Unsupervised Change Detection using Image 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 a 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 synthetic aperture radar(SAR) 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 discrete wavelet 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.

General Terms

Pattern Recognition, Remote sensing, Image Processing

Keywords

Change detection, difference image, image fusion, kernel-k means clustering, Synthetic Aperture Radar.

1. INTRODUCTION

The exploitation of multitemporal images has been prudently done in change detection. In the change detection process two images of the same area are taken at two different time instances and then these multitemporal images are processed to identify the changes that may have taken place between the time instances in which the two images were taken. The output of the change detection process is a binary change map, indicating the location of the changes.

Change detection methods can be extensively classified into supervised and unsupervised paradigms based on the nature of method used for processing the images. In supervised change detection, a training set is required for the learning process of the classifiers. This training set is obtained from the ground truth data [1].The latter technique performs change detection by using only the multitemporal images and in this method no ground truth is needed [2].

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], 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. Amidst them, unsupervised change detection in synthetic aperture radar (SAR) images is tougher because of the inherently present speckle noise. In spite of this difficulty, change detection in SAR images is still alluring, because SAR sensors are capable of capturing the information under all the atmospheric conditions [11].

In the literature, unsupervised change detection in SAR image is achieved in three main steps [12]:1) preprocessing;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 speckle 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. However, in SAR image, ratioing is commonly used because image differencing is not suitable for the statistics of the SAR image.[13].Also by taking the ratio operator, the multiplicative speckle noise can be changed to additive noise. In the third step, the difference image is analyzed by using either thresholding techniques [14] clustering techniques.

Thus, the accuracy of the change detection algorithm in SAR 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 discrete wavelet 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. PROBLEM STATEMENT

In order to perform change detection stringently, let $\{X_1, X_2\}$, be two images of the same area taken at two different time instances. Here every pixel, P in each image, $P \in R^l$ and the intensity, $I(P) \in R^k$. Depending on the value of k images can be either gray scale(k =1),RGB color images(k =3),multispectralimages(k>10),hyperspectral images(k >100).In change detection algorithm, an image sequence is taken as input and the output generated is a binary image $B: R^l \to [0,1]$, called a change map. The proposed approach is shown in figure 1.

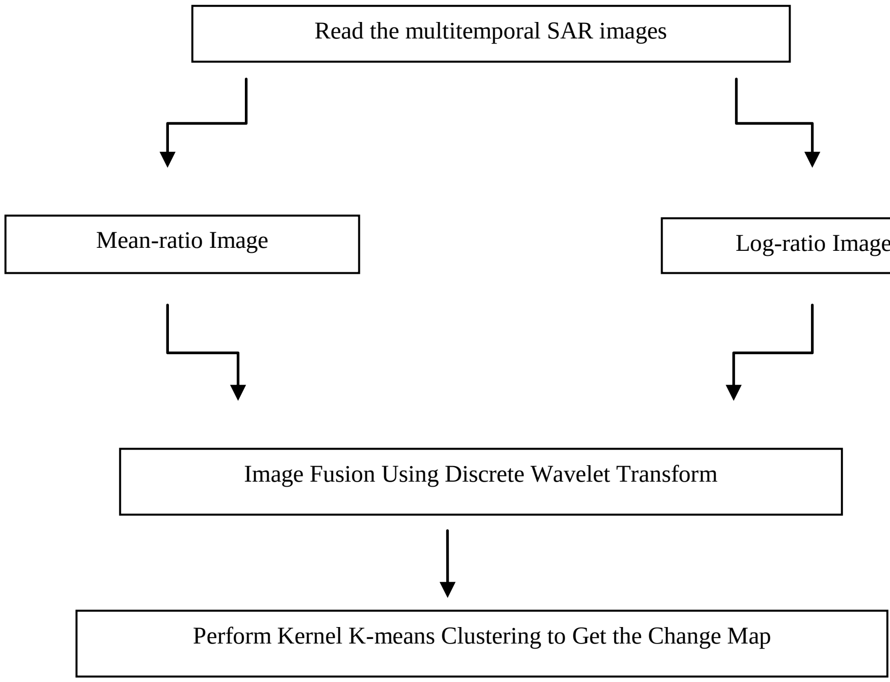


Fig 1: Proposed Approach

3. MEAN-RATIO AND LOG-RATIO IMAGES

As mentioned earlier, in SAR images the difference image is generated using the ratio operator. The mean-ratio and log-ratio are the two most commonly used ratio operators.

The log-ratio operator for the multitemporal images X_1 and X_2can be described as:

$$X_L = |\log X_2 - \log X_1|$$

With the use of log-ratio operator, the multiplicative speckle 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.

Another mode for performing a ratio operator is proposed in [15], which is the ratio mean detector (RMD).In this mean-ratio operator, it is assumed that, a change occurs only when the local mean value of the image changes. This ratio operator is also robust against speckle noise. The mean ratio image can be defined as:

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

where $\mu_1(i,j)$ and $\mu_2(i,j)$ are the mean value of the pixels in the neighbourhood of (i,j) in the images X_1 and X_2 respectively. 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.

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.

4. 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,[16] ,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 wavelet domain and here discrete wavelet transform (DWT) is used .When compared with other multiscale transforms, wavelet transform is more condensed, highly directional and provides unique information at each resolution. The DWT 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 DWT suitable for the change detection process[17]. The steps involved in the image fusion are described below:

Step 1:The discrete wavelet 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:

$$F_{LL} = \frac{L_{LL} + M_{LL}}{2}$$

$$F_{\rho}(i,j) = \begin{Bmatrix} M_{\rho}(i,j), if\ E^{M}(i,j) < E^{L}(i,j) \\ L_{\rho}(i,j), if\ E^{M}(i,j) \geq E^{L}(i,j) \end{Bmatrix}$$

Where L_{LL}, M_{LL} and F_{LL} represent the approximate coefficients(low frequency band) of the log-ratio, mean-ratio and the fused image respectively. F_{ρ} 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 DWT 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 wavelet 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.

5. 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[18]. The higher dimensional feature space is generated by a mapping function $\phi(.)$ applied on the image obtained by fusing the log-ratio and mean ratio image.

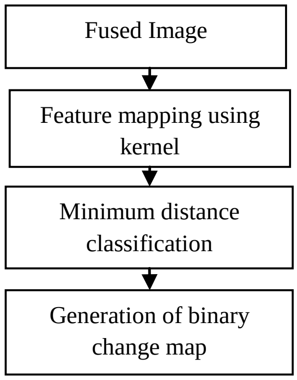


Fig 2: Flow chart for the generation of change map

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 cost function used to perform kernel k-means clustering on fused data samples is given in [],

$$\Theta^{*} = \arg min \begin{Bmatrix} \dfrac{\sum_{p} \frac{1}{|\pi_p|} \sum_{i \epsilon \pi_p} (d^2 \phi(\mathrm{x}), \mu_p)}{\sum_{p \neq q} d^2 \left(\mu_p, \mu_q\right)} \end{Bmatrix}$$

The reduction of the distance between the samples and the centroid is given as,

$$(d^2\phi(\mathrm{x}), \mu_p) = \mathrm{k}(\mathrm{x_i}, \mathrm{x_i}) + \frac{1}{|\pi_p|^2} \sum_{j,m \epsilon \pi_p} \mathrm{k}(\mathrm{x_j}, \mathrm{x_m}) - \frac{2}{|\pi_p|} \sum_{j \epsilon \pi_p} \mathrm{k}(\mathrm{x_i}, \mathrm{x_j})$$

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

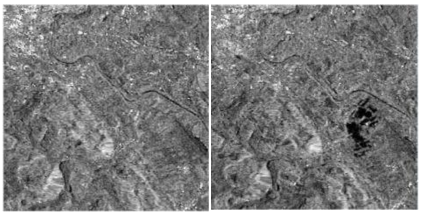
$$\mu_p = \frac{1}{|\pi_p|} \sum_{j \epsilon \pi_p} \phi(\mathrm{x})$$

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

6. EXPERIMENTAL RESULTS

6.1 Description of the Dataset

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 and May, 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.



(a) (b)

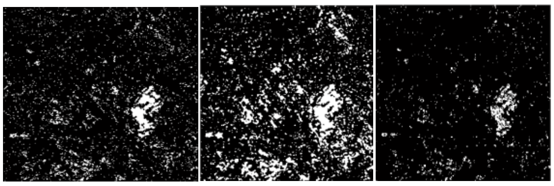
Fig3: Multitemporal images for the city of Bern :(a) April,1999 (b) May,1999.

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.

6.2 Results

Here two tests have been carried out; first one to depict the effectiveness of the image fusion strategy and the second one to show the efficacy of the kernel K-means clustering performed on the fused image.

First to show the effectiveness of the image fusion approach , to the mean-ratio, log-ratio and the fused images simple Thresholding algorithm Otsu has been performed and the results are shown in Table 1.



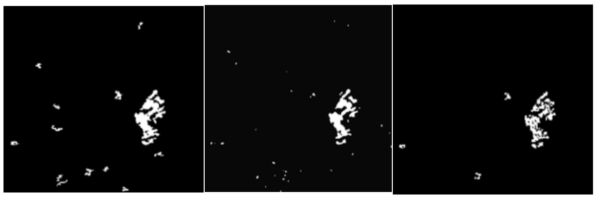
(a) (b) (c)

Fig 4: Change detection results obtained by using Otsu method :(a)on log-ratio image,(b)on mean-ratio image and (c) on fused image.

Table 1.Change Detection Results Obtained By Using Otsu Method on the Difference Images.

Difference Image	Accuracy
Mean-Ratio	81.2761
Log-ratio	89.2860
Fused Image	93.6998

The next 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 and kernel K-means clustering is capable of detecting the changes more efficiently.



(a) (b) (c)

Fig 4: Change detection results obtained by using Kernel K-means clustering :(a) on log-ratio image,(b)on mean-ratio image and (c) on fused image.

Table 2.Change Detection Results Obtained By Using Kernel K-means Clustering on the Difference Images.

Difference Image	Accuracy
Mean-Ratio	89.999
Log-ratio	92.542
Fused Image	94.357

7. CONCLUSION

An innovative method for unsupervised change detection in SAR images which is based on image fusion and improved fuzzy clustering has been implemented in this paper. Here full advantage of the discrete wavelet 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.

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