CHANGE DETECTION FOR AERIAL PHOTO DATABASE UPDATE

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ABSTRACT:

With rapid new technological development during the past 50 years, aerial photos have been increasingly and commonly used not only in geographic information systems but also in various spatially related applications. Many municipalities and government agencies have constructed aerial photo databases all over the world. Keeping these databases up to date is the most important part of making them effective so that aerial photo databases are expected to be updated as frequently as possible. However, in practice, some of them are barely updated because of high cost. In case of detecting where changes occur, aerial photo databases could be frequently and partially updated only in the changed areas.In this study, medium spatial resolution imagery is proposed to detect changes. Instead of using aerial photos, medium spatial resolution imagery could be a good alternative because of its wider coverage and lower price than aerial photos. Free accessible Landsat ETM+ and orthophotomaps are used for change detection. In order to compare with 15 m pan-sharpened Landsat ETM+, 1 m orthophotomaps are decomposed, segmented, and classified through wavelet transform and object-oriented classification. Although the detected changes are rough, the result shows that the method is quite cost-effective and practical. Moreover, it could support decision making for updating aerial photo databases.

1. INTRODUCTIOIN

Aerial photos have been proved to be useful for extracting spatial information or performing spatial analysis since they have been widely used for mapping purposes. In addition, diverse aerial photo products such as topographic maps, digital elevation models, and orthophotos play an important role in various spatially related applications. These are reasons why many municipalities and government agencies have constructed aerial photo databases in Canada and also in other nations. In Canada, for example, in federal case, the National Airphoto Library (NAPL) by Natural Resources Canada archives over six million aerial photos covering all of Canada. In provincial case, the Alberta Sustainable Resource Development collects over 1.4 million aerial photos covering whole province, and the Provincial Softcopy Orthophotomap Database (SODB) by the Service New Brunswick (SNB) was created from aerial photos for the whole province.

Considerable amounts of aerial photo databases have been built all over the country. In general, most databases have an updating problem and it has been a continuous issue in this field. Aerial photo database is no exception, and up-to-date data is indeed necessary to extract and analyze trustworthy spatial information. In practice, the SNB has received numerous inquiries into when the SODB will be updated. Although most aerial photo databases are expected to be updated as frequently as possible, some are barely updated because of high cost.

Human activities and natural phenomena would cause land-cover changes, and in practice they are not occurred in whole area. Hence, in case of cost-effectively detecting where changes occur, aerial photo databases could be frequently and partially updated only in the changed areas. Multitemporal images from same sensor are generally used in change detection, but it is too expensive to use aerial photos. Medium spatial resolution imagery, such as Landsat and SPOT usually has wider coverage and lower price than aerial photos, so it could be a good alternative for change detection.

In this study, a cost-effective and practical method is suggested to detect land-cover changes to support decision making for updating aerial photo databases. It involves wavelet transform and object-oriented classification to compare two different types of images, and then post-classification comparison is applied to find changes.

2. BACKGROUND

2.1 Wavelet Transforms

Wavelets basically intended to address shortcomings of the short time fourier transform (STFT). Instead of using the fixed time and frequency resolution in the STFT, wavelet transforms are able to provide the time and frequency representation of the signal. In order to use the idea of multiresolution, wavelet transforms can be defined as a scaling function and a wavelet function. These functions composed of translations and scalings of a scaling function and a wavelet function are:

$$\varphi_{j,k}(t) = 2^{j/2}\varphi(2^j t - k) \quad (1)$$

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k) \quad (2)$$

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where $\varphi_{j,k}(t)$ and $\psi_{j,k}(t)$ are the scaling function and the wavelet function respectively (Burrus et al, 1998).
According to the basic requirement of multiresolution analysis (MRA), the scaling function space, V_j can be formulated:

$$V_j \subset V_{j+1} \quad \text{for all} \quad j \in Z \tag{3}$$

with

$$V_{-\infty} = \{0\}, \qquad V_{\infty} = \{L^2(R)\} \tag{4}$$

where Z is the set of integers and $L^2(R)$ is the space of all functions $f(t)$ with a well defined integral of the square of the modulus of the function. Then, $\varphi(t)$ can be simply expressed:

$$\varphi(t) = \sum_n h_\varphi(n)\sqrt{2}\varphi(2t-n) \tag{5}$$

where $h_\varphi(n)$ is the scaling function coefficients.
There are some advantages that a scaling function and a wavelet function are orthogonal. Therefore, the related wavelet function space, W_j is the orthogonal complement of V_j in V_{j+1}. Then, the wavelet function space can be defined:

$$V_{j+1} = V_j \oplus W_j \tag{6}$$

in general

$$\{L^2(R)\} = V_j \oplus W_j \oplus W_{j+1} \oplus \Lambda \tag{7}$$

where $\oplus$ is the direct sum. Then, $\psi(t)$ can be expressed:

$$\psi(t) = \sum_n h_\psi(n)\sqrt{2}\varphi(2t-n) \tag{8}$$

where $h_\psi(n)$ is the wavelet function coefficients.

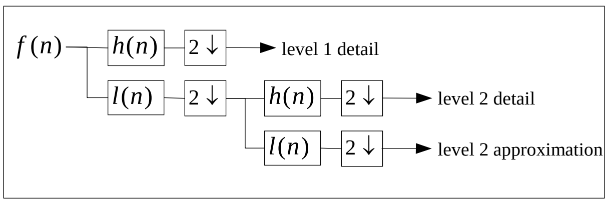


Figure 1. Two-level one-dimensional DWT filter bank

While our interest is in discrete images, discrete wavelet transforms (DWT) is commonly used to implement wavelet transforms. It is easy to apply and reduce a computational burden. The process of DWT can be represented as two operations; filtering and down-sampling. The filtering implements a low-pass filter extracting the approximate coefficients, and a high-pass filter extracting the detail coefficients. Then, the down-sampling reduces the resolution by a factor of two at each level. These processes are called the filter bank illustrated in Fig. 1.

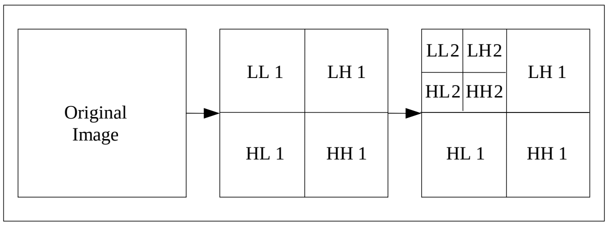


Figure 2. Two-level two-dimensional image decomposition

By applying the DWT filter bank to two-dimensional images, an image is actually decomposed into four images at each decomposed level. It first applies to the columns and then to the rows. Consequently, it produces one approximation coefficient (LL) and three detail coefficients (LH: horizontal, HL: vertical, HH: diagonal). To obtain the next level of detail coefficients, the DWT filter bank applies the LL alone, and it results in two level decompositions as shown in Fig. 2.

2.2 Object-oriented Classification

A pixel is the basic processing unit in conventional classification whereas an object in object-oriented classification. The term, objects, refers to individually resolvable entities located within an image that are perceptually generated from pixel groups (Hay et al., 1997). Objects have been composed of a group of pixels partitioned by image segmentation, and then diverse classifiers (e.g., Maximum Likelihood, ISODATA, Neural Network, Fuzzy Logic and combination of these) operate on objects individually.

Discontinuity and similarity are two basic properties of image segmentation algorithms. Rapid changes in intensity called discontinuity could be used in the edge-based segmentation. It is based on information about edges in the image and diverse edge detecting operators are utilized. According to the similarity specified by a set of predefined criteria, an image can be partitioned into objects or regions that are similar. It is used in thresholding and region-based segmentation. By applying threshold to an image histogram, thresholding can simply divide an image. However, region-based segmentation, such as region growing and region split-merging approach, can directly construct regions using predicated measurements to satisfy the following conditions:

$$R = \bigcup_{i=1}^{S} R_i \qquad R_i \cap R_j = \varnothing \qquad i \neq j \tag{9}$$

$$H(R_i) = TRUE \qquad i = 1,2,\ldots,S \tag{10}$$

$$H(R_i \cup R_j) = FALSE \qquad R_i \text{ adjacent to } R_j \tag{11}$$

where S is the total number of regions in an image, and $H(R_i)$ is a binary similarity (or homogeneity) evaluation of the region R_i (Sonka et al., 1999).

3. METHODOLOGY

3.1 Image Data

Two orthophotomaps from SODB and Landsat ETM+ from GeoBase are used in this study. The SODB is a high quality digital map product which consists of orthometrically corrected aerial photos of New Brunswick. It is a scanned, orthorectified and mosaicked aerial photo clipped in a 1:10,000 topographic map window. It has three bands (RGB) and 1 m spatial resolution. It was acquired in the summer of 1996. Landsat ETM+ was acquired on September 2000. It has one 15 m panchromatic, six 30 m multispectral bands. It is distributed from GeoBase which is a free accessible geospatial database for all of Canada. These images are shown in Fig. 3.

(a) (b)

Figure 3. Image data: (a) top: orthophotomap(SODB no. 46006480), bottom: corresponding subset of Landsat ETM+, (b) top: orthophotomap(SODB no. 46106480), bottom: corresponding subset of Landsat ETM+

3.2 Methodology

The steps associated in this study are summarized in Fig. 4.

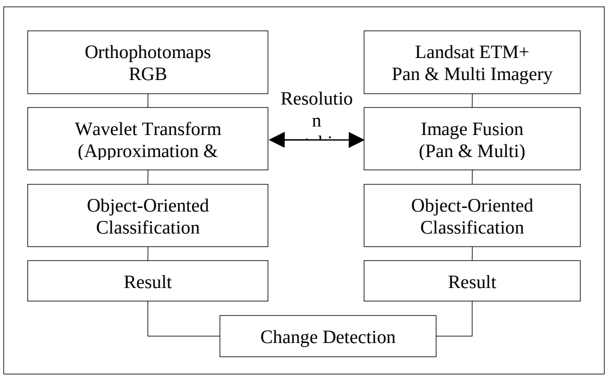
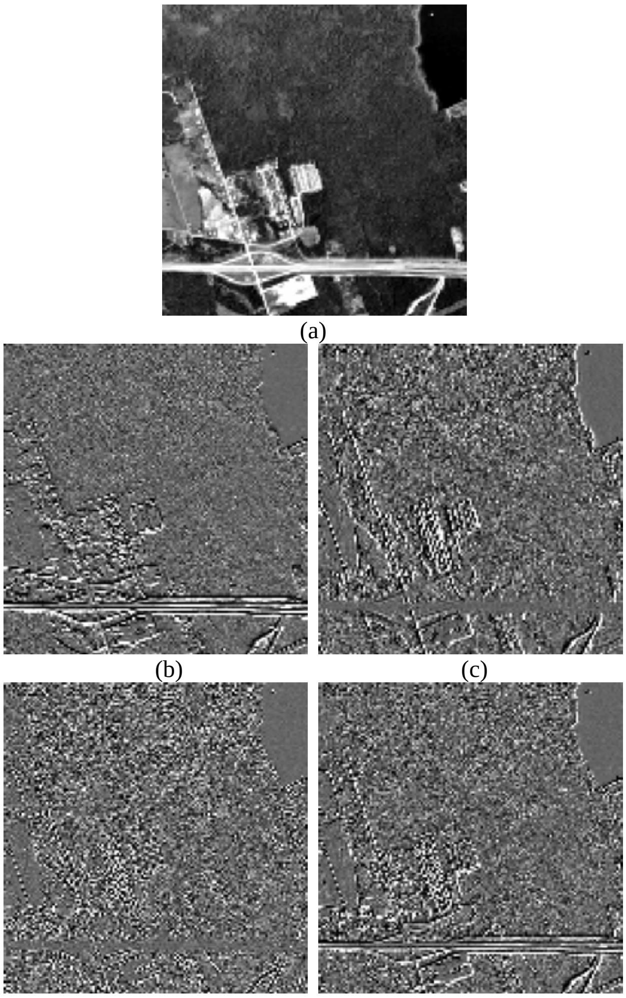


Figure 4. Overview of methodology

3.2.1 Image Fusion: Image fusion combines high spatial resolution of panchromatic images and high spectral resolution of multispectral images. The spatial resolution difference between orthophotomaps and Landsat ETM+ is quite high. In order to enhance the image and reduce the resolution difference, the panchromatic and multispectral images of Landsat ETM+ can be fused by an automatic fusion method called UNB Pan-Sharpening. The method based on least squares is employed for a best approximation of the gray value relationship between the original multispectral, panchromatic and the fused image bands for a best color representation (Cheng et al., 2003).

3.2.2 Wavelet Transform: In change detection, it is important to use the same sensor, same radiometric and spatial resolution data with anniversary acquisition dates (Lu et al., 2004). Although image fusion reduced the spatial resolution difference, the discrepancy between orthophotomaps and pan-sharpened Landsat ETM+ is still subject. Four levels wavelet transform decompose orthophotomaps into one approximation and three detail coefficients from 1 m to down-sampled 16 m spatial resolution. Proper spatial resolution, therefore, can be applied to implement convincible change detection.



(a)

(b) (c)

(d) (e)

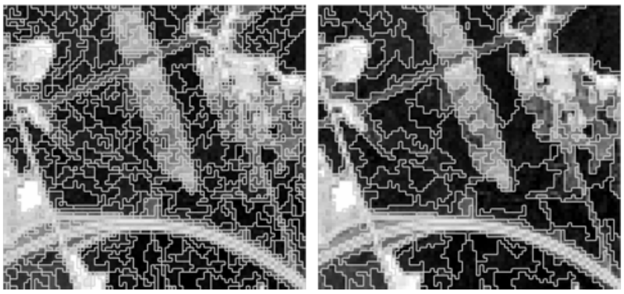
Figure 5. Wavelet transform: 4^{th} level coefficients of Red band of orthophotomap in 16 m spatial resolution (a) approximation, (b) horizontal detail, (c) vertical detail, (d) diagonal detail and (e) sum of detail coefficients

After a few levels of wavelet decomposition, the approximation coefficient loses its high frequency component because of a low-pass filter. The low-pass filter not only removes noise in an image but suppresses overall variation in brightness. It means the brightness of the shadow in forest regions gradually decreases as close to the brightness in water regions. Therefore, it is quite difficult to distinguish which region is forest or water. By adding texture properties to a classification process, the drawback of low-pass filtering could be compensated.

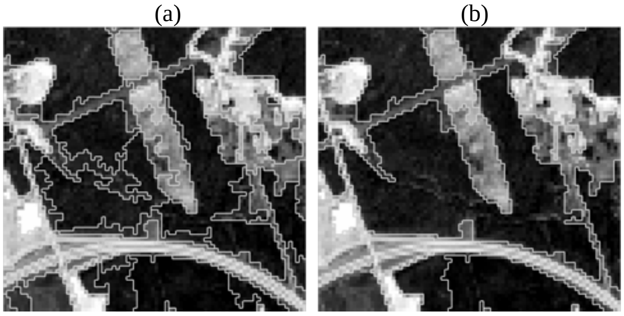
While there is no formal definition of texture, the texture of an image is related to the spatial distribution of the intensity values in the image, and as such contains information regarding contrast, uniformity, rugosity, regularity, etc (Ruiz et al., 2004). For the purpose of text description, detail coefficients were used in this study because they contain the high frequency component which is the relevant texture information. The summation of each detail coefficients was utilized in following classification process, and decomposed 4^{th} level coefficients are shown in Fig. 5.

3.2.3 Object-oriented Classification: Orthophotomaps and Landsat ETM+ have different spatial resolutions, number of bands, and wavelengths. Although the problem of different spatial resolution was resolved through the above steps, some others were still remained. Therefore, the post-classification comparison was applied to change detection instead of the image-to-image comparison.

The classification used in this study is based on a new object-oriented approach. As contrasted with conventional pixel-based classification, object-oriented classification can expect the semantic relation between real-world objects and image objects. This relation improves the value of the final classification (Benz et al., 2004). Meaningful image objects were extracted using the multi-resolution segmentation algorithm. It is one of the basic procedures of the commercial remote sensing image processing software Definiens Professional 5.0 which is formally known as eCognition.



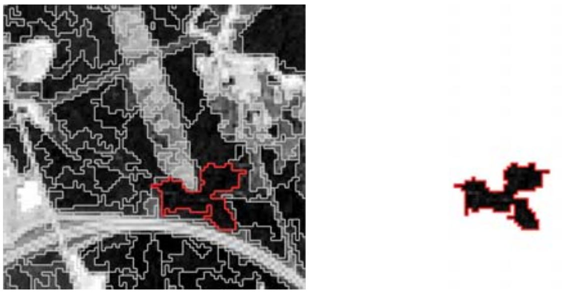
(a) (b)



(c) (d)

Figure 6. Results of multi-resolution segmentation using different scale parameters (a=5, b=10, c=20, d=40)

As many segmentation algorithms rely on user assigned parameters, the multi-resolution segmentation also requires defining parameters, such as scale, color/shape, and smoothness/compactness. It means the size and shape of image objects could be affected by different values of parameters as shown in Fig. 6. In addition, it is time-consuming and tedious to find the most suitable size and shape of objects for classification. For example, the appropriate scale value is 40 to isolate a forest region, and it is revealed through many trials as shown in Fig. 6 (d). In order to avoid this tiresome process, image objects were extracted using default values of parameters without any consideration of size and shape. Then, based on the small but meaningful image objects (see Fig. 7) as the basic process unit, spectral statistics and texture descriptions were calculated for classification.



(a) (b)

Figure 7. (a) the result of multi-resolution segmentation using default values (b) the basic process unit

The mode value was used to represent each spectral value of objects, and the standard deviation of detail coefficient was used to describe the texture information of objects. In general, most text descriptors, such as the gray-level co-occurrence matrix (GLCM) and the local binary pattern (LBP) are calculated using a small window. However, the standard deviation was used to describe the texture information in this study because the shape of image objects is usually irregular (see Fig. 6 (b)) and window-based texture descriptors include pixels on the outside of the image objects in their calculation. In addition, the standard deviation is easy to calculate and simple to represent coarse or fine.
Combined classification was employed after segmentation. First, supervised classification was performed using backpropagation neural network algorithm, and then, unsupervised classification was performed using Kohonen's self-organizing feature map (SOFM) algorithm.

4. RESULTS AND DISCUSSION

Landsat ETM+ was georeferenced, fused and resampled to 16 m spatial resolution, and then orthophotomaps were decomposed using 4^{th} level wavelet transform to compare respectively. The multi-resolution segmentation partitioned both images into meaningful image objects, and then the combined classification was applied to detect changes.

Although the problem caused by different spatial resolution was solved, some extra problems appeared in classification because of the properties of orthophotomaps and wavelet transform. First, available spectral information of orthophotomaps is limited within only visible bands. It affects not only an accuracy of classification but also a discrimination of complex nature. Especially it is quite difficult to distinguish grass, impervious and crop regions. Second, the gray level range of images is decreasing after few wavelet transforms. It means overall brightness of images is getting darker and the spectral range of each land-cover type is gradually closer. It often misclassifies some land-cover types, especially the shadow in forest and water. Finally, the classification results from two different images vary because of different characteristics.

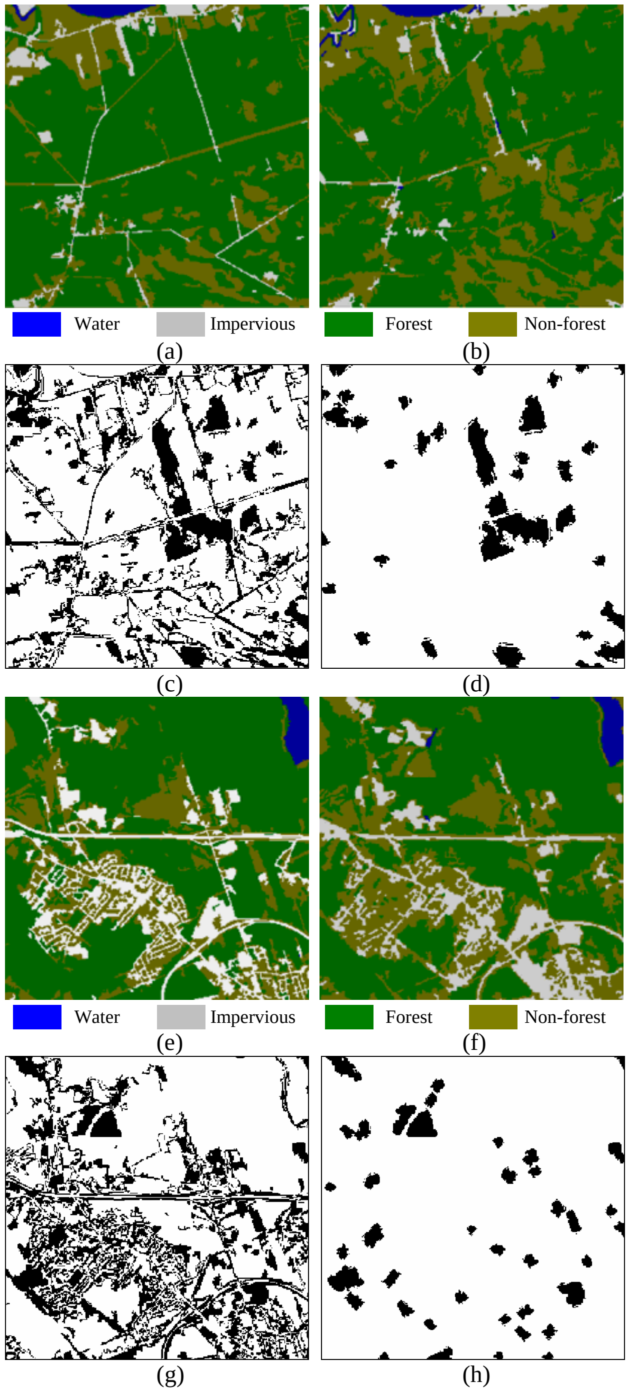


Figure 8. Change detection: (a) classification of 46006480, (b) classification of corresponding Landsat ETM+, (c) changes between (a) and (b), (d) refined changes, (e) classification of 46106480, (f) classification of corresponding Landsat ETM+, (g) changes between (e) and (f), (h) refined changes

These problems practically derived the classification error, and directly affected the classification accuracy. The aim of this study was to detect changes in coarse scale, and it was not necessary to distinguish very detail land-cover types. Therefore, the four land-cover category, such as water, impervious, forest and non-forest, was used in classification. The classification was done in two steps. In the first step, the supervised classification was performed using training sites. Then, the unsupervised classification was performed using 30 classes. After the unsupervised classification was completed, the classes were re-categorized and combined with the supervised classification result. Finally, map-to-map comparison was applied to detect changes, as shown in Fig. 8.

5. CONCLUSION

In this study, images from different sensors have been utilized for change detection. In order to apply map-to-map comparison, the new object-oriented classification discriminates four land-cover types from orthophotomaps and Landsat ETM+ after wavelet transform and multi-resolution segmentation. Through the implementation, the methodology suggests how to compare high spatial resolution imagery with medium spatial resolution imagery and how to improve the classification result when the available spectral information is limited.

Instead of using aerial photos, medium spatial resolution imagery, such as Landsat and SPOT can be a cost-effective and practical alternative in change detection. Although the results in this study could not identify changes in detail, it is enough to represent where changes occur and suggest where should be updated roughly. Moreover, it could be applied to different types of imagery.

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