OBJECT-BASED CHANGE DETECTION
THE TSUNAMI DISASTER CASE

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ABSTRACT: Most of the approaches to image change detection for disasters identify an object in an image by recognizing its properties such as spectral, textural, or spatial features. After a disaster, however, the fundamental properties of an object are likely to have changed. Yet it is still the same object. This situation makes it difficult to link objects after disaster to the same objects in the pre-disaster image. As a result, we cannot effectively evaluate the change. This paper presents an approach to robustly identify objects in an image and link them to the same objects in a changed image by applying object orientation and intelligent agent techniques.

1. INTRODUCTION

Image-based object extraction from remotely sensed imagery has been increasingly researched in the remote sensing community in conjunction with the advancement of sensor technology. Each object is a group of pixels that contain similar properties and are associated together using semantic knowledge. Liu (2005) recognized buildings from tone, texture, shape and context information based on multi-scale object oriented classification. Walter (2004) distinguished between residential and industrial settlement objects from size of house, roof slope, percentage of trees, percentage of sealed ground and homogeneity of texture. The object then becomes the input to other applications. For example, change detection must take objects into account to detect changes. Peggy (2000) applied a snake model to extract road objects by recognizing energy along the road and detecting changes on the road object in its pair image.

After a disaster, the fundamental properties of an object are likely to have changed. Yet it is still the same object. This situation makes it difficult to link objects after a disaster to the same objects in the pre-disaster image. The Indian Ocean tsunami of December 26, 2004 damaged natural resources and man-made objects along the coastal area so that they could no longer be recognized.

In this paper, we used knowledge based intelligent agents to recognize objects of interest before and after a disaster. Due to different sensor conditions, plus the effects of the disaster, the same object that remained intact after a disaster may have different characteristics from the object before a disaster. Our work used two classifiers. One classifier was applied to objects before a disaster and another after a disaster. Since the fundamental properties of an object are not persistent, recognizing an object from its properties is inadequate. We represented an image object as an agent, referred to as *Object Agent*. The key innovation is that the image object contains not only properties but also methods. These associated methods assist the object in searching for its pair object and evaluating the changed conditions. The approach not only quantifies the number of changed objects but also knows which objects have changed.

2. THEORETICAL BACKGROUND

2.1 Object Orientation

Object orientation is a sophisticated technique for system modeling. This technique views a system as consisting of a number of objects that interact with each other in some way (David, 1992; Ivar, 1992). Our coastal area, for instance, consists of objects such as bungalows, houses, bridges, shoreline and sea which are related to each other. In object orientation, the fundamental construct of an object is to combine both properties and methods for interaction in a single entity (Ivar, 1992). Some fundamental properties of a car, for instance, are color, size, shape and model. The examples of method or operation that can be performed by a car are run, park, crash, carry etc. Thus, with such a design method, only a small semantic gap exists between reality and the system model.

In remote sensing, the object-oriented concept has been applied in many studies for object recognition and extraction (Benz, 2003; Quin, 2006; Walter, 2005). Nevertheless, most researchers defined an object only from its attributes such as spectral, textural and spatial features. None of them integrates operations into the object to fully utilize the sophisticated object-oriented technique. Our work attempted to attach change detection operations to the object to improve the accuracy of discovering changes in bi-temporal images.

In object orientation, two main concepts are class and object. A class represents a template for several objects that shares common characteristics. An object is created from a class. Objects of the same class have the same definition both for their properties and operations but different characteristics (Ivar, 1992). Our work applied the concept of class and object in object-oriented approach to the remotely sensed image-based object by implementing *Classifier Agent* and *Object Agent* using an intelligent agent approach.

2.2 Knowledge Acquisition and Intelligent Agents

An intelligent agent is a knowledge-based system that is capable of learning with supervision from an expert (Gheorghe, 1998). After knowledge acquisition and learning, the agent can produce and maintain its knowledge in terms of rules. The knowledge acquisition approach has long been used in remote sensing. A familiar example is supervised classification that involves training samples from an expert. In this paper, we created two types of agent: *Classifier Agent* and *Object Agent* and embedded the supervised classification in our agents. The details of these agents are discussed in next section.

2.3 Object Extraction

Object-oriented approach is more appropriate than ordinary pixel-based approach in identifying a real world object in a very high resolution image. Under this concept, the primitive unit in an image is a group of adjacent pixels that share some common properties (Hay, 2001). The object extraction process is illustrated in Figure 1. The pixel properties are extracted into a feature vector, which can be represented in a simple equation.

$$V(f) = [f_1, f_2, f_3, ..., f_m]^T \tag{1}$$

where f and m denote a feature in the vector and the total number of features, respectively.

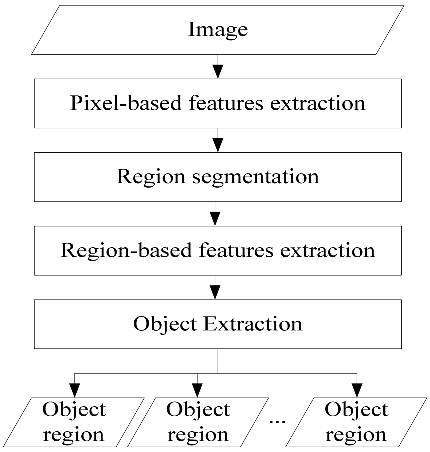


Figure 1. The object extraction diagram

Spectral	Grayscale value		
Textural	**GLCM-based**		
	Angular Second Moment Contrast Inverse Different Moment Homogeneity Variance		
	Laws Texture Energy		
	E5L5TR	S5L5TR	W5L5TR
	R5L5TR	S5E5TR	W5E5TR
	R5E5TR	W5S5TR	R5S5TR
	R5W5TR	E5E5TR	S5S5TR
	W5W5TR	R5R5TR	L5L5T

Table 1. The feature vector containing all features used in this work

For a single image pixel, we can extract two types of features: spectral and textural features. The spectral feature is the grayscale value of the pixel for each spectral band. An experimental result from Ruiz (2004) shows that the combination of GLCM-based (Haralick, 1979) and Laws textural features (Laws, 1980) achieve 85.82% accuracy in classifying urban area while only 61.90%, 67.44% and 84.25% are achieved from using a single feature of spectral, Laws energy, and GLCM-based, respectively. According to this figure, our study used both Laws energy and GLCM-based textural features in additional to spectral feature. Table. 1 shows all features used in this work.

Each image pixel was represented by the feature vector as the input for segmentation. We used the ISODATA algorithm to cluster pixels into regions that contain similar properties. The mathematical operations opening and closing were used to smooth the contour of a region. Since those pixel-based properties for each region was almost the same, within a class, they could no longer be used to differentiate a region from another. Spatial features, which are Area, Perimeter, Circle Diameter from Area, Circle Diameter from Perimeter and Compactness, were then used for this purpose. We extracted object regions and, for each region, attached its spatial features as additional attributes.

3. DESIGN FRAMEWORK

Figure 2 is a simplified overall flowchart of the system.

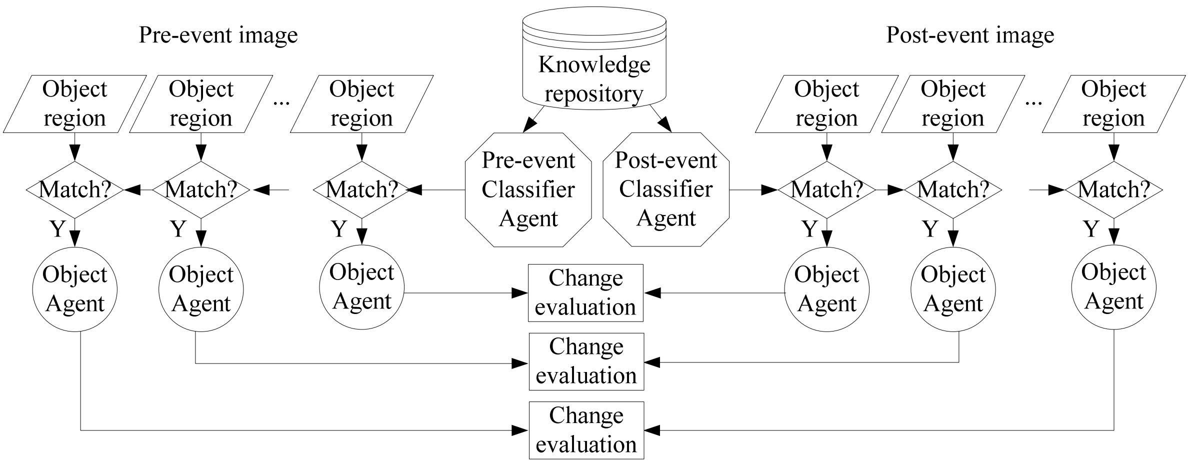


Figure 2. The overall block diagram of the object-based change detection for disasters

3.1 *Classifier Agent (CA)*

For each type of object (class), a *CA* was trained by an expert to recognize the object characteristics from the training sample. There were two *CAs* for each class. One CA was trained to recognize the sample in pre-event image. Another CA was trained to recognize a sample that remained intact after a disaster in the post-event image. This eliminated the need to register and adjust spectral values in the pair of images. An example of *CA* is *Bungalow Classifier Agent*, which captures some fundamental properties of a bungalow template. Each *CA* classifies an object region, from Section 2.3, based on equation (2).

$$Fuzzy\,membership = 1.0 - \sqrt{\sum_{i=1}^{m}\left(\left(f_i^{CA} - f_i^{Obj}\right)/ f_i^{CA}\right)^2} \qquad (2)$$

where m, f_i^{CA} and f_i^{Obj} mean the total number of properties, the ith property of the CA and the ith property of the object region, respectively.

When the fuzzy membership for an object region was greater than a specified threshold, a *CA* then created an *Object Agent (OA)* for this object region. In our experiment, we set the threshold figure to 0.75.

3.2 *Object Agent (OA)*

An *OA* represented an instance of an object class in an image. The key innovation is that an *OA* encapsulates both properties and also methods that it can use to identify and evaluate an *OA* in the pair image. The following change detection operations were attached to each *OA*:

- IsCollapsed(): This operation indicated whether the object partially collapsed.
- IsSizeChanged(): This operation indicated whether the size of the object changed.
- IsMoved(): This operation indicated if the object moved from previous location.
- IsDisappeared(): This operation indicated if the object did not exist or was totally destroyed.

The structure of an OA is illustrated in Table 2. If an *OA* could not find its paired *OA*, this implies that its pair object was not recognized after disaster.

Object Agent	
Properties:	**Methods:**
Area	IsCollapsed()
Perimeter	IsSizeChanged()
DfromA	IsMoved()
DfromP	IsDisappeared()
Compactness	
Geo-coordinate	

Table 2. *Object Agent* Structure

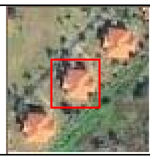
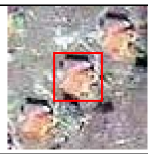
Bungalow CA **Pre-event**		***Bungalow CA*** **Post-event**	
			
Class: Bungalow		Class: Bungalow	
Spatial properties:		Spatial properties:	
Area:	225	Area:	235
Perimeter:	66	Perimeter:	74
DfromA:	16.9222	DfromA:	17.2942
DfromP:	21.0000	DfromP:	23.5454
Compact:	0.6493	Compact:	0.5394

Table 3. *Bungalow Classifier Agents*
a) Pre-event b) Post-event

4. EXPERIMENTS

We evaluated our approach with a pair of 1m-resolution IKONOS images. The test area covered the Blue Village Pakarang Resort area, Thailand, which was imaged before and after the Indian Ocean tsunami of December 26, 2004. In this experiment, we were interested in an assessment of the destruction of bungalows after the disaster. We created two *Bungalow CA* as shown in Table 3. Twenty-one *OA* were automatically created in the pre-event image and seventeen *OA* in the post-event image as illustrated in Figure 3. Initial results indicated that four bungalows were severely damaged as they were unable to be detected by the post-event *Bungalow CA*.

Figure 3. The IKONOS images of the Blue Viallage Pakarang Resort area acquired before (left) and after (right) the disaster.

Table 4 summarizes the assessed results of bungalow damage detected by *OAs* (75% confidence level).

Object Agent's Method	Number of Affected Bungalow
IsCollapsed()	3
IsSizeChanged()	4
IsMoved()	0
IsDisappeared()	4

Table 4. The assessed results of bungalow damage.

5. DISCUSSIONS AND CONCLUSIONS

This paper describes an object-based change detection technique for disasters using object orientation and intelligent agents techniques. We created two types of agents: *Object Agent (OA)* and *Classifier Agent (CA)*. An *OA* represents a specific instance of an object class in an image. The *CA* creates an *OA* for its class based on its rules. The key innovation is that an *OA* encapsulates not only properties but also methods that it can use to identify and evaluate itself in a changed image.

The preliminary results show that the changes evaluated by *Object Agent* are real changes. However, the effectiveness of the approach highly depends on classification approach selected. With the implementation of intelligent agents, the approach is flexible for future extension.

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