Change Detection in Synthetic Aperture Radar Images Using Contourlet Based Fusion and Kernel K-Means Clustering

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Abstract Change detection algorithms play a vital role in overseeing the transformations on the earth surface. Unsupervised change detection has an indispensable role in an immense range of applications like remote sensing, motion detection, environmental monitoring, medical diagnosis, damage assessment, agricultural surveys, surveillance etc. In this paper, a novel method for unsupervised change detection in multitemporal images based on image fusion and kernel K-means clustering is proposed. Here difference image is generated by performing image fusion on mean-ratio and log-ratio image and for fusion contourlet transform is used. On the difference image generated by collecting the information from mean-ratio and log-ratio image kernel K-means clustering is performed. In kernel K-means clustering, non-linear clustering is performed, as a result the false alarm rate is reduced and accuracy of the clustering process is enhanced. The aggregation of image fusion and kernel K-means clustering is seen to be more effective in detecting the changes than its preexistences.

Keywords Change Detection; Difference Image; Image Fusion; Kernel-K Means Clustering; Synthetic Aperture Radar

1. Introduction

Multitemporal remote sensing represents a powerful source of information for investigating the evolution of the Earth’s surface, for instance, in environmental monitoring or disaster management. A relevant task is the identification of the changes that occurred in a given area between two observation dates. Change Detection is aimed at identifying the differences between images of same area acquired during different instance of times. The result is a binary change map that represents the changes that occurred between those two areas. When using an unsupervised approach, i.e., when no training data are available at either date, image differencing and image (log-) ratioing are often applied to address this task with optical and synthetic aperture radar (SAR) data, respectively. Manual or automatic thresholding can then be used to distinguish changed and unchanged areas in the difference and (log) ratio images. The process of change detection is of
widespread interest since it is having a wide variety of applications in diverse domains like remote sensing [3], motion detection [4], video surveillance [5], damage assessment [6], agricultural surveys [7], environmental monitoring [8], analysis of urban changes [9], and medical diagnosis [10].

A wide variety of change detection techniques have been introduced in the literature. Due to the massive growth of the geographic database, it is more practical to focus on the unsupervised approach than the supervised one. Currently, many unsupervised change detection techniques have been proposed. Some of these are image algebra, transformation of the multitemporal images, image classification, advanced models; Geographical Information System (GIS) approaches etc. With the advancement in the remote sensing technology, unsupervised change detection in remote sensing images is becoming vital.

In the literature, unsupervised change detection in multitemporal images is achieved in three main steps [11]: 1) pre-processing; 2) pixel by pixel comparison to get the difference image; 3) Analysis of the difference image. The objective of pre-processing step is to reduce the noise and hence increase the SNR. After pre-processing, difference image is generated by the pixel by pixel comparison of the multitemporal input images. In multitemporal optical images, the subtraction operator is used to generate the difference image. Also by taking the ratio operator, the multiplicative noise can be changed to additive noise. In the third step, the difference image is analyzed by using either thresholding techniques [12] clustering techniques. In Multitemporal SAR Images change detection is performed using a new statistical similarity measure [17] and bivariate gamma distributions [19]. Thus, the accuracy of the change detection algorithm in multispectral images depends on the virtue of the difference image and the efficiency of the classification technique. In this paper, in order to improve the quality of the difference image, image fusion based on countourlet transform is used for fusing two types of ratio images namely the mean-ratio image and the log-ratio image. Secondly the exactness of the classification technique is enhanced by using kernel k-means clustering, in which a linear algorithm is applied in a higher dimensional feature space to consider the non-linearities. Thus the rate of false alarm is reduced, resulting in a better change map than the existing methods.

2. Materials

The dataset is a portion (301x301 pixels) of two images taken by European Remote Sensing 2 satellite SAR sensor above the region in the vicinity of the city of Bern, Switzerland during April (Figure 1 A) and May (Figure 1 B), 1999 correspondingly. During this period the river Aare flooded wholly the cities of Thun and Bern, and hence the Aare valley was selected as the test site. In order to validate the accuracy of the proposed approach quantitatively, the results obtained has been compared with the ground truth for the Bern area. This ground truth was obtained through past information and photo analysis.

3. Methods

Let us consider the two co-registered intensity SAR images:

\[ X_1 = \{X_1(i, j), 1 < i < H, 1 < j < W\} and X_2 = \{X_2(i, j), 1 < i < H, 1 < j < W\} \quad (1) \]

Each image have a size \( H \times W \), i.e., acquired over the same geographical area at two different times. Our objective is aiming at producing a difference image that represents the change information between the two times; then, a binary classification is applied to produce a binary image corresponding to the two classes: change and unchanged. The proposed unsupervised distribution-free change detection approach is made up of two main phases: 1) generate the difference image using the countourlet fusion based on the mean-ratio image and the log-ratio image; and 2) automatic analysis of the fused image by using an improved clustering algorithm.
As mentioned in the previous section, we assume that there is only one typology of changes between the two acquisitions. Hence, the normalized mean-ratio operator should be applied to generate the mean-ratio image. It can be defined as follows:

\[ X_m(i, j) = 1 - \min\left(\frac{\mu_1(i, j)}{\mu_2(i, j)}, \frac{\mu_2(i, j)}{\mu_1(i, j)}\right) \]  
(2)

Where \( \mu_1(i, j) \) and \( \mu_2(i, j) \) represent the local mean values of the pixels involved in a neighbourhood of point \((i, j)\) in \(X_1\) and \(X_2\), respectively. Equation (2) shows that the mean-ratio operator produces DI by using the local mean information of each pair of co-located pixels. In a similar way, the absolute valued log-ratio operator is applied in our letter to indicate the change areas. It can be defined as

\[ X_l = \left| \log\left(\frac{X_2}{X_1}\right)\right| \]  
(3)

Where \( \log \) stands for natural logarithm. Both operators regard the increasing and decreasing radiometry as the same typology of changes. It makes the identification of changed areas independent of the order with which the images are considered in change indicator [8].

With the use of log-ratio operator, the multiplicative noise is changed to additive. The log-ratio operator enhances the low-intensity pixels and deteriorates the high intensity pixels: as a result the categorization of the pixels into the changed and the unchanged classes is made more symmetrical. Also the background of the log-ratio image is flat. But the drawback in using the log-ratio operator is that, the information about the changed areas gained from the log-ratio image is not in accordance with real change trends, since the log-operator deteriorates the high intensity pixels. Thus in the mean-ratio operator the difference image is produced by comparing the mean value of the co-located pixels in the multitemporal input images. The disadvantage of using the mean-ratio image is that, it does not take into account the changes that may occur without altering the local mean value and also the background of the mean-ratio image is rough.

Figure 1: Multitemporal Images for the City of Bern
Thus, both the mean ratio and log-ratio images are having merits and demerits. For this reason, image fusion technique is used in the proposed approach, so that the information from both the ratio images can be combined to get the finest difference image in which the changed pixels will be having high intensity values when compared to the unchanged pixels.

### 3.2. Image Fusion

Image fusion is the method in which information from two or more images are combined to get a fused image which is more worthy for the specified application. In the past for performing fusion, Intensity, Hue, Saturation (IHS) transform, Principle Component Analysis (PCA), statistical and arithmetic combination, [13], and the recently accepted multiscale fusion. One of the popularly used multiscale transform is the wavelet transform. In the proposed approach, the image fusion is done in the frequency domain and here contourlet transform is used when compared with other multiscale transforms, contourlet transform is more condensed, highly directional and provides unique information at each resolution. The contourlet transform focuses on representing point discontinuities and conserving the time and frequency details in image. Its simplicity and its ability to uphold image details with point discontinuities make the fusion scheme based on contourlet transform suitable for the change detection process [14]. The steps involved in the image fusion are described (Figure 2).

![Figure 2: Steps Involved in the Image Fusion](image_url)

**Step 1:** The contourlet transform for both the log-ratio and mean ratio image is taken. Here one level of decomposition is done on both the images.

**Step 2:** The fusion rule is applied on the approximate, diagonal, horizontal and vertical coefficients of both the images. For high frequency and low frequency band, separate fusion rule is proposed. The fusion rule is defined below:

\[ F_{LL} = \frac{L_{LL} + M_{LL}}{2} \]  
\[ F_p(i, j) = \begin{cases} M_p(i, j), & \text{if } E^M(i, j) < E^L(i, j) \\ L_p(i, j), & \text{if } E^M(i, j) \geq E^L(i, j) \end{cases} \]  

Where \( M_{LL}, F_{LL} \) and \( L_{LL} \) represent the approximate coefficients (low frequency band) of the log-ratio, mean-ratio and the fused image respectively. Then \( F_p \) represents the high frequency bands.
(diagonal, horizontal and vertical coefficients). $E^M$ and $E^L$ represents the energy coefficients of the mean-ratio and log-ratio image.

**Step 3:** Perform inverse contourlet transform to get the fused image.

As mentioned above, here the low frequency and high frequency bands are fused individually. The low frequency bands accurately represents the changed regions from both the log and mean ratio image, average operation is done in the low frequency band. For the high frequency band the rule of minimum local energy of the contourlet coefficients is chosen. This is to combine the homogeneous regions of the high-frequency portion from the mean-ratio image and the log-ratio image.

### 3.3. Kernel K-Means Clustering

The purpose to process the difference image is to discriminate changed area from unchanged area. The difference image obtained by image fusion is sorted out into changed and unchanged area using kernel k-means clustering algorithm. In order to improve the accuracy of the binary change map, the data samples obtained by fusing the log-ratio and mean-ratio images are projected to a higher dimensional feature space, in which a linear algorithm can be applied to separate the changed and unchanged pixels.

Mapping to the feature space is done by using kernel functions. The kernel function compute the similarity between training samples $S$ using pair-wise inner products between mapped samples, and thus, the so-called kernel matrix contains all the necessary information to perform classification by means of linear algorithms in the feature space. Kernel K-means clustering algorithm is applied on the data samples of the fused image in order to perform non-linear clustering.

The kernel techniques allows linear evaluation of data in higher dimensional feature space, which results in nonlinear clustering of data samples present in the input space [15]. The higher dimensional feature space is generated by a mapping function $\phi(\cdot)$ applied on the image obtained by fusing the log-ratio and mean ratio image.

![Flow Chart for the Generation of Change Map](image)

**Figure 3:** Flow Chart for the Generation of Change Map

The kernel technique is used instead of dot product; it returns the inner product of the fused image directly in higher dimensional feature space. The flow diagram given below depicts the steps involved in performing clustering on fused image (Figure 3).
The cost function used to perform kernel k-means clustering on fused data samples is given as,

$$
\Theta^* = \arg \min \left\{ \frac{\sum_p \prod_{i=\Pi_p} \sum_{x=\Phi_i} \left( \alpha^2 \Phi(x), \mu_p \right)}{\sum_{p-q} \alpha^2 \left( \mu_p, \mu_q \right)} \right\}
$$

(6)

The reduction of the angle between the samples and the centroid is represented as $$a^2 \Phi(x)$$.

The average samples allocated to the cluster $$p$$ in the feature space is given by,

$$
\mu_p = \frac{1}{|\Pi_p|} \sum_{j=\Pi_p} \Phi(x)
$$

(7)

Where $$\prod_p$$ is the samples assigned to cluster $$p$$ and $$|\prod_p|$$ is the total number of samples assigned to cluster $$p$$.

4. Results and Discussion

Here the efficacy of the proposed blending of the Contourlet transform based image fusion (Figure 4) and kernel K-means clustering (Figure 5) is established by comparing the accuracy of the binary change of the proposed method with the change map obtained from the log-ratio (Figure 4 & 5A) and mean–ratio images (Figure 4 & 5B). The fusion image of Contourlet transform (Figure 4C) and kernel K-means clustering (Figure 5C) are also shown in the figure. The testing is done to show the efficacy of the kernel K-means clustering. So, this clustering is performed on the three difference images and it is shown that the combination of fused image (Figure 5C) and kernel K-means clustering is capable of detecting the changes more efficiently.

4.1. Accuracy Assessment and Performance Evaluation

The quantitative analysis can be done using the ground truth reference and check rules. The general approach to obtain ground truth reference [18] is to perform field survey with the assistance of historical GIS data.

**Table 1: Change Detection Results Obtained by Using Kernel K-Means Clustering on the Difference Images**

<table>
<thead>
<tr>
<th>Difference Image</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean-Ratio</td>
<td>89.999</td>
</tr>
<tr>
<td>Log-ratio</td>
<td>92.542</td>
</tr>
<tr>
<td>Fused Image</td>
<td>95.357</td>
</tr>
</tbody>
</table>
Figure 4: Contourlet Transform Based Image Fusion
Since the input images are subjected to various noises during acquisition, it is necessary to evaluate the robustness of the change detection algorithm (Figure 6) to noise [16]. It can be done by plotting the values of PSNR and tau which can be determined as follows:

$$PSNR = 10 \log_{10} \left( \frac{255}{\sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - \hat{x}(i,j))^2} \right)$$

(8)

Where M and N are number of rows and number of columns of the input image, $x(i, j)$ is the input image in the absence of noise and $\hat{x}(i, j)$ is the noisy version of the input image.
Where \( C_1(i, j) \) the change map is generated from the input images in the absence of noise and \( C_2(i, j) \) is change map generated by using the noisy version of the input images. The change detection results obtained by using kernel K-means clustering on the difference images are tabulated (Table 1).

\[
\tau = 1 - \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} |C_1(i, j) - C_2(i, j)|}{MN}
\]

\( (9) \)

5. Conclusion

An innovative method for unsupervised change detection in SAR images which is based on image fusion and kernel K-means clustering has been implemented in this paper. Here full advantage of the contourlet transform has been utilized to form the fusion rule and hence to get a difference image containing complementary information from the mean ratio and log ratio images. On the fused image kernel K-means clustering has been performed. Since kernel K-means clustering takes into consideration non-linearities. It is suited well for the clustering process in SAR images. Consequently this approach for change detection yields better results than its pre-existences.

References


