Unsupervised change detection in SAR images based on Gauss log ratio image fusion NSCT analysis and compressed projection

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Abstract:-Multitemporal synthetic aperture radar (SAR) images helps in detecting different types of terrain changes. Due to the presence of speckle noise and complex terrain detecting the changes in SAR images has become a complex task. In this paper an unsupervised method for detecting the changes in SAR images has been proposed. First Gauss log operator and log operator are applied on the SAR images to obtain the difference image. Image fusion and then image de noising is performed on the difference image using Non subsampled counter let transform (NSCT).Compressed projection is performed to extract the feature vectors. Finally the feature vectors are partitioned by using Fuzzy clustering approach into two classes, changed class and unchanged class.

I. Introduction

Environmental monitoring, earth-resource mapping, and military systems require broad-area imaging at high resolutions. Often, this imagery must be acquired at night or during inclement weather. Synthetic Aperture Radar (SAR) provides such a capability. Synthetic Aperture Radar (SAR)[1] systems take advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide high resolution imagery. Synthetic Aperture Radar (SAR) complements photographic and other optical imaging capabilities because it is not limited by the time of day or atmospheric conditions and because of the unique responses of terrain and cultural targets to radar frequencies.

Synthetic Aperture Radar (SAR) technology has provided terrain structural information to geologists for mineral exploration, oil spill boundaries on water to environmentalists, sea state and ice hazard maps to navigators, and reconnaissance and targeting information to military operations. There are many other applications for this technology. Some of these, particularly civilian, have not yet been adequately explored because lower cost electronics are just beginning to make Synthetic Aperture Radar (SAR) technology economical for smaller scale uses.

Consider an airborne Synthetic Aperture Radar (SAR) imaging perpendicular to the aircraft velocity as shown in the figure below. Typically, Synthetic Aperture Radar (SAR) produces a two-dimensional (2-D) image. One dimension in the image is called range (or cross track) and is a measure of the "line-of-sight" distance from the radar to the target. Range measurement and resolution are achieved in Synthetic Aperture Radar (SAR) in the same manner as most other radars: range is determined by measuring the time from transmission of a pulse to receiving the echo from a target and, in the simplest Synthetic Aperture Radar (SAR), range resolution is determined by the transmitted pulse width, i.e. narrow pulses yield fine range resolution.

While this section attempts to provide an intuitive understanding, Synthetic Aperture Radars (SARs) are not as simple as described above. Transmitting short pulses to provide range resolution is generally not practical. Typically, longer pulses with wide-bandwidth modulation are transmitted, which complicate the range processing but decreases the peak power requirements on the transmitter. For even moderate azimuth resolutions, a target's range to each location on the synthetic aperture changes along the synthetic aperture. The energy reflected from the target must be "mathematically focused" to compensate for the range dependence across the aperture prior to image formation. Additionally, for fine-resolution systems, the range and azimuth processing are coupled (dependent on each other) which also greatly increases the computational processing.

1.1 Applications of SAR images

SAR's ability to pass relatively unaffected through clouds, illuminate the Earth's surface with its own signals, and precisely measure distances makes it especially useful for the following applications:

- Lake and river ice monitoring
- Sea ice monitoring
- Cartography
- Surface deformation detection

- Glacier monitoring
- Crop production forecasting
- Forest cover mapping
- Ocean wave spectra
- Urban planning
- Coastal surveillance (erosion)
- Monitoring disasters such as forest fires, floods, volcanic eruptions, and oil spills

SAR data can be used to teach or learn the following topics and skills in remote sensing education:

- Glacier monitoring
- Sea ice mapping
- Wind movement on ocean surface
- Mapping of Antarctic
- Principles of volcano inflation and deflation
- Urban signatures
- Land cover mapping/monitoring
- Geomorphology and ocean surface during hurricanes

1.2 What is change detection?

Change detection, the comparison of remote sensing images from different moments in time, is an important technique in environmental earth observation and security. SAR change detection is useful when weather and light conditions are unfavorable. Change detection is an important technique in environmental earth observation and security, and implies the comparison of remote sensing images from different moments in time. Different sensors can be used for this purpose. SAR (Synthetic Aperture Radar) sensors become useful when weather and light conditions are unfavorable. SAR can operate under cloudy skies, day and night. Today the resolution of SAR satellites is not better than 10 m, but in the near future platforms will be launched carrying sensors with a resolution of 1-3 m.

1.3 What are the methods of change detection?

There are basically five methods of change detection[2]. The first method is post classification method. The post-classification change detection, is strongly dependent on the accuracy of classification. Because accuracy can be a problem in SAR images, this is not a proper method. The second one is CFAR detection. This method is only suitable when the changes are small compared to the resolution. The third method uses an adaptive filter and is able to deal with distributed changes as well. Besides, it can be more effective in case of small changes, but it lacks in reproducing the shape of changes. The fourth method makes use of multi-channel segmentation, a method that reproduces the shape of changes well for multi-look images, but lacks in the detection of small changes. The fifth method is a combination of CFAR detection, adaptive filtering and multi-channel segmentation.

STATE OF THE ART METHODS IN CHANGE DETECTION IN SAR IMAGES

The study on change detection in SAR images has been focused since 2006 “Unsupervised change detection on SAR images using fuzzy hidden Markov chains” by Cyrill Carincote[3].In this method log ratio operator is applied on the SAR image to develop the difference image. A new fuzzy version of hidden Markov chains is used to handle the classification issue and then to address the fuzzy change detection with a statistical approach.

In order to deal with the classification issue, a new fuzzy version of hidden Markov chains (HMCs)[4] ,is used and thus to address fuzzy change detection with a statistical approach. The main characteristic of this model is to simultaneously use Dirac and Lebesgue measures at the class chain level. This allows the coexistence of hard pixels (obtained with the classical HMC segmentation) and fuzzy pixels (obtained with the fuzzy measure) in the same image. In this method log ratio operator is applied on the SAR image. Due to the multiplicative nature of the speckle log ratio operator is well suited for SAR imagery. In this work both statistical and fuzzy approaches are combined in a new fuzzy HMC model to resolve the unsupervised change detection task in SAR images.

Another method implemented for change detection in SAR images is “change detection in SAR images using contour let” by Merrin Ayishu Ali and Dr Imraan[5]. In this method Counter let image fusion and fuzzy clustering approach is used. In this method log ratio and mean ratio applied on the SAR images to form the difference image. Fuzzy local information is used to discriminate the changed and the unchanged regions. Three main steps are involved in performing unsupervised change detection.

1. Preprocessing the image
2. Comparison of the image
3. Image analysis.

Preprocessing is done to reduce noise geometric and radiometric corrections and co-registration. After preprocessing two SAR images are taken as input and compared pixel by pixel to produce the difference image.

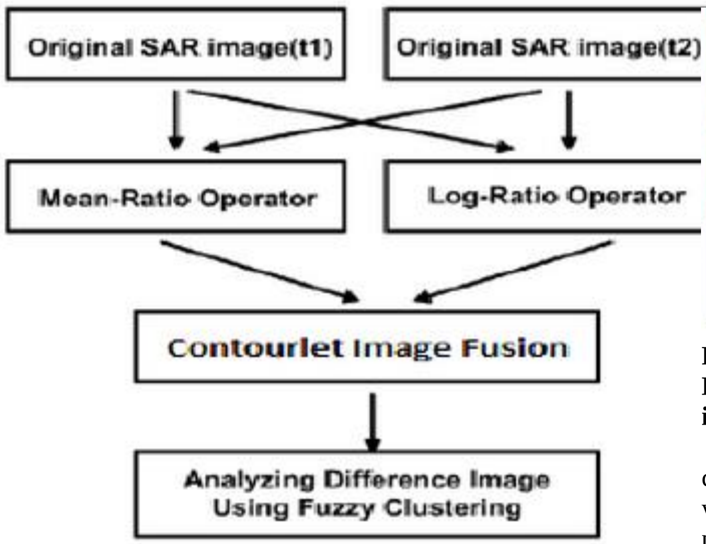


Figure 2.1:-Counter let method for change detection

In this method there are mainly two steps:

1. Generate the difference image using contour let fusion.
2. Detecting changed regions using c means clustering.

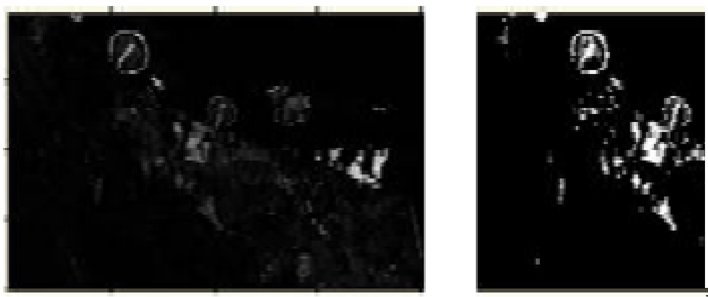
Generate the difference image using contour let fusion – Image fusion is the process of combining two or more image to form a single fused image containing the relevant information in both the images. The main properties of counter let transform include multi resolution ,directionality, local brightness etc. These properties make the fused image more smooth. The two operators log operator and mean operator are applied on the source images to obtain the difference image.

$$X_l = \log X_1 - \log X_2 \quad (1)$$

$$X_m = 1 - \min\left[m1/m2, m2/m1\right] \quad (2)$$

The generated fused difference image is analysed using the fuzzy clustering approach and classified as changed and unchanged regions.

(A) (B)



(C) (D)

Figure 2.2:- Output of contourlet fusion method Dubai in 2000 (B) Dubai in 2010 (C) Contourlet fused image (D) Change detected image.

Another approach for change detection is “Robust change detection in SAR images by using RFLICM and wavelet fusion” by Rinu Varghese and Haritha.K. This paper presents robust change detection in SAR images based on image fusion and reformulated fuzzy clustering. This approach used both mean-ratio and log-ratio to generate the difference image . The wavelet technique is used to enhance the information of changed region which is extracted form background information by using difference image.

The reformulated fuzzy local c means clustering algorithm is used for differentiating both changed and unchanged regions in fused image and it is insensitive to the noise reduce the effect of speckle noise.

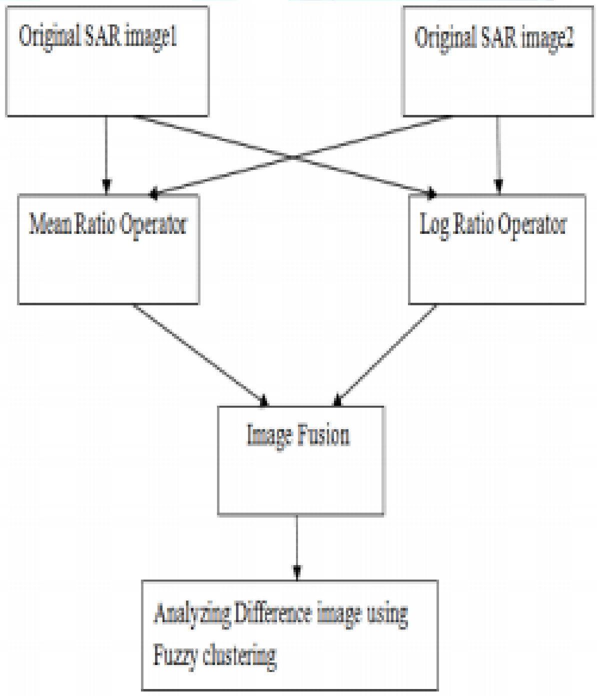


Figure 2.3:- Change detection using RFLICM and wavelet fusion.

Two images taken at different of the same location are first co-registered in order to find the changed area. After co-registering the images log ratio and mean ratio operators are applied on the difference images. Image fusion techniques like Discrete wavelet transform is applied to obtain the fused image of changed regions. Different fusion rules are applied on the low frequency and high frequency bands. After the image fusion clustering algorithm is applied on the fused image to detect the changed and unchanged regions of the images.

Another study done in this field is “Unsupervised change detection in SAR images based on Gauss-Log ratio Image fusion and Compressed projection” used by Biao Hou,Qian Wei and ShuangWang[7]. This method presents a supervised change detection method in SAR images based on image fusion strategy and compressed projection. Gauss log ratio and log ratio operators are applied to obtain the difference image. Discrete Wavelet transform is applied to obtain the fused image. And then Non subsampled counter let transform is performed to obtain the de-noised fused image. Compressed projection is applied to extract the feature vectors. And finally k-means clustering is applied on the extracted feature vectors to classify the pixels as changed and unchanged pixels to differentiate the changed and the unchanged regions in the image.

Two co-registered intensity SAR images acquired at the same geographical area at two different times. The aim of the model is to create the change map which indicates the change between the acquisition dates between the two images. The procedure proceeds as follows:

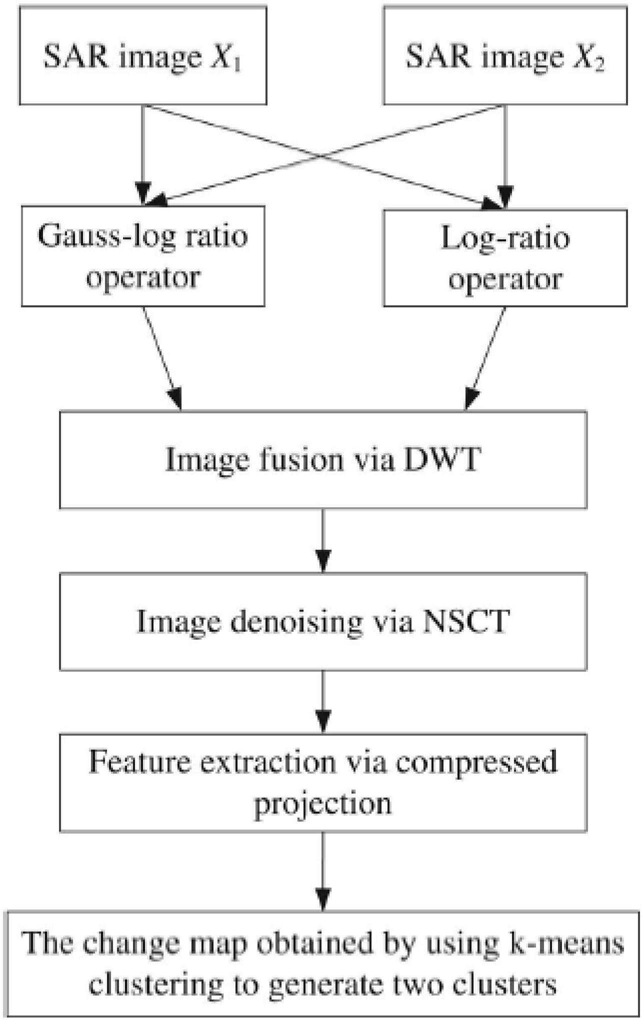


Figure 2.4:- Change detection model based on compressed projection and Gauss log ratio operator.

2.1 Producing the difference image using Gauss log ratio and log ratio operator

The log ratio operator converts the linear scale image to logarithmic scale before the differencing operation and thus transforms the multiplicative noise to additive noise. Although the difference image is expressed in the logarithmic scale so as to find the changes even in the low intensity pixels , the change may not be clearly reflected due to the weakening in the high intensity pixels. In order to identify the real change trends and to suppress the unchanged pixels another operator called the Gauss log ratio operator is also applied on the images. These operators can be defined as:

$$X_{1r}(i,j) = \log(X_1'(i,j)) * G \quad (3)$$

$$X_{2r}(i,j) = \log(X_2'(i,j)) * G \quad (4)$$

X_r(i,j)= $\sum_{m=-1}^{1}\sum_{n=-1}^{1} | X_{1r}$ (i+m,j+n)- X_{2r} (i+m,j+n) | (5)

X_1' (i,j) and X_2'(i,j) are two patches centered at point (i,j) in SAR images X_1 and X_2 respectively.

Although the Gauss-log ratio operator can obtain the expected difference image, the unchanged portion in SAR images is also enhanced, which leads to the error detection. In order to suppress the influence of the enhancement of unchanged portion in SAR image on changed one, the absolute valued log-ratio operator is used to generate the second difference image.

X_l=|log(X_1/X_2)=|log X_1 - log X_2| (6)

The unchanged portion in the difference image obtained by absolute valued log-ratio operator is relatively more uniform ,whereas the changed one behaves like inhomogeneity. For the two difference images, we use image fusion strategy based on wavelet and the local contrast to generate a better difference image.

2.2 Image fusion via DWT

In order to obtain a better difference image, we fuse the information of the difference image. Here, the "better" means the difference image is of greater contrast between the changed and unchanged portions and of the homogeneity in the changed one, which can improve the accuracy of the subsequent clustering or classification. Image fusion refers to a process of combining relevant information from two or more images into a fused image that possesses more information than any of the input images .

In recent years, wavelet transform[8] has been widely used in image fusion. Wavelet transform overcomes the defect of the poor correlation between the adjacent scale image information and fully reflects local variation of the original image. Since DWT has lower computational complexities , we also use the DWT for image fusion in this paper. Wavelet image fusion lies in the choice of fusion rules which should improve the quality of the difference map. In this paper, the weight averaging for the low-frequency band and the rule of selecting the maximum local contrast coefficients for the high-frequency bands. Let and be the Gauss-log ratio image and the log-ratio image as before, respectively. And represent the low-frequency wavelet coefficients of and respectively. and stand for three high-frequency wavelet coefficients of and , respectively.The fusion rules can be described as follows:

$$D_f^{LL} = \alpha * D_r^{LL} + (1-\alpha) D_l^{LL} \quad (7)$$

D_f^{ω}(i,j)=

$$\begin{cases} D_l^{\omega}(i,j), con_l^{\omega}(i,j) \geq & con_l^{\omega}(i,j) \\ D_r^{\omega}(i,j), con_l^{\omega}(i,j), \ x \geq & \end{cases} \quad (8)$$

X_r- Gausss log ratio

X_l- log ratio

D_f^{LL}-low frequency wavelet coefficient of X_r.

D_l^{LL}-low frequency wavelet coefficient of X_l.

α – weighing factor.

D_f^{LL}- low frequency wavelet coefficients of fused image.

D_f^{ω}-high frequency wavelet coefficient of fused image.

2.3 Image de-noising using Non subsampled counter let transform

In this paper NSCT[9] is used to reduce the noise of the fused difference image . The main steps are described as follows.

1. Decomposition of the fused difference image leads to the formation of sub band images in different scales and directions. These images will have the same size as the fused image. The sub band image will contain both high frequency and low frequency sub bands.
2. The coefficients of the high frequency sub bands are suppressed by the Donoho coefficient[10]. The coefficients of low frequency sub bands remain unchanged. It is defined as ,λ = σ$\sqrt{2\log N}$ where σ represents noise standard deviation and N denotes the sample size. is generally unknown, so estimation method is used to determine . When the high-frequency coefficients are larger than the threshold, the coefficients remain unchanged. Otherwise, the coefficients are set to zero. Finally, the de-noised difference image is obtained by using inverse NSCT transform[11].

2.4 Feature extraction through compressed projection

Compressed projection has recently emerged as a surprisingly useful tool in signal processing. The compressed projection can preserve the relevant structure in a signal when the signal is projected onto a small number of random basis functions. Although some information may be lost through such a projection, this information tends to be incoherent with the relevant structure in the signal. That is to say, a small number of compressed vectors obtained by compressed projection contain enough information to preserve the underlying local texture structure. In this sense, compressed projection[12] is a universal measurement tool. Another benefit is that compressed projection can provide dimensionality reduction, which can greatly reduce the amount of data to be processed. Based on the above analysis, compressed projection is used to extract the feature vector of each pixel in the de-noised difference image X_d in this paper. The compressed vector can be obtained as follows:

$$v(i,j) = A^{CS} X'_d(i,j). \quad (9)$$

v(i,j) – compressed vector

A^{CS} - cs information operator

X'_d (i,j) – one dimensional vector.

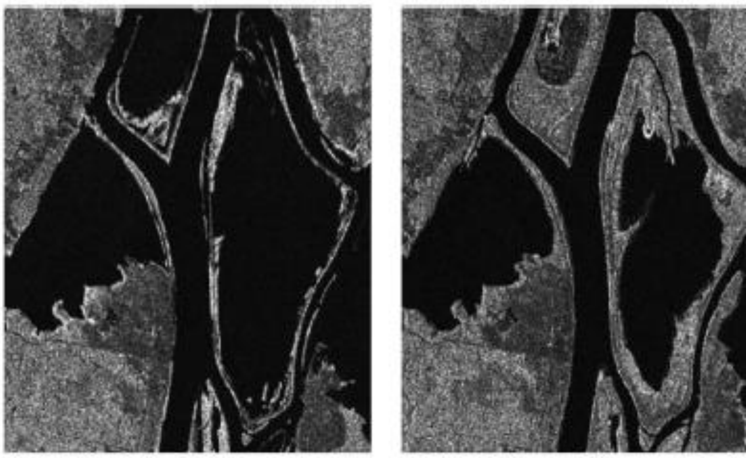
2.5 Change map obtained by using k-means clustering

In this approach k-means clustering[13] is used to categorize the feature vectors into two categories with k=2.V_C and V_u are the two cluster mean feature vectors for the changed and the unchanged class. The change map is given by

The changed map cm

$$(i,j) = \begin{cases} 255, & \|v(i,j) - V_c\| <= \|v(i,j) - V_u\| \\ 0, & otherwise \end{cases} \quad (10)$$

255 represents changed pixel and 0 represents unchanged pixel.



(a) (b)

Figure 2.5:-Ottawa dataset (a) Image acquired in July 1997 (b) Image acquired in august 1997 (c) changed region detected.

PROPOSED MODEL OF CHANGE DETECTION USING NSCT, GAUSS LOG RATIO AND FUZZY CLUSTERING APPROACH. In this proposed model of change detection in SAR images the main methods used are gauss log ratio and log ratio operators, Non subsampled counter let transform compressed projection and fuzzy clustering methods. The discrete wavelet transform method for image fusion that is used in the previous approach has been replaced by non subsampled counter let transform. The k-means clustering approach that has been used in the previous method for categorizing the changed and unchanged pixels is replaced with fuzzy clustering approach.

3.1 Discrete wavelet transform for image fusion – Drawbacks

DWT, the fused image can conserve more spectral characteristics of the multi-spectral image. So the fusion method based on DWT[14] is frequently used and become one of main fusion methods. But the DWT has two main disadvantages

1. Lack of shift invariance. This means that small shifts in the input signal can cause major variations in the distribution of energy between DWT coefficients at different scales.
2. Poor directional selectivity for diagonal features, because the wavelet features are separable and real.

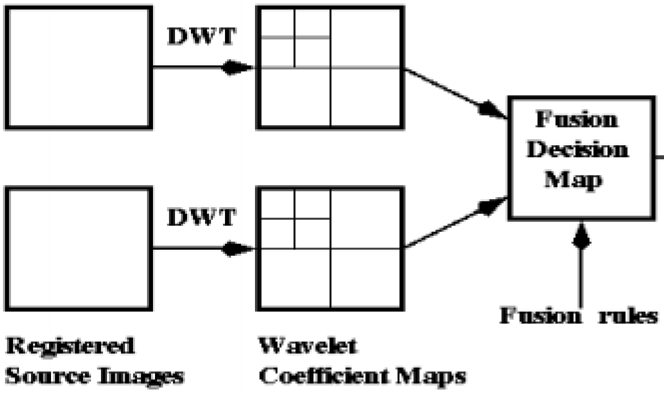


Figure 3.1:-Image fusion using DWT.

Processing steps of wavelet based image fusion :

1. Decompose a high resolution P image into a set of low resolution P images with wavelet coefficients for each level.
2. Decompose a low resolution MS image into a set of low resolution MS images with wavelet coefficients for each level
3. Replace a low resolution MS images with LL component of a PAN image a MS band .
4. Perform a reverse wavelet transform to convert the decomposed and replaced P set back to the original P resolution level.

3.2 Image fusion using non subsampled counter let transform

Image fusion provides the means to integrate multiple images into a composite image which is more suitable for the purpose of human and machine perception or further image-processing tasks. This paper presents the use of non subsampled contourlet transform (NSCT)[15] for image fusion. All the input images are decomposed firstly. Then the decomposition coefficients on the different scale are combined using different rule, and the fusion image is obtained by taking the corresponding inverse non subsampled contourlet transform of the fused coefficients. NSCT is used to perform a multiscale decomposition of source images to express the details of images, and we present a dictionary learning scheme in NSCT domain, based on which we can represent low-frequency information of the image sparsely in order to extract the salient features of images. Furthermore, it can reduce the calculation cost of the fusion algorithm with sparse representation by the way of non-overlapping blocking. NSCT is a fully shift invariant multiscale and multi direction expansion that has full implementation. The design problem is much less constrained than that of counterlets. This enable us to design filters with better frequency selectivity thereby achieving better sub band decomposition.

3.3 K-means clustering and fuzzy clustering –Comparison

K-Means[16] or Hard C-Means clustering is basically a partitioning method applied to analyze data and treats observations of the data as objects based on locations and distance between various input data points. Partitioning the objects into mutually exclusive clusters (K) is done by it in such a fashion that objects within each cluster remain as close as possible to each other but as far as possible from objects in other clusters. Each cluster is characterized by its center point i.e. centroid. The distances used in clustering in most of the times do not actually represent the spatial distances. I general, the only solution to the problem of finding global minimum is exhaustive choice of starting points. But use of several replicates with random starting point leads to a solution i.e. a global solution. In a dataset, a desired number of clusters K and a set of k initial starting points, the K-Means clustering algorithm finds the desired number distinct clusters and their centroids. A centroid is the point whose co-ordinates are obtained means of computing the average of each of the co-ordinates of the points of samples assigned to the clusters.

Bezdek introduced Fuzzy C-Means clustering[17] method in 1981, extend from Hard C-Mean clustering method. FCM is an unsupervised clustering algorithm that is applied to wide range of problems connected with feature analysis, clustering and classifier design. FCM is widely applied in agricultural engineering, astronomy, chemistry, geology, image analysis, medical diagnosis, shape analysis and target recognition . With the development of the fuzzy theory, the FCM clustering algorithm which is actually based on Ruspini Fuzzy clustering theory was proposed in 1980's. This algorithm is used for analysis based on distance between various input data points. The clusters are formed according to the distance between data points and the cluster centers are formed for each cluster. Infact, FCM is a data clustering technique in which a data set is grouped into n clusters with every data point in the dataset related to every cluster and it will have a high degree of belonging (connection) to that cluster and another data point that lies far away from the center of a cluster which will have a low degree of belonging to that cluster.

K-Means has been around for many years to discover patterns by grouping objects based on some similarity measure. It is faster and simple. However, it takes uniform clusters and needs to know the number of clusters beforehand. Another important feature of K-Means is that it keeps an object into a specific cluster. However, in the real world an object might be closer to more than one cluster. The K-Means clustering is also known as hard clustering. To overcome the limitations of K-Means, Fuzzy K-Means came into existence which is known as soft clustering approach. Fuzzy K-Means is flexible enough and can allow an object to belong to more than one cluster. In the literature it is found that Fuzzy K-Means has better utility in the real world applications than K-Means with respect to the quality of clusters.

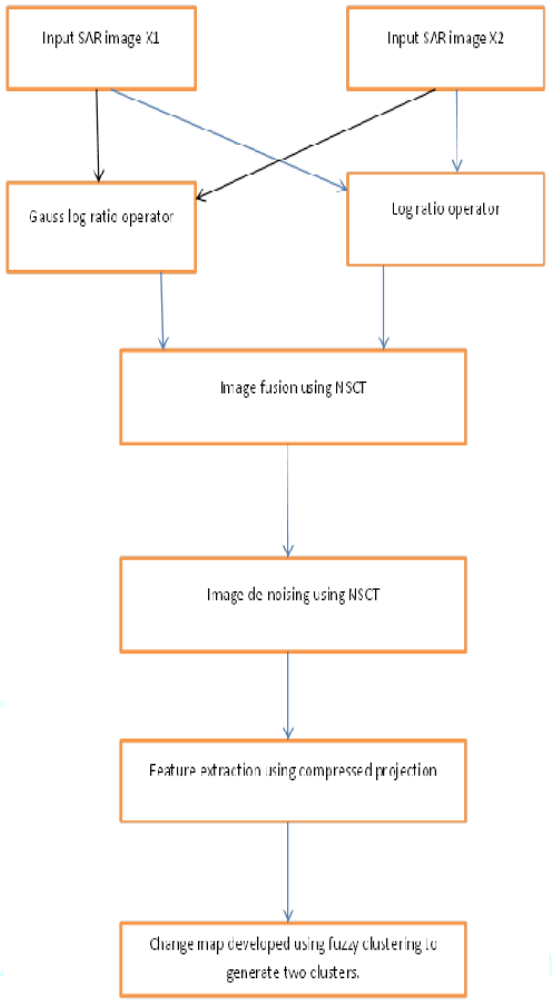


Figure 3.2:- Workflow of the proposed model.

Let X_1 and X_2 be two co-registered intensity SAR images acquired at same geographical area at two different times.The objective of this model is to develop a change map that represents the changes between the acquisition dates of the two images X_1 and X_2.This paper is divided into five sections:

3.4 Developing the difference image using Gauss log ratio and Log ratio operators

Two ratio operators are applied on the SAR images to form the difference image. The commonly used Log-ratio operator converts the linear scale of SAR data to a logarithmic scale before the differencing operation, and thus transforms the multiplicative noise into additive noise. Although the ratio image is expressed in a logarithmic scale to enhance low-intensity pixels, the information of changed portions obtained by the log-ratio image cannot completely reflect the real changed trends because of the weakening in the areas of high-intensity pixels .In order to enhance the real change trend as well as suppress the unchanged portions in the difference image and preserve the homogeneity of the changed portions, the Gauss-log ratio operator is proposed in this paper, which considers the relationship between the intensities of local patches of multi-temporal images.

We define the operator as follows:

$$X_{1r}(i,j) = \log(X_1'(i,j)) * G \quad (11)$$

$$X_{2r}(i,j) = \log(X_2'(i,j)) * G \quad (12)$$

$$X_r(i,j) = \sum_{m=-1}^{1}\sum_{n=-1}^{1} | X_{1r}(i+m,j+n) - X_{2r}(i+m,j+n) | \quad (13)$$

X_1' (i,j) and X_2'(i,j) are two patches centered at point (i,j) in SAR images X_1 and X_2.G is a rotationally symmetric Gaussian low-pass filter.

Although the Gauss-log ratio operator can obtain the expected difference image, the unchanged portion in SAR images is also enhanced, which leads to the error detection. In order to suppress the influence of the enhancement of unchanged portion in SAR image on changed one, the absolute valued log-ratio operator is used to generate the second difference image. It is defined as follows :-

$$X_l = |\log(X_1/X_2)| = |\log X_1 - \log X_2| \quad (14)$$

3.5 Image fusion using Non subsampled counter let transform

Image fusion provides the means to integrate multiple images into a composite image which is more suitable for the purpose of human and machine perception or further image-processing tasks. In this paper non-subsampled contour let transform (NSCT) is used for image fusion. These images may be captured at different times using different devices with different spatial and spectral characteristics.

The main objective of performing image fusion is to retain the important characteristics of each component image. With the development of multi spectrum images the process of image fusion has been receiving greater importance and has a wide spectrum of applications. In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms.NCST is a multi-dimensional, multi-scale fully shift invariant computational framework for discrete images. NSCT framework consists of a non-subsampled pyramid and non-subsampled directional filter banks.

3.5.1 Non-subsampled pyramidal(NSP) filter bank

The non subsampled pyramidal filter bank[18] provides a subband decomposition similar to that of a Laplacian pyramid, which provides the multiscale property of the non sub sampled contourlet transform. This can be obtained by using the two-channel non subsampled 2-Dfilter banks.Fig.3.3 shows the proposed model of non subsampled pyramid decomposition with J=3 levels. Every decomposition level of NSP produces one low frequency and one high frequency images. The subsequent NSP decomposition stages are carried out to decompose the low-frequency components of the image. The property of NSP is obtained by NSFB structure which is similar to that of Laplacian pyramid which is achieved by using the Nonsubsampled filter banks.

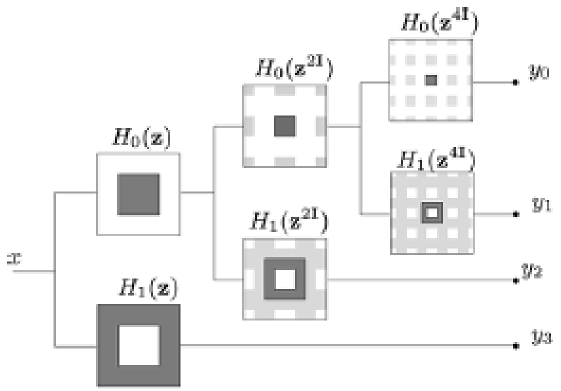


Figure 3.3: Three stage pyramidal decomposition.

3.5.2 Non subsampled directional filter banks

The directional filter bank[19] is constructed by combining two-channel fan filter banks. It splits the input frequency plane into directional wedges. NSDFB provides a shift invariant directional expansion.

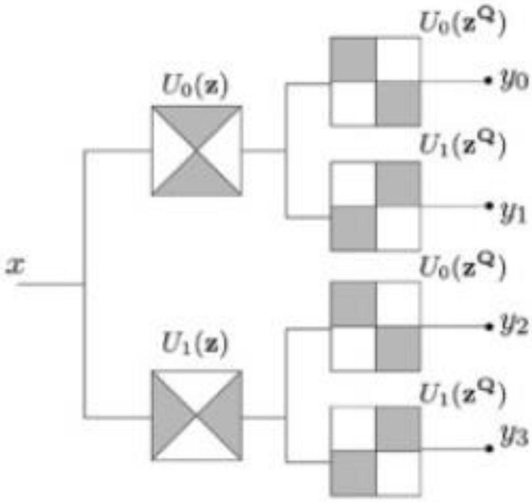


Figure 3.4:The four channel non subsampled directional filter bank constructed with two fan filters.

The directional filter bank is constructed by combining critically-sampled two-channel fan filter banks and resampling operations. The resulting tree-structured filter bank splits the 2-D frequency plane into directional wedges. A shift-invariant directional expansion is obtained with a nonsubsampled DFB (NSDFB). This results in a tree composed of two-channel NSFBs.

While performing image fusion using non subsampled contour let transform (NSCT) all the input images are decomposed firstly. Then the decomposition coefficients on the different scale are combined using different rule, and the fusion image is obtained by taking the corresponding inverse non subsampled contour let transform of the fused coefficients. Image fusion is performed on the basis of fusion rules.

While performing *l*-level NSCT on the input images one low frequency and a series of high frequency sub images will be obtained at each level and direction Ɵ.A: $\{C_l^A, C_L^A, \Theta\}$ and B: $\{C_l^B, C_L^B, \Theta\}$.Here C_l^*-low frequency sub-images. C_L^* represents high frequency sub-images in the orientation Ɵ.Low frequency components are fused to obtain the approximation components of the source image. Initially the features are extracted from the low frequency subimages and then averaging method is applied. The fusion rules for low frequency sub images is as follows:

$$C_l^F(x,y) = \begin{cases} C_l^A(x,y)\ ,if\ pC_l^A\ (x,y) > pC_l^B(x,y) \\ C_l^B(x,y)\ ,if\ pC_l^A\ (x,y) < pC_l^B(x,y) \\ \sum(K\epsilon(A,B)\ C_l^K(x,y))/2\ \ ,if\ pC_l^A\ (x,y) > pC_l^B(x,y) \end{cases} \quad (15)$$

The fusion rule for the high frequency sub images is as follows:

$$C^{F}_{l,\theta}(x,y) = \begin{cases} C^{A}_{l,\theta}(x,y)\ , if\ DC^{A}_{l,\theta}(x,y) > DC^{B}_{l,\theta}(x,y) \\ C^{B}_{l,\theta}(x,y)\ , if\ DC^{A}_{l,\theta}(x,y) < DC^{B}_{l,\theta}(x,y) \end{cases} \quad (16)$$

Inverse NSCT transform is performed on the low frequency and high frequency sub images to produce the fused image.

The resulting image will be more informative than any of the input images. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. Image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the

3.6 Image de-noising using non subsampled counter let transform

NSCT is used to remove the noise[20] present in the fused difference image.First a noisy image is generated by adding noise to the existing fused difference image.The various steps involved in image denoising are:

1. The fused difference image obtained is decomposed in different scales and different directions to obtain the subband images.Each sub band image will have the same size as that of the fused image.
2. Sub band images will contain both low frequency sub band images and high frequency sub band images.
3. Coefficients in the low frequency subband is kept unchanged and that of the high frequency directional subbands in different scales is suppressed using the Donoho Threshold.
4. The Donoho threshold is defined as $\lambda=\sigma\sqrt{2logN}$ where σ represents noise standard deviation and N denotes the sample size.
5. The value of σ can be estimated using the equation σ = Y_j/0.6745. Y_j denotes the intermediate value of high frequency coefficients while arranging the high frequency coefficients according to the order of amplitude at scale j.
6. When the coefficient value is higher than that of threshold the coefficients remain unchanged otherwise the coefficients are set to zero.
7. By applying the inverse NSCT transform we obtain the denoised difference image.

3.7 Feature extraction through compressed projection

Compressed projection[21] has recently emerged as a surprisingly useful tool in signal processing. The compressed projection can preserve the relevant structure in a signal when the signal is projected onto a small number of random basis functions. Although some information may be lost through such a projection, this information tends to be incoherent with the relevant structure in the signal. That is to say, a small number of compressed vectors obtained by compressed projection contain enough information to preserve the underlying local texture structure. In this sense, compressed projection[22] is a universal measurement tool. Another benefit is that compressed projection can provide dimensionality reduction, which can greatly reduce the amount of data to be processed. Based on the above analysis, compressed projection is used to extract the feature vector of each pixel in the de-noised difference image X_d in this paper. The compressed vector can be obtained as follows:

$$v(i,j) = A^{CS} X'_d(i,j). \quad (17)$$

v(i,j) – compressed vector

A^{CS} - cs information operator

X'_d (i,j) – one dimensional vector.

Although a SAR image can be considered to be composed of a number of small homogeneous regions , the high-frequency texture and target geometrical structure of the SAR image are very abundant . That is to say, the real backscattering coefficient value of terrain varies greatly, even does it in a small patch X_d (i,j). For the measurement process in , one important problem is how to design a A^{cs} with stable measurement such that the salient information in X'_d (i,j) is not damaged by the dimensionality reduction from X'_d (i,j) to v(i,j) and v(i,j) can interpret the frequency characteristics of the difference image, and hence, v(i,j) can be better clustered in the subsequent clustering and classification.

Therefore, in this paper, the measurement matrix is acquired from FFT-based double-star shape sampling filter[23] in the 2-D Fourier plane. This sampling pattern tries to determine the important frequency components and is generated by using the frequency information extracted from an image patch. Figure gives an example of double-star shape sampling patterns with different densities of radial lines corresponding to an image of size . If we want to get different numbers of measurements, we can change the density of lines in the sampling patterns. Fig. 3.5(a) and 3.5(b) illustrates the case where one can gather the required samples along each of 14 and 28 radial lines, respectively. FFT-based double-star shape sampling filter is very stable in each experiment compared with the traditional random matrix. Fig. 3.6 shows the block diagram of computing a compressed vector. As shown in Fig. 3.6, we compute fast Fourier transform (FFT)[24] of a vectorized image and then the measurement is multiplied with double-star shape sampling filter shown in Fig. 3.5, the compressed vector is thus obtained.

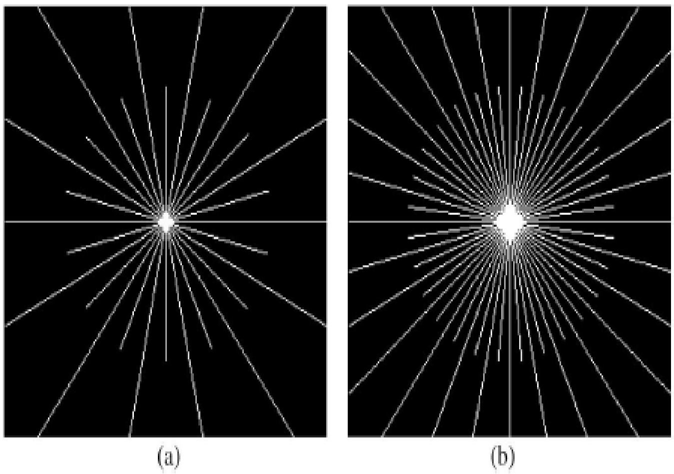


Figure 3.5:-Double star shaped sampling patterns.

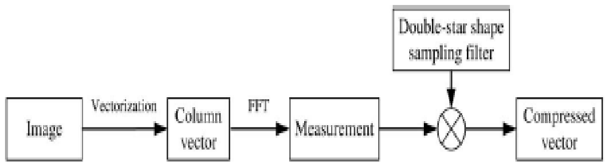


Figure 3.6:- Computing compressed vector.

3.8 Fuzzy clustering approach used to find the changed pixel

Clustering means portioning a data set into a reasonable number of disjoint groups where each group containing similar samples. In this partitions , the patterns are similar within the clusters and different between the clusters that is maximizing the intra class similarities and minimizing the inter class similarities..

In fuzzy clustering[25] the samples are assigned not only to one cluster In fuzzy clustering the samples are assigned not only to one cluster, but belongs to different clusters. That is samples with certain degree of belonging to all clusters. Among the fuzzy clustering methods, the FCM algorithm is one of the most popular methods since it can retain more information from the original image and has robust characteristics for ambiguities. Here clustering is done to discriminate changed regions from unchanged regions.

A. *For improving the performance of image clustering, we use improved version of fuzzy clustering technique. That is fuzzy local information c means clustering algorithm. Here we introduce, a novel fuzzy factor into the object function of FLICM. The peculiarity of fuzzy local information c means algorithm is the main use of local similarity measure, which is aimed at ensuring the image detail preservation and noise insensitiveness.*

The main concern while dealing with SAR images is the presence of speckle noise. The presence of speckle noise make it very difficult to classify the pixels into two classes. In order to overcome this problem and to reduce the effect of speckle noise in the difference image generation step log ratio operator is widely used. Threshold method can be used to divide the difference image ino two classes. In the standard FCM algorithm ,objective function refers to the function which is related to the membership and dissimilarity which will be minimized in each iteration. But the normal FCM algorithm is very much sensitive to noise and has least consideration about the spatial context.

A Markov Random field serves as a tool in order to bring information about the mutual influences among the image pixels. Here for change detection FCM algorithm with MRF[26] with a novel form of energy function is being used. This algorithm is computationally simple and its objective function can return to the objective function of standard FCM thereby making it less time consuming when compared with the other modified FCM algorithms. In order to reduce the effect of speckle noise it focuses on the membership function modification. By introducing the information provided by the spatial context it modifies the membership of each pixel. The central pixel, its neighbors and their inter relationships are considered during this process involving the markov random field.

Markov random field provides the basis to model the information about the mutual influences among the image pixels. Another important factor of the MRF is the energy function that directly influences the way to make use of the spatial context. As far as the problem of the presence f speckle noise in SAR images is concerned the relationship among the pixels is of more complex than that of any other kind of images. For reducing the effect of speckle noise a novel form of the energy function of MRF modifies the FCM algorithm membership instead of modifying the objective function. The time complexity for computing the objective function is $o((2m+7)N)$ for the traditional FCM algorithm where as the time complexity in this approach is $o(4N)$ where N is the number of pixels in an image and m is the number of pixels in its neighborhood. This shows that MRFFCM is less complex than the other improved FCMs.

Generally an image itself is considered as a field and each pixel in the image is considered as an element. If some property of each element is related only to the neighbor ones

and there is no relation to the rest of the pixels then the random field p(x) is considered as a Markov random field. Figure 3.7 illustrates the concept. The black triangle represents the central element j ,white area represents its neighborhood and the grey area is the rest of the pixels. Some properties of the black triangle are not independent but depends on the neighborhood that is the white area and is independent of the rest of the pixels. This field forms a Markov random field.
Step by step procedure of Markov random field fuzzy c-means.

1. First derive the mean and the standard deviation of the two classes during the first iteration.By using the original FCM algorithm generate the membership matrix.By setting the threshold as 0.5 perform hard division to generate the same kind number matrix.
2. Find the energy matrix in the kth iteration which is the key to make use of the spatial context.
3. Compute the pointwise probabilities of the MRF by making Use of the Gibbs expression and calculate the pointwise probability matrix.
4. Generate the distance matrix using the conditional probability expression.
5. Calculate the objective function using the difference image generated using the log ratio operator.
6. Compute the new membership using the new membership matrix.
7. Update the mean and the standard deviation.

For change detection in SAR images a robust energy function is used in order to make maximum use of the information provided by the neighbourhood pixels.For this w take the mean of the membership of all the neighbours.

$$E_{ij} = -\ln(mu_{ij}) \qquad (18)$$

Where mu_{ij} = mean $\{u_{im}\}$

IMPLEMENTATION AND ANALYSIS

4.1 Implementation

Software used : MATLAB - MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, you can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable you to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java. You can use MATLAB[27] for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing.

Version:- 7.14

4.1.1 Advantages of MATLAB

1. A very large (and growing) database of built-in algorithms for image processing and computer vision applications
2. MATLAB allows you to test algorithms immediately without recompilation. You can type something at the command line or execute a section in the editor and immediately see the results, greatly facilitating algorithm development.
3. The MATLAB Desktop environment, which allows you to work interactively with your data, helps you to keep track of files and variables, and simplifies common programming/debugging tasks
4. The ability to read in a wide variety of both common and domain-specific image formats.
5. The ability to call external libraries, such as OpenCV
6. Clearly written documentation with many examples, as well as online resources such as web seminars ("webinars").
7. Bi-annual updates with new algorithms, features, and performance enhancements
8. If you are already using MATLAB for other purposes, such as simulation, optimation, statistics, or data analysis, then there is a very quick learning curve for using it in image processing.
9. The ability to process both still images and video.
10. Technical support from a well-staffed, professional organization (assuming your maintenance is up-to-date)
11. A large user community with lots of free code and knowledge sharing
12. The ability to auto-generate C code, using MATLAB Coder, for a large (and growing) subset of image processing and mathematical functions, which you could then use in other environments, such as embedded systems or as a component in other software.

4.1.2 Disadvantages of MATLAB

Matlab is an interpreted language. The main disadvantage of interpreted languages is execution speed. When a language is compiled, all of the code is analyzed and processed efficiently, before the programmer distributes the application. With an interpreted language, the computer running the program has to analyze and interpret the code (through the interpreter) before it can be executed (each and every time), resulting in slower processing performance.

4.2 ANALYSIS

In order to analyse the effectiveness of the proposed system of change detection in SAR images , the proposed model has been applied on three different datasets as (i)Ottawa dataset (ii) Bern dataset (iii) small yellow dataset.

Ottawa dataset of figure 4.1 is a section of two SAR images captured by Radarsat SAR sensor in May and August 1997 by the Defense Research and Development Canada,Ottawa.In these images there are mainly two portions that is land and water.By integrating prior information with input image based photo interpretation the ground truth is generated.

Bern dataset of figure 4.2 is a pair of two SAR image captured by the European remote sensing satellite SAR sensor over an area near the city of Bern in April and May 1999.A river flooded the area , so the valley was selected as a test site to find the flooded areas.The ground truth is generated same as above.

Small yellow dataset of figure 4.3 is a pair of SAR images captured at the Yellow river estuary in China in june 2008 and june 2009 .These include vegetation areas.The ground truth image is developed same as the above.

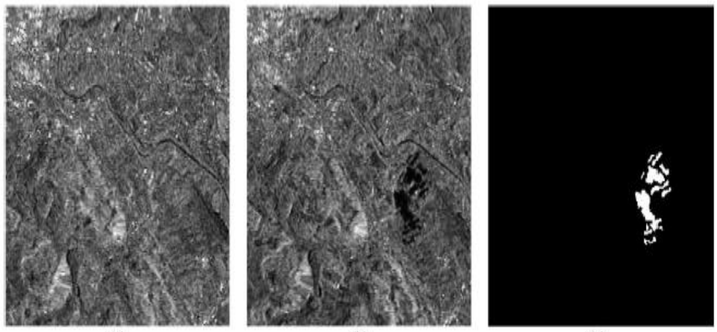
The proposed method is analysed by finding out the peak signal to noise ratio of the SAR images and the corresponding ground truth.PSNR and the mean square error are inversely related.As the PSNR value goes high it indicates that the error or the deviation of the found output from the ground truth is less.PSNR is found as the ratio between the maximum possible power of a signal and the power of the corrupting noise present.

The table below shows the PSNR values[28] calculated by applying the proposed model and comparing with the ground truth values.

Dataset	PSNR value
Ottawa dataset	57.6039
Bern dataset	56.55
Small Yellow	59.0972

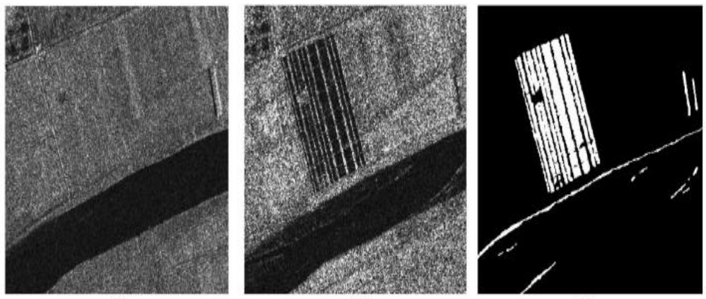
Table 4.1 Calculated PSNR values.

Figure 4.1 Ottawa dataset (a) Image acquired in july 1997 (b) Image acquired in august 1997 (c) Ground truth



(a) (b) (c)

Figure 4.2 Bern dataset (a) Image acquired in April 1999 (b) Image acquired in May 1999 (c) Ground truth



(a) (b) (c)

Figure 4.3 Small yellow dataset (a) Image acquired in June 2008 (b)Image acquired in June 2009 (c) Ground truth

1) *CHAPTER 5*

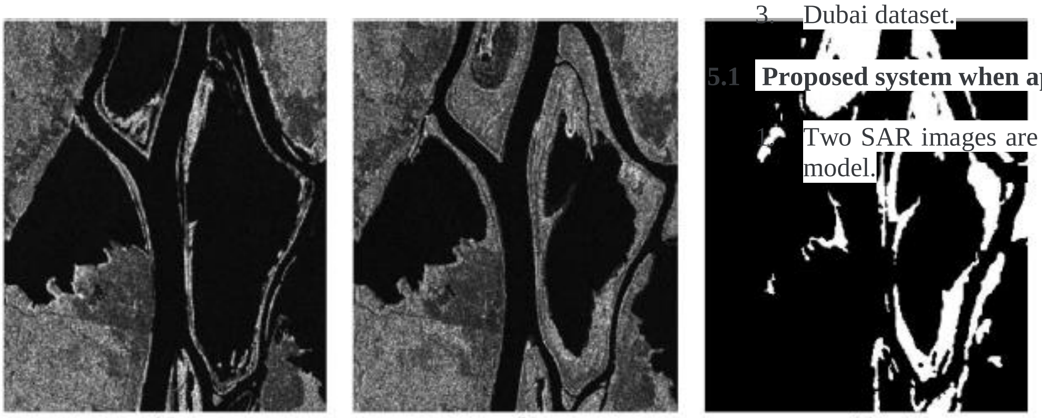
EVALUATION AND RESULTS

The proposed method is evaluated using different datasets.

1. Ottawa dataset
2. Bern dataset
3. Dubai dataset.

5.1 Proposed system when applied on Ottawa dataset.

1. Two SAR images are given as input to the proposed model.



(a) (b) (c)

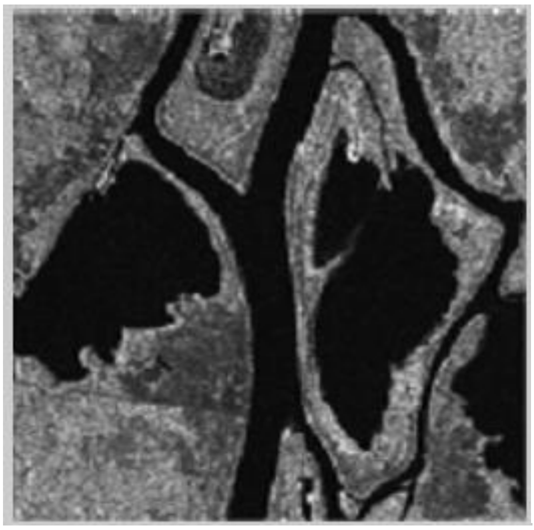


Fig 5.1.Ottawa dataset, image acquired in July 1997.

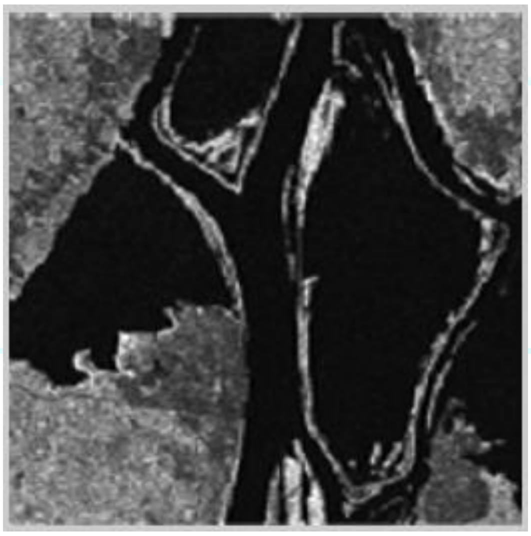


Fig 5.2.Ottawa dataset, image acquired in august 1997.

2. Develop the difference image using Gauss log ratio Operator.

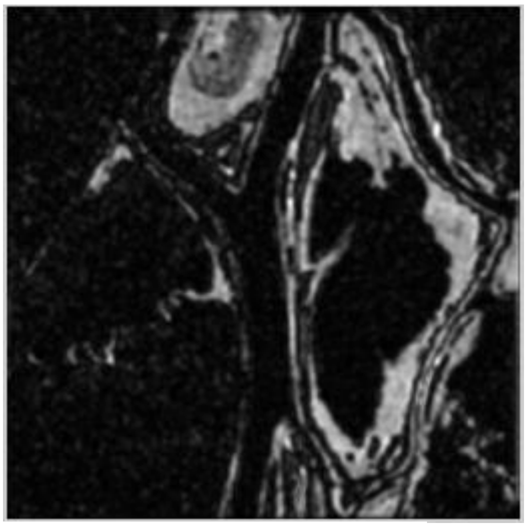


Fig 5.3 Gauss log ratio operator image.

3.Develop the difference image using log ratio operator.

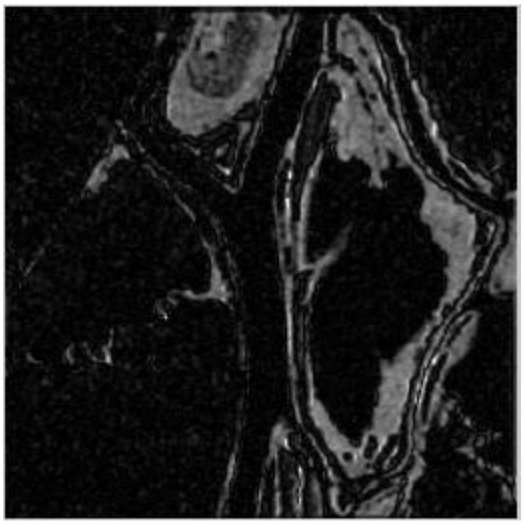


Fig 5.4. Log ratio operator image.

4.Image fusion using non subsampled counterlet transform.

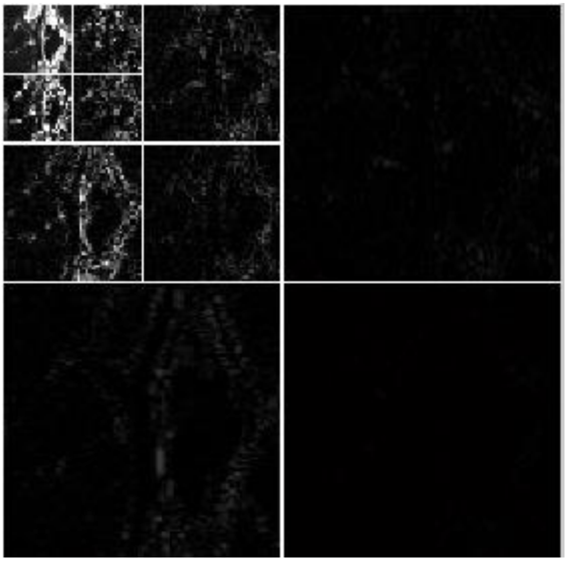


Figure 5.4 Fused image using NSCT

4. Fused image with noise

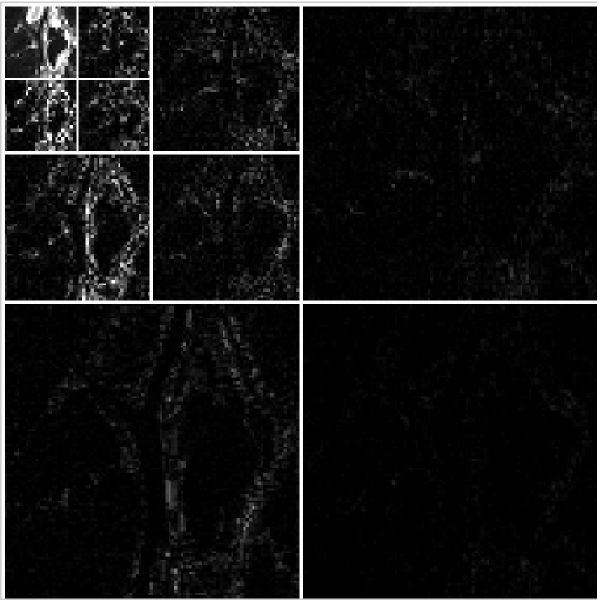


Figure 5.6 Fused image which contains noise.

6. Denoised image using NSCT

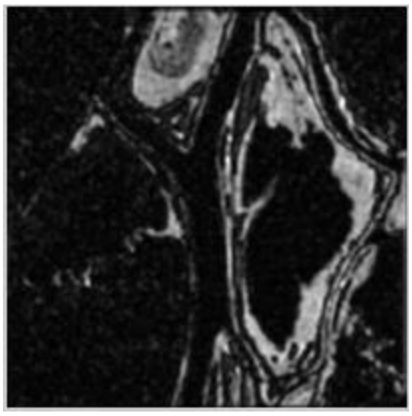


Figure 5.7 NSCT denoised image.

7. Extracting the feature vectors using compressed projection

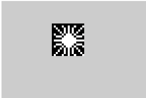


Figure 5.8 Compressed vector generated.

8. Change map developed.

Figure 5.9 Change map.

CONCLUSION

In this paper I have introduced a method for unsupervised change detection in SAR images . In this method Gauss log ratio and log ratio operators are applied over the SAR images. The Gauss log ratio operator can enhance the information on the changed portion in the difference image. NSCT method is applied on the difference image so as to generate the fused image and then the fused difference image is de-noised. Compressed projection method helps in extracting the feature vectors and these feature vectors are categorized into changed and unchanged classes by using the approach of fuzzy clustering. The use of Gauss log ratio and compressed projection and the fuzzy clustering make this approach efficient when compared with the existing system.

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