An Approach for Automatic Change Inference in High Resolution Satellite Images

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Abstract - Recently, more detailed change detection is becoming possible due to increases in the availability of satellite imageries for practical use and improvements in their spatial resolution. While the amount of data is increasing, manual interpretation is still being used as a conventional method of change detection. For these reasons, practical change detection techniques are required. This paper proposes a knowledge-based change detection approach, which can obtain change information that includes not only land cover changes, but also contextual changes, such as types of damage caused by natural hazards. This approach mainly consists of two processes: information extraction and change inference using Bayesian network. Information extraction employs object-based image analysis for extracting spatial information. Change inference uses extracted information and the Bayesian network constructed from knowledge of change detection process. To demonstrate this approach, change detection of mudslide damage caused by heavy rain in Yamaguchi Pref., Japan was conducted.

Keywords: probabilistic inference, change detection, object-based image analysis, object recognition, Bayesian network

1. INTRODUCTION

Change detection is a major subject in the field of satellite remote sensing. It is useful in various situations, such as land cover and land use analysis and monitoring of damage due to natural hazards. Recently, more detailed change detection is becoming possible due to increases in availability of satellite imageries for practical use and improvements in their spatial resolution. While the amount of data is increasing, manual interpretation is still being used as a conventional method of change detection, requiring special knowledge and experiments. Moreover, it is a labor-intensive and time-consuming task. For these reasons, automatic change detection techniques have been widely studied by many researchers.

Typical techniques of automatic change detection were investigated by Lu et al. (2004). According to this review, change detection techniques are classified into two categories based on the types of information that can be obtained by the techniques. The two categories are: 1) change/non-change information (e.g., image differencing, image regression, normalized difference vegetation index (NDVI) differencing, image ratioing, change vector analysis (CVA), and principal component analysis (PCA)) and 2) "from-to" information (e.g., post-classification comparison, artificial neural networks, and unsupervised change detection). These techniques are referred to as pixel-based approaches, which perform per-pixel analysis to extract information from imageries.

However, the pixel-based approach is limited in its ability to recognize objects in high-resolution satellite imagery. Pixel sizes become smaller than geospatial objects as the spatial resolution of satellite imagery improves. This enables us to recognize objects in detail. While this is an advantage, object recognition using high-resolution satellite imagery requires a method of analysis that goes beyond the pixel-based approach.

To overcome this problem, an object-based approach has been developed and gained considerable attention in recent years (Stuckens et al. 2000, Blaschke 2000, and Benz et al. 2004). The object-based approach first segments an image into image objects, and then associates them with geospatial objects by considering their spatial information in addition to spectral information.

Object-based change detection has been proposed by some researchers. Zhou et al. demonstrated the object-based post-classification comparison (2008). This approach classifies land cover in bi-temporal aerial images into five classes (Building, Pavement, Bare Soil, Coarse Vegetation, and Fine Vegetation) and then classifies the bi-temporal classes into change classes. Im et al. proposed change classification incorporating object correlation images (OCIs) (2008). This method first generates OCIs, which contain the images of three object-based features: correlation, slope, and intercept, and then conducts classification of bi-temporal datasets and the OCIs into three change classes ("Bare land to built-up," "Bare land to paved road," and "Bare land to vegetation").

This paper proposes a change detection approach that conducts knowledge-based inference in the Bayesian Network to implement more expressive and generic interpretation like manual interpretation. Our approach can obtain change information that includes not only land cover changes, but also contextual changes, such as the types of damage caused by natural hazards.

2. DATASETS

This study is based on multi-spectral data observed by the Advanced Visible and Near Infrared Radiometer type-2 (AVNIR-2) on board the Advanced Land Observing Satellite (ALOS). AVNIR-2 has three visible bands and one infrared band with spatial resolution of 10 m.

The datasets used for change detection are bi-temporal images that are ortho-rectified and atmospherically corrected images that are registered within geometric errors of 0.5 pixels (RMS).

3. OVERVIEW OF THE CHANGE DETECTION APPROACH

Our change detection approach computationally emulates change detection using manual interpretation in order to recognize contextual change information. Manual interpretation subconsciously conducts highly complex processes, extracting various kinds of semantic information and inferring an answer from known information. Emulating this process, our approach
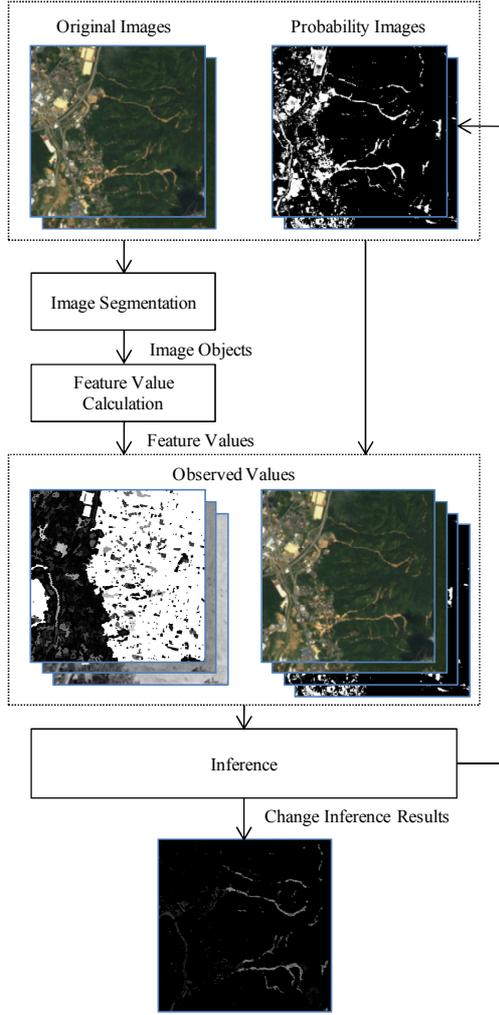
Figure 1 Flow diagram of the change detection approach in this paper.

first extracts some low-level information and then infers change information from it.

Figure 1 shows the flow diagram of our change detection approach, which mainly consists of two processes: information extraction and change inference. In this paper, information extraction is described in Section 4, and change inference is described in Section 5.

4. OBJECT-BASED INFORMATION EXTRACTION

The information extraction implemented by our approach is intended to obtain various clues for change inference. High-resolution satellite data contains rich information on geospatial objects. Most of it is not available for inference because it is intrinsically implicit. Expressive inference depends on the extraction of information from satellite data.

Object-based image analysis is employed for extracting spatial information included in satellite data. Object-based image analysis generates image objects, which are groups of pixels that have similar characteristics. Spatial information can be extracted by analyzing their feature values. Object-based image analysis is applied not only to original satellite data, but also to probability images obtained by inference.

Image objects are generated with image segmentation employing iterative region growing (Tomita et al. 1982). The region-growing algorithm scans the whole image, checking region-to-region connectivity, and if two adjacent regions are connected, they are merged into one region. At first, one pixel represents one region. Iterative region growing is an improved algorithm of region growing that repeats the merging process, relaxing the connection check. The iterative strategy can separate gradual edges more appropriately than normal region growing.

Feature values of image objects are calculated after image object generation. Examples of feature values defined in this paper are as follows: area, elongatedness, orientation, complexity and circularity.

5. KNOWLEDGE-BASED CHANGE INFERENCE WITH A BAYESIAN NETWORK

Inference implemented in manual interpretation usually contains uncertainty. Our approach models this property using Bayesian probability, which can be described as a graphical model or a Bayesian network (Pearl 1988). Bayesian probability is an interpretation of the probability that expresses the degree of belief, as well as the statistical frequency. Bayesian probability is used for the following reasons: 1) high affinity for human knowledge, 2) high credibility on the theory, and 3) high expandability for machine learning.

A Bayesian network is a directed acyclic graph in which a node represents a random variable and an arc connecting one node to another node represents a probabilistic relation between them. The direction of the arc represents the direction of the effect, for example, the arc connecting node A to node B means that the value of node A affects the value of node B, where node A is called the "parent" and node B the "child." The probabilistic relation is described with the conditional probability of the child for each state of each parent. A node that has no parents has only the prior probability distribution of itself, and a node that has at least one parent has only the conditional probability distribution. That alone enables us to calculate the joint probability distribution of all the nodes composing the Bayesian network. The joint probability distribution of the set of all the nodes X_{all} is:

$$P(X_{all}) = \prod_{X_{all}} P(X_i \mid Parents(X_i)) \tag{1}$$

where $Parents(X_i)$ is the set of parents of node X_i.

By marginalizing from this joint probability distribution $P(X_{all})$, the prior probability distribution of certain node X_k is calculated as:

$$P(X_k) = \sum_{X_{all} \setminus X_k} P(X_{all}) \tag{2}$$

Moreover, the posterior probability distribution of the node X_k under the condition that all the nodes included in the set $X_{observed}$ are observed is:

$$P(X_k \mid X_{observed}) = \alpha \sum_{X_{all} \setminus (X_k \cup X_{observed})} P(X_{all}) \tag{3}$$

where α is a normalizing constant that guarantees that the sum of the probability $P(X_k|X_{observed})$ at all the values of X_k is 1.

In our Bayesian network, nodes are assigned to a binary random variable or a continuous random variable. The binary random variable represents whether a concept exists with its probabilistic distribution. The conditional probability distribution of it for each state of each parent is described respectively with one discrete probability. The continuous random variable represents one continuous value with its probabilistic distribution. For simplicity, we assumed that the continuous random variable must not have any children and its value must be observed. Therefore, the parents of it are limited to binary random variables. The conditional probability distribution of it for each state of each parent is described respectively with one continuous function that assigns one discrete probability to each input of the value. We use the cumulative distribution function of the normal distribution as this function:

$$\Phi(x) = \int_{-\infty}^{x} N(x \mid \mu, \sigma^2) \qquad (4)$$

where $N(x|\mu,\sigma^2)$ represents the normal distribution in the mean of μ and the variance of σ^2. This expression is considered a fuzzy thresholding.

Knowledge of the inference process of change detection with its degree of belief is modeled using the Bayesian network. The probabilistic relation between some nodes represents the relation that one concept is inferred from the other concepts. The Bayesian network is constructed as the more essential concepts are set at an upper node in order to make the probabilistic relations simpler. The concept represented by binary random variable includes geospatial objects, changes, features used for recognition, and so on. If the fact of whether one concept exists is able to characteristically affect an observed value, then the continuous random variable of the observed value is added as a child of the concept.

Inference is executed by calculating the posterior probability distribution of targeted concepts (Eq. 3) for each pixel. Inference uses clues: the object-based feature values extracted in the previous process and pixel-based values that are calculated from multi-spectral reflectance of the pixel. They are input into the Bayesian network as the observed value of a continuous random variable. As the result of the inference, the images of the posterior probability distribution of targeted concepts are obtained. They represent the belief of existence of each concept.

6. EXPERIMENTS AND RESULTS

Experiments were conducted to demonstrate our change detection approach. The test case of the experiments was detection of damaged areas caused by heavy rains on July 21, 2009, in Yamaguchi City, Japan. The datasets were observed by AVNIR-2 on board ALOS and acquired on June 14, 2009 (Day 1), shown in Fig. 4 (a), and July 30, 2009 (Day 2), shown in Fig. 4 (b).

The Bayesian network for the mudslide detection was constructed as shown in Fig. 2 and Fig. 3 (these two networks are connected). In this case, it was assumed that there exist five types of substance: *chlorophyll*, *soil*, *asphalt*, *cloud*, and *water*. The Bayesian network in Fig. 2 shows that their existence affects five observed values. These values are calculated from multi-spectral reflectance of the pixel. The Bayesian network in Fig. 3 is constructed on the basis of following knowledge:
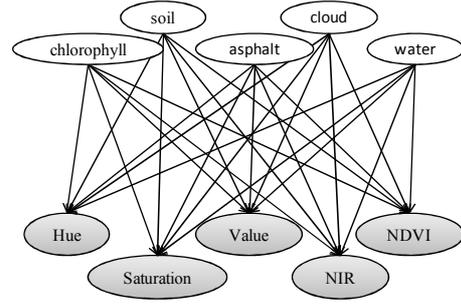

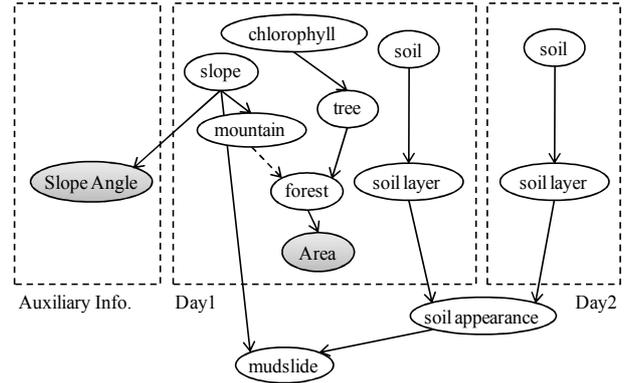Figure 2 The Bayesian network for the mudslide detection focused on the part of substance recognition.

Figure 3 The Bayesian network for the mudslide detection focused on the part of objects and change recognition.
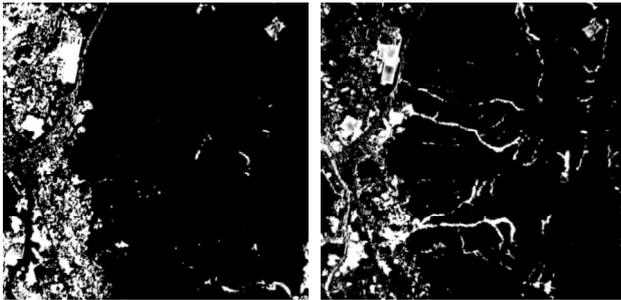
- a *mudslide* is one kind of *soil appearance*,
- *mudslides* occur on *slopes*,
- *soil appearance* is a change of the *soil layer*,
- a *soil layer* is composed of *soil*,
- a *mountain* is made up of *slopes*,
- *forests* frequently exist on a *mountain*,
- a *forest* has a large *area*,
- a *forest* is composed of *trees*, and
- a *tree* has a lot of *chlorophyll*.

In this case, digital surface model (DSM) generated from Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) on board ALOS was available for calculating slope angle. The inference using Bayesian network can also refer such auxiliary information.
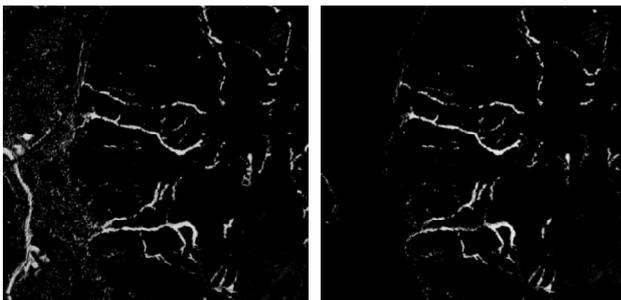
The results of the inference using this Bayesian network are displayed in Fig. 4 (c), (d), (e), and (f). These images show the posterior probability distribution of each concept with brightness. Figure 4 (c) and (d) are the posterior probabilities of soil on the Day1 and Day2 data. These results obtained by inference using the Bayesian network shown in Fig. 2. Figure 4 (e) is the posterior probability of soil appearance. This result indicates the place where the soil layer was not found on Day1 but found on Day2. Figure 4 (f) is the posterior probability of mudslide. The difference between the result of soil appearance inference and mudslide inference is whether the soil appearance on the flatland is detected or not. This result implies that our change detection approach can detect the changes described as knowledge.

Figure 4 Images (a) and (b) are original AVNIR-2 images. Image (a) was acquired on June 14, 2009 (Day 1, before the disaster), and image (b) was acquired on July 30, 2009 (Day 2, after the disaster). Image (c) (d) (e) and (d) are the posterior probabilities obtained by inference. Image (c) and (d) are soil on the Day 1 and the Day 2. Image (e) is soil appearance on the Day 2. Image (f) is mudslide on the Day 2.

Comparing our mudslide detection results and the Yamaguchi prefectural government's report, it was found that the producer's accuracy (PA) was 88.2 percent and the user's accuracy (UA) was 90.7 percent as shown in Table 1 (note that the comparison was not of detected areas but of detected points because the reference did not exactly describe the areas of mudslides).

More expressive and accurate change detection is considered possible if the amount of knowledge is increased. More improvements in knowledge description and further experiments of this system are ongoing.

Table 1. A comparison of mudslide points between our mudslide detection result and the Yamaguchi prefectural government's report

		Results		PA
		Landslide	No-Landslide	
Reference	Landslide	97	13	88.2%
	No-Landslide	10		
UA		90.7%		

7. CONCLUSION

In this paper, we have proposed a knowledge-based change inference approach using a Bayesian network. This approach extracts object-based information, constructs the Bayesian network based on knowledge of the inference process of change detection with its degree of belief, and implements the inference of targeted change from the extracted clues using the Bayesian network. The experiment results show that our change detection approach can detect the changes described as knowledge. More improvements in knowledge description and further experiments of this system are ongoing.

8. REFERENCES

U.C. Benz, P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen, "Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 58, pp. 239-258, 2004.

T. Blaschke, S. Lang, E. Lorup, J. Strobl, and P. Zeil, "Object-oriented image processing in an integrated GIS/remote sensing environment and perspectives for environmental applications," *Training*, vol. 2, pp. 555-570, 2000.

J. Im, J.R. Jensen, and J.A. Tullis, "Object-based change detection using correlation image analysis and image segmentation," *International Journal of Remote Sensing*, vol. 29, pp. 399-423, 2008.

D. Lu, P. Mausel, E. Brondízio, and E. Moran, "Change detection techniques," *International Journal of Remote Sensing*, vol. 25, pp. 2365-2401, 2004.

J. Pearl, *Probabilistic reasoning in intelligent systems: networks of plausible inference*, Morgan Kaufmann, 1988.

J. Stuckens, P.R. Coppin, and M.E. Bauer, "Integrating Contextual Information with per-Pixel Classification for Improved Land Cover Classification," *Remote Sensing of Environment*, vol. 71, pp. 282-296, 2000.

F. Tomita, Y. Shirai, and S. Tsuji, "Description of textures by a structural analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pp. 183-191, 1982.

W. Zhou, A. Troy, and M. Grove, "Object-based land cover classification and change analysis in the Baltimore metropolitan area using multitemporal high resolution remote sensing data," *Sensors*, vol. 8, pp. 1613-1636, 2008.