Abstract - In this paper, several classification methods are presented and a fusion structure is included to improve the final classification performance. The definition of “layer” and the method to create it are then introduced. Based on “layer”, a multiple level change detection algorithm is proposed, which gives the details of the changes in each region and is demonstrated to be an easy, effective and reliable method. Experimental results are provided using RADARSAT images, which have been registered with the automated registration algorithm of A.U.G. Signals that is currently available under the distributed processing system www.signalfusion.com.

Keywords: Distributed Processing, Change Detection, Fusion, Classification

1 Introduction

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. It is useful in such diverse applications as land use change analysis, monitoring of shifting cultivation, assessment of deforestation, crop stress detection and so on. It is essential for studying changes on the earth’s surface. Such changes may determine the rate of change for disaster management (e.g. flooding), ice monitoring, earthquake prediction and monitoring, urban planning etc.

Remotely sensed data are now able to estimate changes with very high accuracy. The accuracy is proportional to the image resolution, i.e. the higher the resolution of the images used, the higher the accuracy of the change detection. There are several sensors used for change detection. SAR sensors offer the advantage of providing additional phase information that may be used for change detection. This is due to the fact that the pixels are complex numbers. When the pixel-to-pixel phase information is being used we say that this change detection process is based on interferometry. When only the amplitude of the images is used this process is called photogrammetric change detection.

Change detection may be applied directly on images by using only the pixel amplitude or both the magnitude and phase, or transformed pixel values. The well-known change detection techniques are image differencing, image ratioing, image regression, Principal Component Analysis (PCA), wavelet decomposition, change vector analysis and so on. In topographic change detection, for example if we want to study changes in a region where the water level changes, we are interested in studying only the changes between the two regions (land or water) [1, 2]. Hence, all land pixels may be assigned one value and all the water pixels another value. In this case, study of changes is much easier and all unnecessary image land or water information has been eliminated through an image segmentation transformation.

To detect the changes for each region, classification should be performed first. There exist many classification methods. In this paper, we used three methods, which are thresholding, fuzzy C-mean and decision tree. To improve the overall performance, the decisions resulted from different classification algorithms could be fused before performing the change detection.

The remainder of the paper is organized as follows. A detailed topographic change detection method based on region classification is described in Section 2. Section 3 outlines the fusion structure. The definition of “layer” is introduced in Section 4. Section 5 discusses the distributed computing technique. Some simulations are given in Section 6. In Section 7, the conclusions of the paper are drawn.

2 Region Classification

Region classification is a widely used method for extracting information on surface land cover from remotely sensed images. The resulting cartography is helping decision makers in different research fields. There exist a lot of image classification methods. The change detection approach that will be proposed in section III is a kind of post-classification method. In this paper, the classification methods we used are: thresholding, fuzzy C-means (FCM) and decision trees.
2.1 Thresholding

Considering a grayscale image, it is possible to do the classification by applying the thresholding technique using the map histogram. Thresholding permits the distinction of relevant topographic information, such as the lakes, rivers, wetlands, wooded areas, eskers, roads, etc., from contours and grid lines. The map thresholding classification technique is based on the fact that different textures have different mean gray values on the map. This technique is defined as follows. If a pixel represents the texture of interest, we set its value to “1” in the new classified image, and all the other pixels are set to “0”, such as

\[
f(x, y) = \begin{cases} 
1 & \text{for } r(x, y) \leq g_j, \\
0 & \text{for } r(x, y) < g_i \text{ and } r(x, y) > g_j,
\end{cases}
\]

where \( f(x, y) \) is the pixel value in the new classified image, and \( r(x, y) \) is the original pixel value. \( g_i \) and \( g_j \) are gray-scale values used as thresholds. Normally, we are interested in more than one region. In this case, different values will be assigned to \( f(x, y) \) for different regions to distinguish them. The most appropriate threshold values have to be determined by the operator, since these values may vary according to the printing and scanning specifics.

Take a look at Figure 1, in which there are two RADARSAT images taken in May and August 1997. These images were provided by the Defence Research and Development Canada (DRDC)-Ottawa. These images were registered by the automatic registration algorithm of A.U.G. Signals Ltd that is available through the distributed computing at www.signalfusion.com. Roughtly there are three regions in these images: deep water, shallow water and land. We can easily see the differences of water levels due to flooding of the river in May. We extract the regions of interest from Figure 1 and display them in Figure 2. To apply the thresholding method to find the exact water and land regions, we have to determine the threshold first. Pick up some small regions with known classes (water or land) from the two images. The pixels in these regions are used as the training data. The histogram of these training data will then be plotted. Suppose there are \( N \) regions needed to be classified, the histogram should have \( N \) peaks. The thresholds should be set as the lowest points between every two consecutive amplitude peaks in the histogram. Figure 4 gives the classification results of these two images using this thresholding method, where the black regions represent the deep water, grey ones are the shallow water, and the white regions stand for the lands.

2.2 Fuzzy C-Means

Fuzzy clustering is very well suited for the imprecise nature of geographical information including remote sensing data. According to the fuzzy clustering framework, each cluster is a fuzzy set and each pixel in the image has a membership value associated to each cluster, ranging between 0 and 1, measuring how much the pixel belongs to that particular cluster [13]. There have been many different families of fuzzy clustering algorithms proposed in the last decade. The one used in this work is the Fuzzy C-Means algorithm (FCM), which is an iterative technique based on the minimization of a generalized group sum of squared error objective functions [14], [15].

\[
J_m(U, \mathbf{v}; x) = \sum_{i=1}^{c} \sum_{k=1}^{n} (u_{ik})^m \| x_k - v_i \|^2,
\]

where the real number \( m \) is a weighting exponent on each fuzzy membership with \( 1 \leq m < \infty \). \( c \) is the total number of clusters and \( n \) is the total number of pixels in the image being classified. \( \mathbf{v} = (v_1, v_2, \cdots, v_c) \) are geometric cluster prototypes. \( U = \{u_{ik}\} \) is a \( c \times n \) matrix, where the element of \( U \), \( u_{ik} \), satisfies \( u_{ik} \in [0,1] \) and \( \sum_{i=1}^{c} u_{ik} = 1 \) for all \( k \).

![Figure 1: Two registered RADARSAT images](image1)

![Figure 2: sub-images of the images in Figure 1](image2)

Minimization of \( J_m \) is based on the suitable selection of \( U \) and \( \mathbf{v} \) using an iterative process using the following steps.

1. Determining values for \( c, M, \) error (e) and loop counter \( t=1 \).
2. Creating a random \( c \times n \) membership matrix \( U \).
3. Computing cluster centers.

\[
v_i^{(t)} = \frac{\sum_{k=1}^{n} (u_{ik}^{(t)})^m x_k}{\sum_{k=1}^{n} (u_{ik}^{(t)})^m}
\]
where s represent sub-band images, acquired from stationary wavelet transform.

4. Updating the membership matrix U.

\[
U^{(l+1)}_{ik} = \left[ \frac{\sum_{j=1}^{m-1} \left( \frac{\|x_k - V_j\|}{\|x_k - V_j\|} \right)^{2^{m-1}}} \right]^{-1}
\]

Stop if \(U^{(l+1)} - U^{(l)} < e\), otherwise increase t and go to step 3.

The FCM algorithm is very well suited to remote sensing image segmentation. But at the same time it exhibits sensitivity to the initial settings with regard to both speed and stability and also shows sensitivity to noise. Figure 5 is the three-region classification results for the images in Figure 2 using the FCM method.

### 2.3 Decision Trees

Another common approach to classification is to use decision trees. The decision tree itself is a set of decision rules that describe each group’s patterns learned from these given examples. The decision tree algorithm used here is the "Quick, Unbiased, Efficient Statistical Trees" (QUEST). The algorithm is described in [16] and the performance of this algorithm compared with other classification methods can be found in [17]. Applying the QUEST to the original images in Figure 2 to discriminate regions of land and water, Figure 6 gives the classification results. The three-region results are plotted in Figure 8.

We must note before applying the above classification techniques, denoising method should be applied to the original images. In this paper, we use the wavelet denoising method combined with simple nonlinear speckle reduction filters (i.e. median filters). At first we apply median filtering to the original images. Median filtering is a widely used nonlinear process useful in reducing impulses, or salt-and-pepper noise. It is also useful in preserving edges in an image while reducing random noise. The wavelet denoising method is then applied. Wavelet transform is a useful tool for the time-frequency analysis of signals. From the viewpoint of signal processing, wavelet analysis represents a signal by its components in a series of independent frequency channels (scales). By analyzing the behavior of the signal in each scale, we can find the features of the signal or discriminate different parts (such as the noise and the useful signal) of the combined signal. Mallat’s [11] research indicated that the local maximums of the wavelet transform of noise and signal have different variation rules with the change of the scale. So denoising by wavelet method can be realized by observing these local maximums at each scale. A commonly used wavelet denoising method proposed by Donoho [12] regards the wavelet coefficient below a threshold as noise and set them to zero.

Comparing the classification results using these three different techniques, it is easy to find that the classified images in Figure 4 using thresholding method are the clearest. The FCM algorithm is very noise sensitive. The images in Figure 5 present a lot of salt-and-pepper noise. Since in this example the images are single band, the decision tree method is very similar to the thresholding method. By analyzing the training data, a tree is structured with the pixel value being the only split variable for each node. It is like using the sample data to find the threshold and then do the thresholding classification. The performance of the decision tree method depends on the accurateness of the sample data and is more sensitive to the additive noise than the thresholding technique. Among these three methods, the FCM algorithm is the most automatic one, which doesn’t need the training data, but at the same time, gives the worst results.

### 3 Fusion Architecture

The aim of fusing the decision result from different classification methods is to increase the overall performance. Hierarchically there are three levels of fusion: data fusion, feature fusion and decision fusion [17]. Decision level fusion was chosen over the other forms of fusion for a variety of reasons. The most important of these is that, unlike the others, it is always a feasible approach, though not necessarily the most desirable. The obvious practical reason aside, decision level fusion does have many desirable qualities in a change detection application. First it is the most tolerant to individual errors in the data. Secondly it has a lower computational complexity than feature level fusion. Thirdly, because of its low coupling of information, it is more robust to the removal or addition of individual data sources. The main disadvantage of this form of fusion is that information lost from a lower level of fusion cannot be recovered from a higher level, although some of this can be compensated for by providing information about the quality of the decision reached.

Each of the subsystems, D(DSi), operating on a data source, DSi, can be viewed as a Feature In - Decision Out configuration while the final fusion of all the subsystems is a Decision In - Decision Out configuration. In the general case we will have L Data source measures of an underlying object, o, that can belong to one of c classes in \(\Omega = \{\omega_1, \omega_2, ..., \omega_c\}\). Then dij(o) is the support that the subsystem working on the i’th data source, DSi, gives to the hypothesis that object, o, comes from class oj. This information can be summarized in a Fusion Matrix, FM(o), as given in Figure 3. Here the i’th row of the matrix corresponds to the output of the subsystem operating on the i’th data source, while the j’th column represents the support for class oj, from all of the subsystems [18].
There are two general approaches to using the information present in the Fusion Matrix, FM(o). The first takes into account that the columns of FM(o) are the support for a class, and so a level of support can be developed using all the subsystems. Examples include taking the average, product, maximum, minimum, etc and then choosing the class that has the largest support. The second approach is to treat all of the outputs of the Fusion Matrix as an intermediate feature space regardless of the context and then train a new classifier on this intermediate feature space.

Using the first general approach, the decisions resulted from thresholding, FCM and decision tree could be fused by majority rule. Figure 7 presents the fused three-region classification results.

4 Creation of Layers

“Layers” can be defined as images containing part of the information of the original image. For example, for a multi-band image, each band can be viewed as a layer. The mean of all the bands could also be viewed as a layer. Applying the Principle Component Analysis (PCA) to the multi-band image, the images generated by the principle components are also layers of the original image. Another example of layers is applying the orthogonal decomposition to the original image, the resulting orthogonal components are the layers of the image. A set of layers is “complete” if original image can be fully generated using the set of layers.

The layers are generated based on a user’s need with each layer containing only information of interested. Normally, compared with the original image, each layer contains less information, so it’s easier to perform the calculations, and transformations based on layers. Furthermore, in some cases, only parts of the layers are useful such as in image fusion by PCA.

For the topographic change detection, we are interested in the region changes at different times, so the layers we used in this paper are based on the region classifications. Each layer contains only one region from the original image. In Figure 5, each image contains three regions that are land, shallow water and deep water. These regions should be extracted one by one to generate the layers. Figure 8 shows the corresponding layers of both images. The images in red are the layers of the image taken in May, and the layers taken in August are plotted in green. (a) and (d) are the layer-of-land with land represented in red/green. In (b) and (e), except the regions of shallow water, all the others are in black. So they are the layer-of-shallow water. Similarly, (c) and (f) are the layers-of-deep water.

5 Topographic Change Detection

5.1 Change Detection Based on Region Classification

Topographic change detection detects changes on the surface of the earth. Satellite images are used to perform topographic detection at very high accuracy. In this paper we present a topographic change detection method that applies the automatic update algorithm presented in [1]. Namely, for a two level classification problem we consider an image \( I = S_1 + S_2 \), where \( S_i \), i=1,2 are compact regions of the image represented by contours. The contours enclose pixels that correspond to the same region. When a change occurs, two groups of pixels are changing region. Those that move from region S1 to region S2 are named as “additions” (A), while the others that change from region S2 to region S1 are called “deletions” (D). The total change \( C \) in the image I is expressed as the summation of additions and deletions, \( C=A+D \). Namely,

\[

t_i = S_i^{(i)} + S_i^{(i-1)} \\
\bar{t}_{i-1} = S_i^{(i-1)} + S_i^{(i)} \\
D_i = S_i^{(i)} - S_i^{(i-1)} \cap S_i^{(i)} \\
A_i = S_i^{(i-1)} - S_i^{(i-1)} \cap S_i^{(i)}
\]

where the subscript “i” and “i-1” are the time index, which represent the current and previous time, respectively. The advantage of this method is that details of the changes are provided. In many applications, we are not only interested in where the changes happen, but also how they change.

In the following, we will extend this concept to multiple regions and automatic update of information. In a distributed processing system this mechanism may be programmed to keep updates of changes of classification regions or other features over time.
For the images with multiple level classification, we are interested in the changes in each region, i.e. addition and deletion. Assume we have M regions of interest, which are presented in M “layers”, $L_1, L_2, \ldots, L_M$, where the region-of-interest in the layer $L_i$ is denoted as $R_i$. The pixels in $R_i$ have values “1” and all the other pixels are set to zero. The basic idea is to compare the pairs of layers taken at different times, one by one. Namely, find the addition and deletion for each $L_i$. For each pair of layers, the region-of-interest $R_i$ is exactly the $S_i$ in our previous discussion, and the other part having zero values is the $S_{\bar{i}}$. In this way, if we use $L_k^{(i)}$ to denote the kth layer at time i, the common region of interest will be:

$$R_k^{(i-1)} \cap R_k^{(i)} = \langle L_k^{(i-1)} \circ L_k^{(i)} \rangle,$$

(2)

where the operator “$\circ$” represents the element-by-element multiplication of two matrices, and “$\langle \rangle$” represents a region which is composed of the pixels whose values are ones in "$\circ$". In this way, the addition of $R_k^{(i)}$ will be:

$$A_k^{(i)} = \langle L_k^{(i)} - L_k^{(i-1)} \circ L_k^{(i)} \rangle,$$

(3)

and the deletions is:

$$D_k^{(i)} = \langle L_k^{(i-1)} - L_k^{(i)} \circ L_k^{(i-1)} \rangle.$$

(4)

The total change for the $k$th region will be:

$$C_k^{(i)} = A_k^{(i)} + D_k^{(i)} = \langle L_k^{(i)} + L_k^{(i-1)} - 2L_k^{(i)} \circ L_k^{(i-1)} \rangle.$$

(5)

However, if we perform frame-to-frame subtraction, we will obtain:

$$R_k^{(i-1)} \cap R_k^{(i)} = \langle L_k^{(i)} \circ L_k^{(i)} \rangle,$$

(6)

and we have:

$$C_k^{(i)} = C_k^{(0)}.$$

From the above we can see in a two level classification problem the total change may be expressed through the absolute value of a frame-to-frame differencing. In practice we are interested in more details of the changes such as additions and deletions. Our proposed formulations give these details.

Apply the above procedures to each pair of layers. Step by step the addition and deletion for every class will be detected sequentially.

### 5.2 Change Detection Based on Pixel Level Characteristics

The ability to preserve the pixel characteristics from frame to frame when change detection is performed is essential if multiple classification inferences are derived from the changes. In this case image classification process is carried out on the change detection results. Two methods have been studied for change detection on images with multiple classification regions, i.e. the principal component analysis and the wavelet method.

### 5.3 Matched filtering and change detection.

Change detection may be applied using matched filters. Matched filters tend to suppress clutter and emphasize the changes of interest. When matched filters are applied the change detection performance increases. Matched filtering for change detection is normally applied to multispectra and/or multipolarized images [3], [5]-[7].

### 6 Example

Let’s consider the two images in Figure 2. Their layers are presented in Figure 8. We apply the proposed multi-level change detection method to the pair of layers \{(a), (d)\}, \{(b), (e)\} and \{(c), (f)\}, respectively. The result is displayed in Figure 9, where the red regions represent deletions, green ones stand for additions, and the yellow means no change happens. Figure 9 clearly gives the details of change in each region. It is easy to find from Figure 9 (c), because of the flooding in May, some regions of shallow water and land in the image of August become deep water (the red region in (c)). For the same reason, in (a), the green regions are the parts that are changed from shallow and deep water in May to land in August. Using this method avoids need for strict radiometric calibration, and it designates the types of changes occurring for each region of interest. It is simple, reliable and effective.
7 Conclusion

In this paper, several classification methods are first presented and the results are compared. A general fusion structure is then provided for the purpose of enhancing the final performance. Afterwards we introduce the definition of “layer” and how to create it. Based on the “layer”, a multiple level change detection algorithm is proposed, which gives the details of the changes in each region and is demonstrated to be an easy, effective and reliable method. Experimental results are provided using RADARSAT images.

Figure 5: Three level region classification results using FCM method.

Figure 6: Three level region classification results using the decision tree method.

Figure 7: Three level region classification results using majority fusion method.

Figure 8: The layers of the images in Figure 4 generated using the thresholding classification method

Figure 9: Change detection results of the regions of land, shallow water and deep water. Yellow—no change, green—addition, red—deletion, black—region of no interest

References


