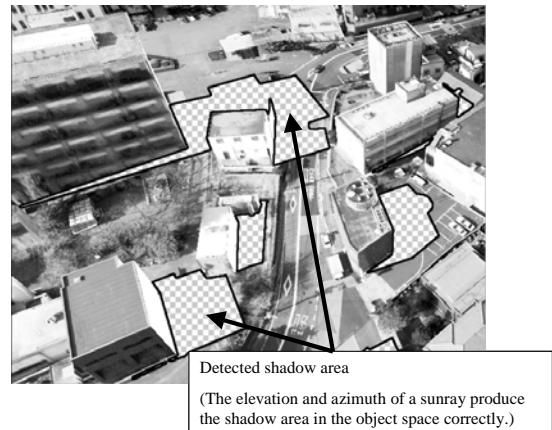
Figure 6. Sunray simulation using 3-D data

2.2.2 Image segmentation approach: Active binarization processing

Various objects can be recognized in ultra-high-resolution imagery, such as three-line sensor (TLS) images. For example, there are vehicles, street trees, as well as pedestrians, antennae, electric poles, laundries and gardens and as a matter of course, shadows of these are in the images. If models of all objects are constructed, it is easy to achieve accurate shadow detection. However, complete 3-D model construction is an unrealistic approach. Therefore, the image segmentation approach is also applied to detect shadow areas that remain after the shadow detection processing using 3-D geometrical data.

Here, active binarization processing is applied to make image masks, which are the extracted shadow area. An actual threshold value of the binarization is set at a concaved edge point of an image histogram from 10% to 20% of brightness (see, Figure 7).

As a result, bright regions are almost completely separated from shadow regions. Each region is converted to two mask images. After this processing, four mask images are extracted from the reference image and the comparison image. Then, a common area of a bright region in the reference image and the comparison image is extracted, or a common area of a dark region in the reference image and the comparison image is extracted. Finally, shadow areas, including shadows of small objects, can be detected in the images.
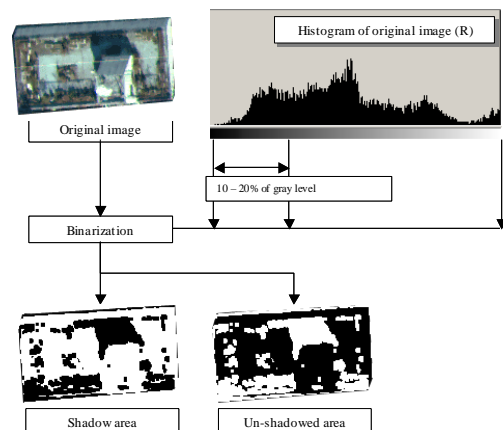

Figure 7. Active binarization processing

3. EXPERIMENTS

Building changes in actual urban data were extracted using the model-based change detection algorithm with shadow area detection algorithm. The following detection algorithms were tested:

- Model-based change detection (cross-correlation)
- Improved model-based change detection (cross-correlation and shadow detection)
- Improved model-based change detection (histogram subtraction and shadow detection)

The histogram subtraction and the cross-correlation calculation are applied to evaluate an object's similarity in the two images. Additionally, each threshold for change detection was set to detect changed building objects with a 100% success rate, because changed building objects are rare, as shown in the dataset described below. The purpose of this experiment was to confirm the accuracy and performance of this detection approach from the viewpoint of the recognition of buildings.

3.1 Data

- Study area:

Urban dense area (Tokyo, Japan) was selected. This area includes detached buildings along a main street.
- Aerial images:

Temporal three-line sensor images (reference images and comparison images) as shown in Figure 8 were used. The spatial resolution is 5 cm approximately. Table 1 shows the details of these images including image acquisition time. Two buildings were changed in one month.
- 3-D building data:

A high-resolution 3-D model was constructed using the three-line sensor triplet images (reference images). A screenshot of this model is shown in Figure 9. The spatial resolution is 10 cm. These test data consist of 767 buildings.
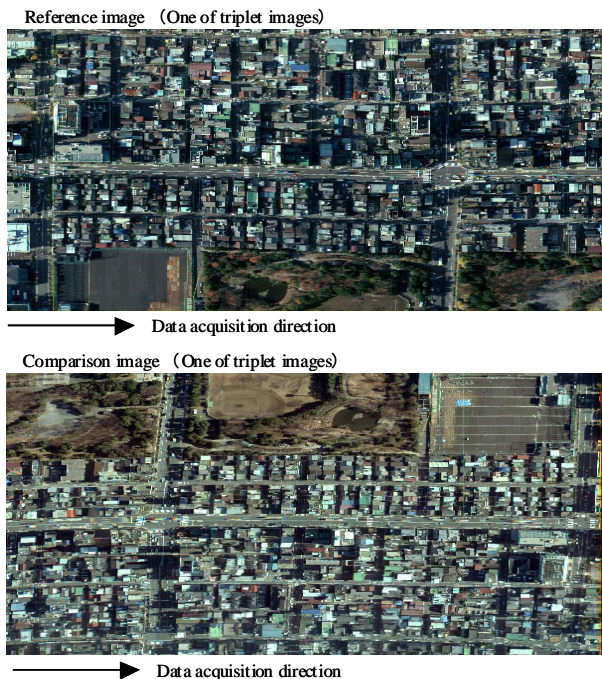
Reference image （One of triplet images）

→ Data acquisition direction

Comparison image （One of triplet images）

→ Data acquisition direction

Figure 8. Aerial images (Temporal three-line sensor images)

Table 1.Details of three-line sensor image acquisition

Study area: Tokyo, Japan		Situation: Overcrowded	
	Date and time of data acquisition	Altitude	Weather
Reference image	10:01,15 Dec. 2003	450[m]	Fine
Comparison image	11:42, 20 Jan. 2004	450[m]	Fine

Figure 9. Referenced 3-D data (precise 3-D data) constructed from three-line sensor images

3.2 Results

The results of this experiment are shown in Tables 2 to 7. In this research, a percentage value, which is the number of successfully recognized objects divided by the total number of objects, is defined as the 'object recognition rate'. From the image-processing viewpoint, almost all buildings change because almost all textures changed with shadow movement. However, only buildings that are categorized as a "Change of building" as described below, have actually changed. Moreover, the other objects should be categorized as unchanged objects. The object recognition rate for those objects that have not been actually changed is the 'invariable detection rate' and the recognition rate of objects that have actually been changed is the 'change detection rate'. In Tables 2, 4 and 6, objects that have been changed are separated from objects that have not been changed.

Moreover, these results are classified according to situation changes between the reference image and the comparison image. The authors describe the recognition rates according to situation changes between the reference image and the comparison image, as shown in Tables 3,5 and 7, as follows.

- Fine (no influence): No situation changes between the reference image and the comparison image
- Shadow of contiguous object: Noticeable changes by contiguous building shadows
- Shadow of building components: Noticeable changes by building components
- Continuous texture: One pixel texture gap makes misrecognition as noticeable changes in the image comparison.
- Smear: Smears in images degrade similarly to noises
- Specular reflection of sunlight: Saturation of sensor's dynamic range degrades similarly noise
- Changed some things on roof: Change of fence, garden, laundry, puddle, etc.
- Change of building: Structural change of building, including exterior

Table2. Result of model-based change detection without shadow specification: Cross-correlation

Threshold (Normalized cross-correlation) = 0. 860

Object type	Number of successfully recognized objects / Total	Object recognition rate
Unchanged object	[645/765] (Number of recognized objects as same object / Total)	84% (Invariance detection rate)
Changed object	[2/2] (Number of recognized objects as different object/ Total)	100%
Total	[647/767]	84%

Table3. Classification of result of model-based change detection without shadow specification: Cross-correlation

Condition of image comparison	Number of successfully recognized objects / Total	Object recognition rate
Fine	[428/460]	93%
Shadow of contiguous object	[77/145]	53%
Shadow of building components	[44/55]	80%
Continuous texture	[54/57]	95%
Smear	[7/8]	88%
Reflection of sunlight	[5/5]	100%
Changed things on roof	[30/35]	86%
Change of building	[2/2]	100%

Table4. Result of model-based change detection with shadow specification: Cross-correlation

Threshold (Normalized cross-correlation) = 0. 887

Object type	Number of successfully recognized objects / Total	Object recognition rate
Unchanged object	[685/765] (Number of recognized objects as same object / Total)	90% (Invariance detection rate)
Changed object	[2/2] (Number of recognized objects as different object/ Total)	100% (Change detection rate)
Total	[687/767]	90%

Table5. Classification of result of Model-based change detection with shadow specification: Cross-correlation

Condition of image comparison	Number of successfully recognized objects / Total	Object recognition rate
Fine	[437/460]	95%
Shadow of contiguous object	[101/145]	70%
Shadow of building components	[51/55]	93%
Continuous texture	[54/57]	95%
Smear	[7/8]	88%
Reflection of sunlight	[5/5]	100%
Changed things on roof	[30/35]	86%
Change of building	[2/2]	100%

Table6. Result of model-based change detection with shadow specification: Histogram subtraction

Threshold (Subtracted pixel value) = 120

Object type	Number of successfully recognized objects / Total	Object recognition rate
Unchanged object	[764/765] (Number of recognized objects as same object / Total)	100% (Invariance detection rate)
Changed object	[2/2] (Number of recognized objects as different object/ Total)	100% (Change detection rate)
Total	[766/767]	100%

Table7. Classification of result of model-based change detection with shadow specification: Histogram subtraction

Condition of image comparison	Number of successfully recognized objects / Total	Object recognition rate
Fine	[460/ 460]	100%
Shadow of contiguous object	[144/145]	99%
Shadow of building components	[55/55]	100%
Continuous texture	[57/57]	100%
Smear	[8/8]	100%
Reflection of sunlight	[5/5]	100%
Changed things on roof	[35/35]	100%
Change of building	[2/2]	100%

4. DISCUSSION

The overall results of this research are shown in Table 8. The basic model-based change detection methodology achieved an 84% recognition rate. Moreover, with shadow area specification, the recognition rate improved from 84% to almost 100%.

Table8. Overall result of model-based change detection

Change detection methodology	Number of successfully recognized objects / Total number of objects	Object recognition rate
Without shadow detection		
- Cross correlation	[647/767]	84%
With shadow detection		
- Cross correlation	[687/767]	90%
- Histogram subtraction	[766/767]	100%

In addition, the cross-correlation and histogram subtraction were applied to evaluate the similarity of the images. There are two characteristic points. The first is an improvement of the model-based change detection procedure. The procedure without shadow detection processing often provides false results, as shown in Table 3. In particular, the failed examples are described as 'Shadow of contiguous object'. On the other hand, the procedure with shadow area specification provides a

good result. Shadow detection improves the reliability of object recognition processing.

The second point is the sensitivity of functions in evaluating 3-D texture similarity. As shown in Tables 5 and 7, the cross-correlation is more sensitive in recognizing an object's changes than histogram subtraction. Even if the changed area is a part of a building, minute changes can be recognized through cross-correlation, as shown at 'Changed thing on roof' in Table 7. However, the histogram subtraction is advantageous in recognizing approximate changes, such as ignoring minute noise.

As a result, the authors confirmed that the histogram subtraction is effective in detecting large changes, such as demolition and replacement of buildings, and the cross-correlation is effective in detecting small changes, such as building extensions and remodeling. Therefore, a combination of two or more methodologies may be effective for reliable change detection, although a weighting decision for the parameters is a problem.

5. CONCLUSION

In this research, the model-based change detection algorithm was developed in order to achieve reliable detection of building changes. By use of fine 3-D building data as reference data, the change parameters, such as building colors, shapes and height, are recognized simultaneously in the algorithm. Moreover, this algorithm was implemented and similarity parameters calculated to evaluate "no-change", "demolition", "replacement" and "extension and remodeling" of individual buildings in our experiments.

When aerial images acquired at different times are used, the shapes of shadow features are different between the reference image and the comparison image. In a sense, almost all building textures are changed, from the viewpoint of basic image processing. Therefore, the authors show that it is important to match texture changes and actual object changes to recognize building changes in a time sequence with the model comparison algorithm. Texture comparison with 3-D geometrical restrictions, and accurate shadow detection of temporal images are important to improve the reliability of the change detection for database revision.

Two functions were used experimentally to evaluate the similarity of temporal textures. One is the cross-correlation function and the other is the image subtraction function. Model-based change detection with cross-correlation achieved a 90% recognition rate and image subtraction achieved almost a 100% recognition rate, even in a difficult area, such as a densely populated urban area.

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