Object Oriented Change Detection of Buildings After a Disaster

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ABSTRACT

Following a disaster, geoinformatics can provide critical information pinpointing the location and nature of serious damage. However, using geoinformatics in this situation imposes unusual constraints: opportunistic use of whatever pre- and post-disaster data may be available without regard to quality or sensor compatibility, analysis of data by relatively untrained personnel, and limited data processing facilities. This paper describes an approach to dealing with these limitations, undertaken by our Remote Sensing Laboratory at the Computer Engineering Department of King Mongkut's University in Thonburi, Bangkok, Thailand.

To assess the severity of devastation, most damage assessments focus on the destruction of man-made objects, particularly buildings. Although there is a rich literature on building extraction, existing approaches often mis-detect small-size buildings. In this paper, we present a robust rectangular building detection process that can discover both small-size buildings in residential areas and large-size buildings in industrial areas with about 75 percent accuracy. We also propose an object-based change detection approach that is flexible for disaster cases in which the pre-disaster and post-disaster images may not be captured with the same resolution. We evaluated our methodology using data from the tsunami of December, 2004 which devastated the Andaman coast of Southeast Asia including Thailand. According to our results, we conclude that, in conjunction with accurate inputs from the building detection, our change detection can discover real changes.

INTRODUCTION

The tsunami of December 26, 2004 was one of the worst disasters in recent human history. The event caused extensive loss of life and destruction of settlements and natural resources. As with any disaster, recovery follows in successive stages: immediate rescue, medical and food aid for survivors, then disease prevention, followed by reconstruction. For all of these stages, recovery planning requires determining the location and extent of the damage.

Change detection is a prerequisite for quick assessments of damage. The most immediate need is to bring assistance to the survivors. However, locating humans is not within the current capability of satellite remote sensing; accordingly most damage assessments focus on locating the destruction of man-made objects, particularly buildings.

To assess changes in buildings after a disaster, building detection is always the starting point. For decades, building detection from remotely sensed imagery has been increasingly researched in the remote sensing community (Huertas, 1990; Lagunovsky, 1999; Liu, 2005; Muller, 2005). Despite the rich literature on building extraction, existing approaches all have weaknesses. Most approaches fail to detect small-size buildings in residential areas (Huertas, 1990; Lagunovsky, 1999). As a result, rehabilitation activity may not be provided promptly.

The Remote Sensing Laboratory at King Mongkut's University, which is located in the Computer Engineering Department, is oriented toward the development of new computing capabilities for geoinformatics. Our focus is to address the needs, especially in developing countries, for solutions which are effective but also are inexpensive and easy-to-use by relatively untrained people.

In this work, we are exploring a processing model which is focused on using relatively primitive radiometric and geometric analysis methods to extract objects with a high real-world semantic content. We believe that, once these semantic objects (buildings, in this case) have been discovered, change detection and other operations can easily produce useful and meaningful results which are automatically expressed in terms which are most meaningful to the human analyst.

Our specific domain for this experiment is development of a robust rectangular building detection methodology that can detect both small buildings in residential areas and large buildings in industrial areas. We use edge detection and region growing approaches to supplement each other. The discovered buildings then become the inputs to our change detection. We recognize that working only with such simple shapes is an artificial constraint, but believe (in keeping with our laboratory's philosophy) that useful results, such as localizing and estimating destruction after a disaster, can be obtained even with such limitations.

To accomplish the change detection for this experiment, we employ knowledge based intelligent agents (Tecuci, 1998) to recognize buildings before and after a disaster. Due to different sensor conditions, plus the effects of the disaster, a building that remains intact after a disaster may have different characteristics from the building before a disaster. Our change detection creates two classifiers, referred to as Classifier Agents (CA). One CA is trained to recognize buildings before a disaster and another after a disaster. In this work, we also construct a building object (David, 1992; Jacobson, 1992), referred to as the Object Agent (OA), which corresponds to each actual building in an image. The building object contains not only the properties of each specific building, but also computational processes which "know about" the common properties of buildings. In this way, each building object is an active computational element (called an *agent*) which can interact with other agents to match up pairs of before-and-after objects. Thus, our approach can both quantify the number of changed buildings and also discover which buildings have changed.

RECTANGULAR BUILDING EXTRACTION

Because we are primarily interested in buildings, we consider *a priori* that a building is a rectangle; *i.e.* four straight lines forming a quadrangle (Lagunovsky, 1999). In remotely sensed images, however, it is difficult to find such four lines due to the resolution limitations. Note that with 1-meter resolution, a small building will only occupy a few pixels in each direction. In many cases, the two lines forming the shorter side of the buildings are missing or discontinuous. With this difficulty, our approach begins by locating a pair of parallel lines which determine the skeleton of the building on the major axis. This line pair will be considered to be part of a building if there exists a homogeneous and compact region inside. Figure 1 presents the outline of our approach to finding the initial building objects.

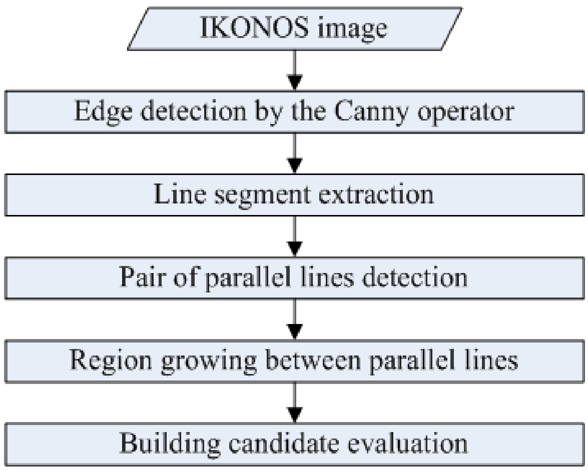


Figure 1. Rectangular building extraction diagram.

Line Segment Extraction

In this work, we apply the Canny edge detector to find gradient magnitude and gradient orientation of each pixel in the entire image. The pixels with large gradient magnitudes are considered to be edges. A line segment is then built up from a group of connected edge pixels with similar gradient orientation. The following conditions are used to merge an edge pixel into a line segment:

(a) It must be an edge pixel.
(b) It must be a pixel with 8-neighborhood connectivity to the tail pixel of the line segment under construction.
(c) Its gradient orientation must not differ from those of pixels in the current line segment by more than 45 degrees.

We next apply a linear regression model (Walpole, 2002) to each extracted line segment to find its line equation in the form of slope and y-intercept.

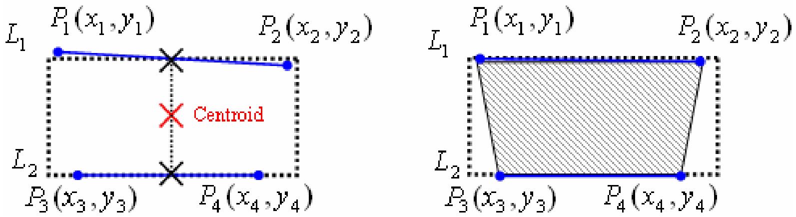
Building Region Extraction

Two linear segments, L1 and L2 , can form the major axis of a building if the following conditions are true:

$$Length(L1) > Tw \quad (1)$$
$$Length(L2) > Tw \quad (2)$$
$$Distance(L1, L2) > Th \quad (3)$$
$$|\ Slope(L1)\ | \approx |\ Slope(L2)\ | \quad (4)$$

where T_w and T_h are the minimum length of the line on the major and minor axis of buildings, respectively.

For each parallel line pair found, there exists a high probability that a building exists. Alternatively, however, there is the possibility that these are the edges of adjacent, parallel-oriented buildings. To distinguish these cases, we examine the putative interior of each candidate building. If the line pair correctly implies the skeleton of a building, then there should be a homogeneous and compact region filling the space between the lines. We perform a seeded region growing operation to extract the building region. In this work, we automatically calculate a seed point from the centroid of the line pair. The range of values of pixels between this line pair must be less than some threshold in order to qualify as a region. Figure 2 depicts our approach in selecting these two parameters.



(a) Seed point (b) Threshold

Figure 2. Region growing parameters.

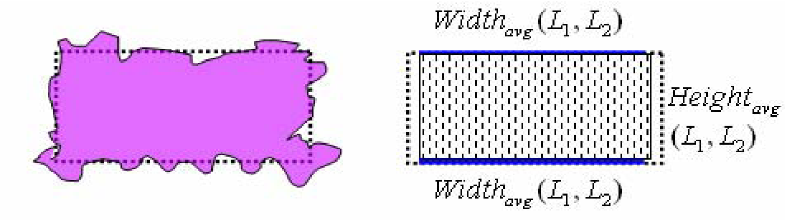
A region is likely to be a building if the size of the region is compact compared with the estimated size, $Area_{est}$, which is calculated by equation (5).

$$Area_{est} = Width_{avg}\ (L_1, L_2) \times Height_{avg}\ (L_1, L_2\ ) \quad (5)$$

where $Width_{avg}$ is the average length of the two lines forming the major axis of the building region and $Height_{avg}$ is the distance between this line pair, as shown in Figure 3.

Using equation (6), a region is classified as a building candidate if the size of the region, measured by number of pixels or ***nPixels*** , does not deviate from the estimated size by more than 25%.

$$0.75 < nPixels/\ Area_{est} < 1.25 \quad (6)$$



(a) Grown region. (b) Estimated area

Figure 3. Compactness evaluation.

Once the potential building region has been located, the building can be constructed in vector format as depicted in Figure 4.

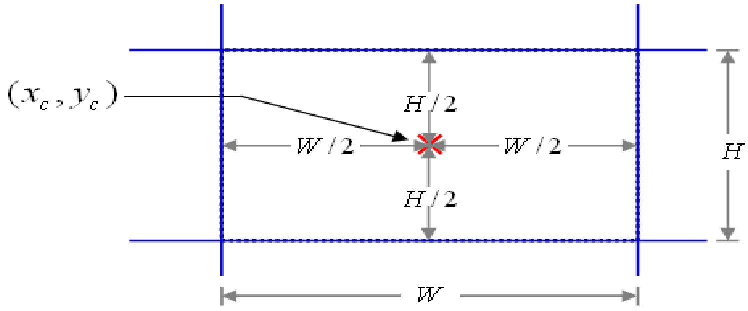


Figure 4. A rectangular building construction.

In Figure 4, ***H*** refers to ***Height$_{avg}$*** as shown in Figure 3(b) and ***W*** *r*efers to the width of the building calculated by equation (7).

$$W = nPixels / H \tag{7}$$

Finally, the fundamental properties of a building are extracted as shown in Table I. These become the inputs to our object-based change detection.

Table I Building Extracted Properties

Property	Description
Area	The size of the building.
Height	The length of the shorter size of the building.
Width	The length of the longer size of the building.
Aspect ratio.	The ratio of height and width of the building
Major orientation	The orientation of the major axis of the building.
Average blue	The average blue color of the building area.
Average green	The average green color of the building area.
Average red	The average red color of the building area.
Centroid	The geo-reference centroid of the building.
Corners	The four points corresponding to the building corners.

OBJECT-BASED CHANGE DETECTION

Our change detection method is based on the concept of object-oriented intelligent agents. We introduce two types of agents called *Classifier Agent* (CA) and *Object Agent* (OA). The CA aims to remove false building candidates discovered by the building detection approach and to classify the extracted building candidates as true buildings. An OA represents an instance of a building in an image. The OA contains not only properties of its associated building but also methods that it can individually use for evaluating changes in its pair OA located in the changed image. Figure 5 shows the overall framework of our change detection method.

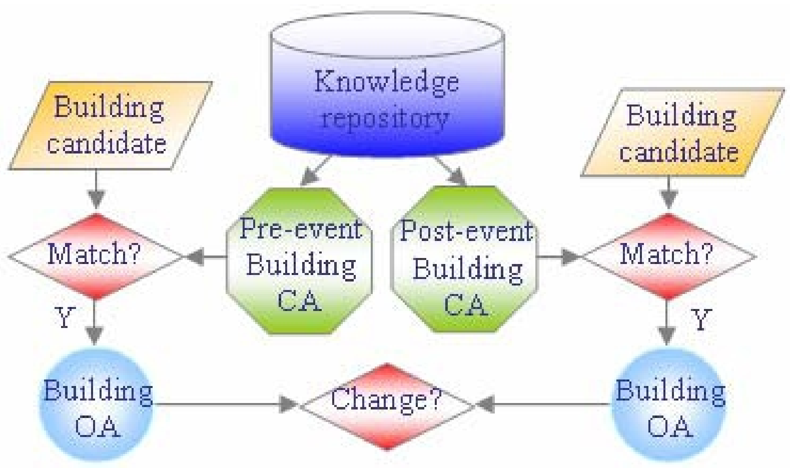


Figure 5. The overall framework of the object-based change detection.

Classifier Agent

A Classifier Agent (CA) works based on two inputs: a rule set and an acceptable closeness factor. A rule set is a set of rules about the characteristics of buildings that a CA is trained to recognize. In this work, a CA recognizes buildings from area, height, width and aspect ratio of height and width. A CA measures how well a candidate matches the rule set by using equation (8) to calculate the closeness factor. If the closeness factor is above the acceptable closeness factor, a CA classifies the building candidate as a true building and creates an OA for this object.

$$\textbf{\textit{ClosenessFactor}} = \mathbf{1.0} - \sqrt{\sum_{i=1}^{m}((f_i^{CA} - f_i^{Obj})/f_i^{CA})^2} \qquad \mathbf{(8)}$$

where $\boldsymbol{m}$, $\boldsymbol{f_i^{CA}}$ and $\boldsymbol{f_i^{Obj}}$ mean the total number of properties for a rule set, the $\mathbf{i}^{th}$ properties of the rule set and the $\mathbf{i}^{th}$ property of the building candidate, respectively.

Object Agent

An Object Agent (OA) represents an instance of an object class in an image. An OA encapsulates both properties of its associated building and methods (computational processes) that it can individually use to identify and evaluate changes in its pair OA. Table I presents the properties of an OA. Table II summarizes the built-in change detection methods. The OA in the pre-event image reports changes if those values of its pair OA in the post-event image differ above a tolerance.

Table II Change Detection Method

Method	Description
IsSizeChanged()	To evaluate whether the size of the building changes.
IsStructureChanged()	To evaluate whether the height, width and major orientation of the building change.
IsSpectralChanged()	To identify whether the spectral characteristics change.
IsDisappeared()	To indicate whether the hypothetical paired object disappeared.

The following change detection operations attached to each OA for evaluating its pair OA are described in the next section.

IsSizeChanged()

This operation indicates whether the size of the object changed. One unit equals the pixel size of the acquisition images. For example, in our experiment, one pixel equals one meter square. The current OA compares its size with its pair OA's size and returns whether they are in equal size, larger or smaller.

If the size of the paired OA differs by less than a tolerance τ, the current OA considers there is no change in size. If the size of the paired OA is greater or less by more than the tolerance, the current OA considers that the size has changed. Equations 9 and 10 are used by the IsSizeChanged() operation.

No change: $$|s_1 - s_2| \leq \tau \qquad \textbf{(9)}$$

Change: $$|s_1 - s_2| > \tau \qquad \textbf{(10)}$$

IsStructureChanged()

This operation indicates whether the structure of the building has changed. The structural properties of a building includes the boundary of the building and the orientation. Changes in width, height, and major orientation are included in this operation. The method reports that there has been a change if width, height or major orientation differs by more than a tolerance τ . Equations 11 and 12 are used by the IsStructureChanged() operation.

No change: $$\begin{aligned} &|w_1 - w_2| \leq \tau \\ &|h_1 - h_2| \leq \tau \\ &|o_1 - o_2| \leq \tau \end{aligned} \qquad \textbf{(11)}$$

Change: $$\begin{aligned} &|w_1 - w_2| > \tau \\ &|h_1 - h_2| > \tau \\ &|o_1 - o_2| > \tau \end{aligned} \qquad \textbf{(12)}$$

IsSpectralChanged()

This operation indicates whether the spectral properties of the building have changed. The method reports change if the spectral values of the blue band, green band or red band differ by more than some tolerance τ. Equations 13 and 14 are used by the IsSpectralChanged() operation.

No change:
$$\begin{aligned} &|blue_1 - blue_2| \le \tau \\ &|green_1 - green_2| \le \tau \\ &|red_1 - red_2| \le \tau \end{aligned} \quad \textbf{(13)}$$

Change:
$$\begin{aligned} &|blue_1 - blue_2| > \tau \\ &|green_1 - green_2| > \tau \\ &|red_1 - red_2| > \tau \end{aligned} \quad \textbf{(14)}$$

IsDisappeared()

This operation indicates whether the hypothetical paired object has disappeared. The method reports non-existence if it cannot find its paired object at its expected location.

EXPERIMENTAL METHOD

To test the system we used two IKONOS images with 1-meter resolution captured on 24 January 2004 and 29 December 2004, provided by the Geo-Informatics and Space Technology Development Agency (GISTDA) in Thailand. These images covered Phuket Island in the Andaman Sea coastal region of Thailand. Within that region, some towns and villages were badly damaged while others escaped almost intact.

One study area which we chose contains a number of large buildings (probably warehouses). This study area, which is located in Patong, Phuket, has UTM geographic coordinates in the upper-left corner of 871984N 422331E and dimensions of 192 x 163 meters. We refer to this as the *industrial* study area.

The other study area contains numerous smaller buildings (probably houses). This study area, located in Kamala, Phuket, has geographic coordinates in the upper-left corner of 882991N 421607E and dimensions of 75 × 80 meters. We refer to this as the *residential* study area.

The statistics reported below are based on a comparison with building detection by visual interpretation.

All of the software used in our tests was written by Ms. Supannee Tanathong as part of her Master's thesis in Computer Engineering, and she conducted all of the testing described in this paper. Determination of the various thresholds was obtained by manual inspection. In doing so, we attempted to discover values which would be robust across different types and sizes of buildings.

During development of the building detection software, we considered the three cases of correctly identified buildings, buildings which were not identified, and things other than buildings which were incorrectly identified as buildings. During development of the building matching software, we considered the cases of buildings which were correctly matched between before and after, buildings which could not be matched due to destruction, and buildings which should have been matched but were not.

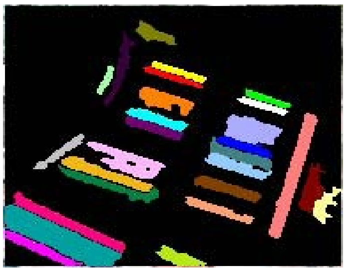
EXPERIMENTAL RESULTS

Building Extraction

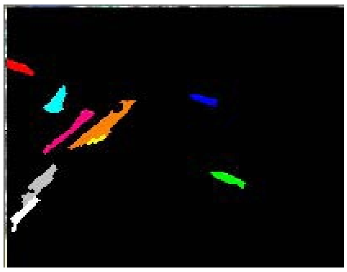
Figure 6 shows the input images for the industrial study area captured before, Figure 6(a), and after the event, Figure 6(b). Figure 6(c) and (d), respectively, show the results of the building candidate extraction in raster format.

(a) Pre-event image
24 January 2004

(b) Post-event image
29 December 2004



(c) Candidates for pre-event image



(d) Candidates for post-event image

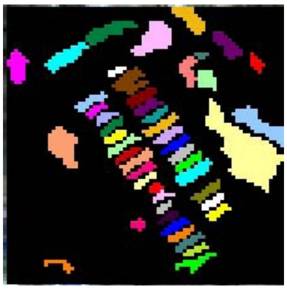
Figure 6. The IKONOS images covering an industrial area in Patong, Phuket.

Figure 7 shows the input images for the residential study area in Kamala, Phuket. The building candidate extraction results are shown as Figure 7(c) and (d), respectively.

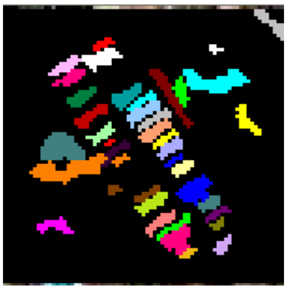
In the before-disaster images, Figure 6(a) and Figure 7(a), we could detect buildings with 75% and 85% accuracy, respectively. However, in the post-disaster residential area, we could only detect buildings with 70% accuracy as seen in Figure 7(b). Visual inspection does show significant differences between Figure 7(a) and (b) even though there is no apparent destruction. We are not clear on the cause of this appearance difference which seems to have significantly affected the accuracy of our detection.

(a) Pre-event image
24 January 2004

(b) Post-event image
29 December 2004



(c) Candidates for pre-event image



(d) Candidates for post-event image

Figure 7. The IKONOS images covering a residential area in Kamala, Phuket.

Overall, our approach was able to detect buildings with 75 percent accuracy. However, not all of the objects discovered are buildings. To classify the building candidates from Figure 6, we assigned both CAs with the rule set for typical industrial buildings as presented in Table III. Table IV presents the parameters that we assigned to the CAs for recognizing the residential buildings seen in Figure 7.

Table III Building CA's Parameters for Industrial Buildings

Pre-event CA			Post-event CA		
Feature	Min	Max	Feature	Min	Max
Area (sq. m)	100.0	1000.0	Area (sq. m)	100.0	1000.0
Height (m)	3.0	18.0	Height (m)	3.0	18.0
Width (m)	12.0	72.0	Width (m)	12.0	72.0
Aspect ratio	0.08	0.25	Aspect ratio	0.08	0.25
Acceptable closeness factor: 75%			Acceptable closeness factor: 65%		

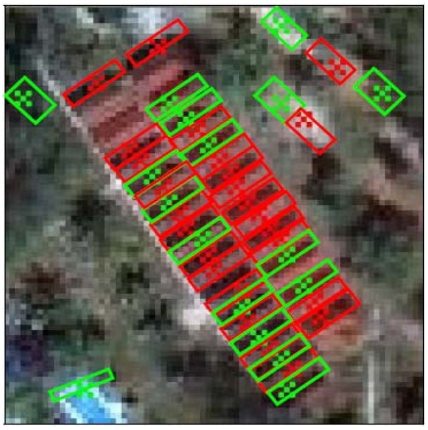
Table IV Building CA's Parameters for Residential Buildings

Pre-event CA			Post-event CA		
Feature	Min	Max	Feature	Min	Max
Area (sq. m)	10.0	45.0	Area (sq. m)	10.0	45.0
Height (m)	2.0	4.5	Height (m)	2.0	4.5
Width (m)	3.5	12.0	Width (m)	3.5	12.0
Aspect ratio	0.25	1.00	Aspect ratio	0.25	1.00
Acceptable closeness factor: 75%			Acceptable closeness factor: 75%		

Building Matching

Once the buildings were detected in the pre- and post-disaster data sets, the four agent methods described above were invoked to match up the pre- and post-disaster buildings. Figure 8 shows the changes detected. The buildings highlighted in red have been identified as the buildings that were changed after the disaster. The buildings highlighted in green have been identified as the buildings which disappeared. Figure 8(a) shows the changes detected in the industrial study area. The system detected that two buildings had changed after the disaster while the remaining had disappeared or were no longer recognized as buildings, which is true as expected. Figure 8(b) shows the changes detected in the residential study area. For Figure 8(b), only the building area is discussed here. The system detected that 23 buildings had changed in the post-disaster image in either area or structure, which is true as expected. However, due to the failed detection of some buildings in the post-disaster image, our change detection falsely reported that 12 buildings had disappeared in the post-disaster image. Thus, destruction was significantly over estimated.

(a) Change in Industrial Area



(b) Change in Residential Area

Figure 8. Change detection results.

From these experiments experiments, we conclude that our building detection can detect both large-size buildings in industrial areas and small-size buildings in residential areas. With accurate inputs from building detection, our change detection can discover real change.

DISCUSSION AND CONCLUSION

This paper presents an object oriented change detection approach for rectangular buildings, which includes a novel building detection method and an object-based change detection method. Our building detection method employs edge detection and region growing approaches to supplement each other in order to locate building candidates. Our approach can detect both large-size buildings in industrial areas and small-size buildings in residential areas with 75 percent accuracy. The use of an agent-based approach permits us to fine-tune the object detection for different types of objects by having different rule sets and parameters (as illustrated in Table III and IV).

Our change detection is implemented by applying the concepts of object-oriented intelligent agents. With such a design, we may be able to eliminate the need to use images with the same resolution; however, that possibility was not tested in the current experiments. From our experiments, we conclude that, in conjunction with accurate inputs from the building extraction, this change detection method can discover real changes.

ACKNOWLEDGMENT

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