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CHANGE DETECTION IN MULTISPECTRAL SAR IMAGES USING NSCT AND SFCM

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Abstract

In this paper, change detection in multispectral SAR images using NSCT (Non- Subsampled Contourlet Transform). The proposed method fuses complete difference and change vector analysis image using fusion rules. The image fusion technique is introduced to generate a distinct image by using correspondent information from mean-ratio image and log-ratio image. A fuzzy local-information C- means clustering algorithm is proposed for group changed and unchanged regions in the fused difference image. It absorbs the information about spatial context in a novel fuzzy way for the purpose of improving the changed information and reducing the effect of speckle noise. Differencing (subtraction operator) and rationing (ratio operator) are prominent techniques for producing a difference image for the remote sensing images. In differencing, changes are obtained by subtracting the intensity values pixel by pixel between couple of temporal images. The fused image highlights the changed areas while suppress unchanged areas In rationing, changes are detected by applying a pixel-by-pixel ratio operator to the couple of temporal images. In SAR image case, the ratio operator is commonly used instead of the subtraction operator. Since the image differencing method is not adapted to the statistics of SAR images. The results are proven that rationing generates best difference image for change detection using spatial fuzzy clustering way and efficiency of this algorithm will be exhibited by sensitivity and correlation evaluation.

Key words: SAR Image, NSCT, C-Mean clustering algorithm, Image fusion, DI

I. Introduction

Change detection occurring on the earth surface through the use of multi-temporal remote sensing images is one of most the important applications of remote sensing technology. This depends on many public and private institutions. The knowledge of the act of either natural resources or man-made structures is a valuable source of information in decision making. Here, satellite and airborne remote sensing sensors have proved particularly useful in addressing change detection applications. The applications include environmental monitoring, agricultural surveys, urban studies, and forest monitoring. Generally, change detection involves the analysis of two co-registered remote sensing images acquired over the same geographical area at different times. This analysis is called unsupervised K.Srilatha et al [1]. when it aims at discriminating between two opposite classes. Opposite classes are nothing but which represent changed and unchanged areas. This will be done without any prior knowledge about the scene that is no ground truth is available for modeling the classes. Yifang Ban et al [2] In the analysis of multi temporal remote sensing data acquired by multispectral sensors, various automatic and unsupervised change-detection methods have been developed. Most are based on the so-called "difference image" (DI). By change vector analysis the DI is generated. This technique deed a simple vector subtraction operator to compare pixel-by-pixel the two multispectral images under analysis. Depending on the specific type changes to be identified in some of the cases. The differentiation is form on a subset of the spectral channels. Synthetic aperture radars have been less accomplishment than optical sensors. This is due to SAR images suffering from the presence of the speckle noise. This speckle noise makes it difficult to analyze such imagery, and unsupervised difference between changed and unchanged classes. In spite of the presence of speckle noise, the uses of SAR sensors in change detection is potentially attractive from the operational viewpoint. The advantage of active microwave sensors (unlike optical ones) are independent of atmospheric and sunlight conditions. This means that microwave sensors are capable of monitoring geographical areas periodically (even if covered by clouds) and also of controlling polar region. Even during the local winter period when solar light is critically limited. This makes it feasible to plan the monitoring of a region (by repeat-pass imaging) with advance timing defined according to end-user demands (e.g., seasonal and agricultural calendars). Changes detection of multi temporal image in the state of remotely sensed natural surfaces is changed. By observing natural surfaces at different times is one of the important applications of Earth orbiting satellite sensors because they can provide multi date digital imagery with consistent image quality, at short period, on a global scale, and during complete seasonal cycles. A lot of work has already been accumulated in traverse change detection techniques for visible and near infrared data gathered by Landsat.

In the case of space borne synthetic aperture radar (SAR) imagery, change detection process have been developed for the temporal tracking of multiyear sea-ice floes using Seasat SAR observations, and rain fall case have been detected based on spatial radiometric Variations in multi date Seasat SAR imagery. However Seasat SAR did not provide calculated radar measurements, and Due to the short duration of the mission the multi data observations were produced limited quantity. Change detection methods for space borne SAR data have not yet been totally explored. Change detection techniques for SAR data can be separated into several classifications, each corresponding to different image quality requirements.

The first one, changes are detected based on the temporal tracking of objects image features of recognizable geometrical area shape. Absolute calibration of the data is not required, but the data should be rectified from geometric disturbances due to differences in imaging geometry or SAR processing parameters, and the exact spatial registration of the multi date is more important. Combining information acquired from multiple sensors has become very rewarding in many signal and image processing applications.

In the case of earth observation applications, there are two reasons for that. The first one is that the fusion of the data produced by distinct types of sensors gives a complementary which overcomes the drawback of a specific kind of sensor. The other reason is that, generally, in operational applications, the user does not have the possibility to choose the data to work with and has to use the possible archive images or the first acquisition available after an action of interest. This is particularly for monitoring applications where image registration and change detection methods have to be developed on different types of data.

Both image registration and change detection methods consists of analysis two images , the reference, and the secondary image, acquired over the same landscape scene at two different dates.

II. Existing Method

One aim has been to compile an introduction to the subject of Image Fusion. There exist a number of studies on various algorithms, but finishes treatments on a technical level are not as common. Material from papers, journals, and conference proceedings are used that best describe the different parts.

Another goal has been to search for algorithms that can be used to implement for the image fusion for different applications. A third goal is to evaluate their performance of with different image quality poetry.

These properties were chosen because they have the greatest impact on the detection of Image fusion algorithm. A final goal has been to design and implement the Wavelet based fuzzy and Neural approaches using MATLAB.

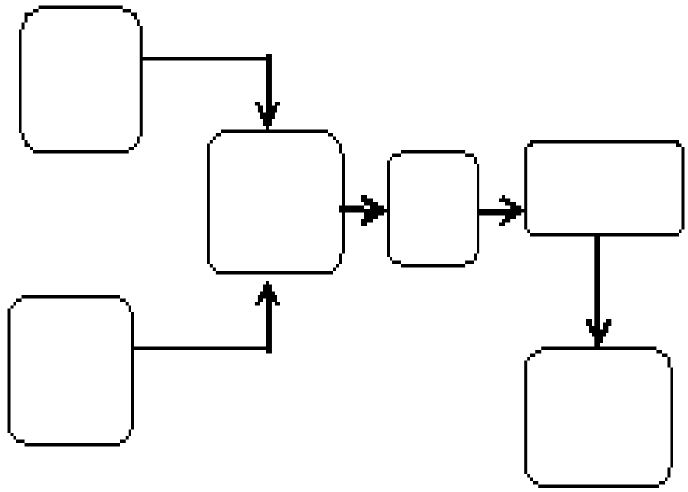

Figure 1: Existing Block Diagram.

Discrete Cosine Transform:-

Discrete Cosine Transform split the image to number of blocks. In these blocks first block has the low frequency information. We can observe clear information in low frequency sub band. DCT fuses the corresponding areas of the original images corresponding to the DCT coefficient high frequency energy.

Drawbacks of DCT

- Only spatial correlation of the pixels inside the only one 2-D block is considered and the correlation from the pixels of the nearby blocks is neglected.
- Impossible to totally de-correlate the blocks at their boundaries using DCT
- Abominable blocking artifacts affect the reconstructed images or video frames.

DWT Based Image Fusion:-

Discrete Wavelet transform (DWT) is a mathematical tool for hierarchically decomposing an image. The DWT decomposes an input image into four components classified as LL, HL, LH and HH. The first letter corresponds to applying either a low pass frequency or high pass frequency operation to the rows, and the second letter refers to the filter enforced to the columns.

The lowest resolution level LL consists of the approximation part of the original image. The remaining three resolution levels subsist of the detail parts and give the vertical high (LH), horizontal high (HL) and high (HH) frequencies. Figure 2 shows three-level wavelet decomposition of an image.

III. Proposed Model

Change detection methods for synthetic aperture radar images based on an image fusion and a spatial fuzzy clustering algorithm. The image fusion method is introduced to generate a difference image by using complementary information from a mean-ratio and a log-ratio image .NSCT (Non- Subsampled Contourlet Transform) based fusion involves an average operator and maximum gradient coefficient collection are chosen to fuse low-frequency and a high-frequency band to restrain the background information and improve the information of changed regions in the fused difference image K.Srilatha et al [1].

A spatial fuzzy clustering algorithm will be proposed for categorizing changed and unchanged regions from fused image with performance analysis.

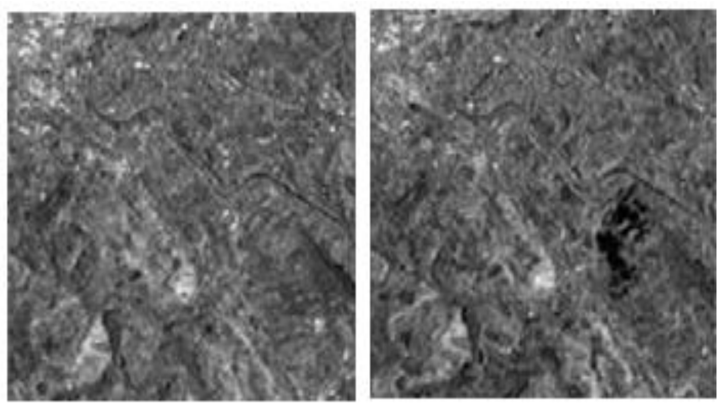

Figure 2: Input images.

System Architecture

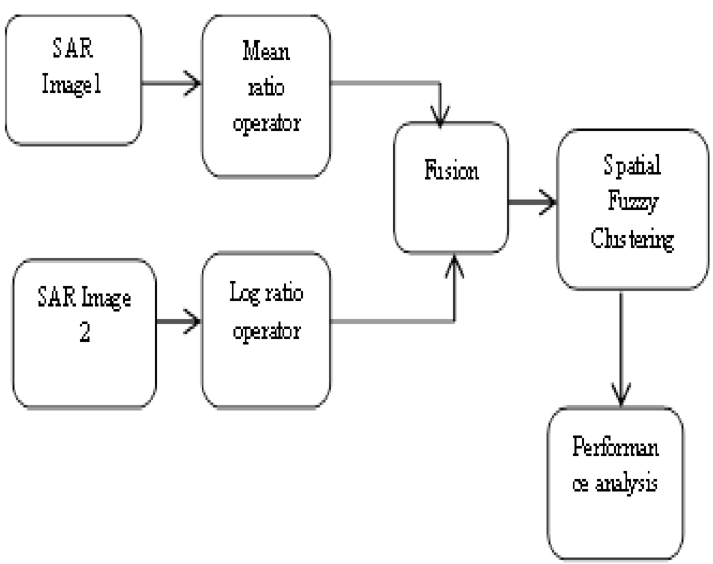

Figure 3: Proposed Method Block Diagram for Change detection.

Image Preparation

Digital images of melanoma and benign nevi were composed in JPEG format from different sources totaling 72, half melanoma and half benign. MATLAB's Wavelet Toolbox supports only for indexed images with linear monotonic color maps. Because of these limitations the RGB images were converted to gray scale images. The next step in the process was to segment the wound from the surrounding skin. Since a clear color difference existed between lesion and skin, thresholding was very suitable for this task. A binary image was produced and its size increased by six pixels all around in order to include the entire border region in the segmented image.

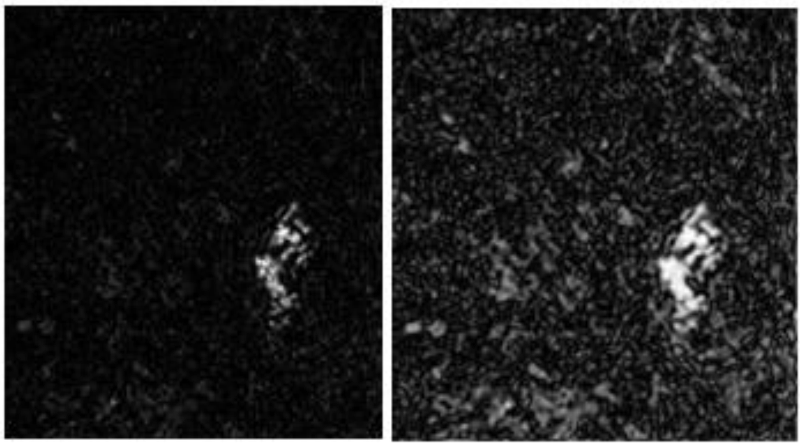

Figure 5: SAR Difference Image.

Image Fusion Process

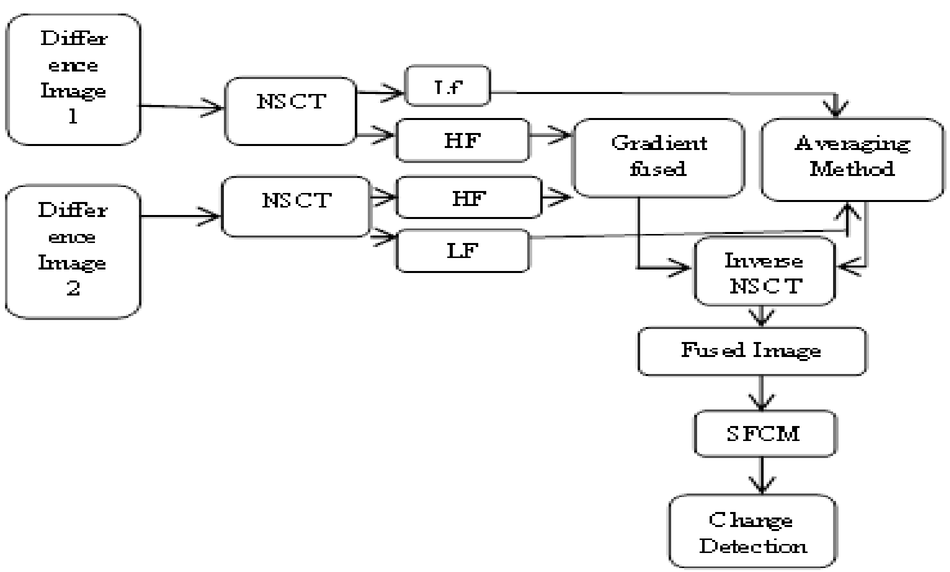

Figure 6: Block Diagram for NSCT fusion process.

NSCT-based Fusion Algorithm:

In the foremost Contourlet transform K.Srilatha et al [1] down-samplers and up-samplers are presented in both the Laplacian pyramid and the DFB. Therefore, it is not shift-invariant. Shift-variant causes pseudo-Gibbs phenomena around singularities. NSCT is an improved form of Contourlet transform. This Contourlet transform is employed in some applications, in which redundancy is not a major issue. For example, image fusion. Non-subsampled pyramid structure and non-subsampled directional filter banks are employed in NSCT in contract with Contourlet transform.

The non-subsampled pyramid structure is achieved by using two-channel non-subsampled 2-D filter banks. By switching off the down-samplers/up-samplers in each two-channel filter bank DFB is achieved. As a result, NSCT is shift-invariant which in turn leads to better frequency selectivity and regularity than the existing contourlet transform. The decomposition framework of contourlet transform and NSCT is shown below (fig.6)

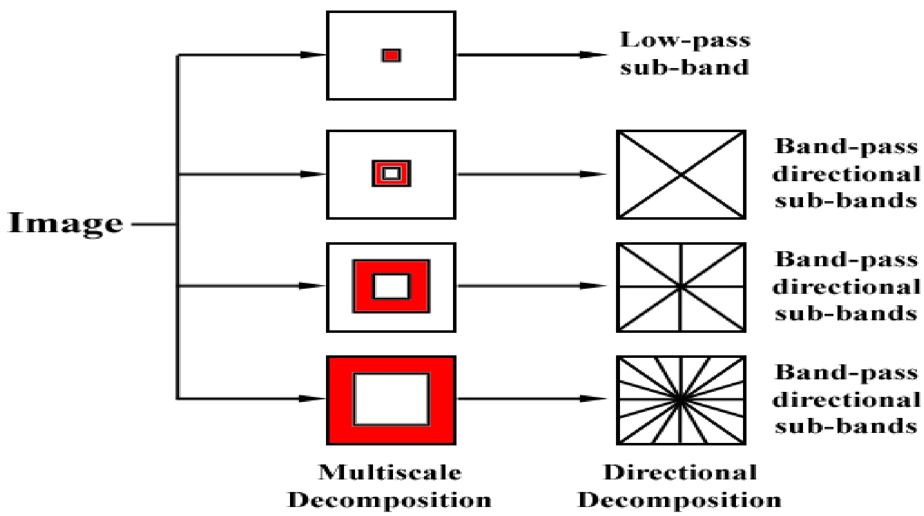

Figure 7: Decomposition Framework of contourlet Transform and NSCT

Image decomposition performed by the NSCT is described in this paper. We hope that predominance of NSCT will be more suitable for image fusion and other image processing. It includes shift-invariant, multi-resolution, localization, directionality, and anisotropy, target recognition, object detection, etc.

Both neighborhood coefficients and cousin coefficients information are utilized in the fusion process.

Fusion of low-frequency coefficients

Considering the images' approximate information is constructed by the low-frequency coefficients, average rule is adopted for low-frequency coefficients. Suppose B_F (x, y) is the fused low-frequency coefficients, then

$$B_F(x,y) = \frac{B_1(x,y) + B_2(x,y)}{2} \quad (1)$$

Where B_1 (x, y) and 2 B_2 (x, y) denote the low-frequency coefficients of source images.

Fusion of high-frequency coefficients High-frequency coefficients always contain edge and texture features. In order to make full use of information in the neighborhood and cousin coefficients in the NSCT domain, a salience measure, as a combination of region energy of NSCT coefficients and correlation of the cousin coefficients, is proposed for the first time. We define region energy by computing the sum of the coefficients' square in the local window. Suppose C_l^k (x y) is the high-frequency NSCT coefficients, whose location is (x,y) in the sub band of k-th direction at l-th decomposition scale. The region energy is defined as follows:

$$E_l^k(x,y) = \sum_{m,n \in S_{M \times N}} \left(C_l^k(x+m, y+n) \right)^2 \qquad (2)$$

where $S_{M\times N}$ denotes the regional window and its size is M × N (typically 3×3).Region energy, rather than single pixel value, will be more reasonable to extract features of source images by utilizing neighbors' information.\

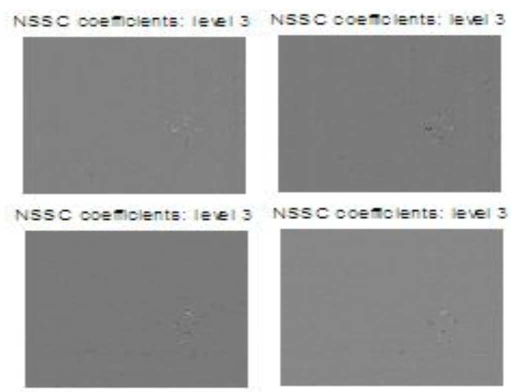

Figure 8: NSCT level-3 Images.

IV. Unsupervised Segmentation-SFCM

Fuzzy clustering plays an important role in fuzzy model identification and also in solving problems in the areas of pattern recognition. There are various fuzzy clustering methods which have been proposed. Most of them are based upon distance criteria [6].

One frequently used algorithm is the fuzzy c-means (FCM) algorithm which uses reciprocal distance to compute fuzzy weights. There is also an efficient algorithm than FCM which is the new FCFM. It computes the cluster center using Gaussian weights.

It also uses large initial prototypes, and adds processes of eliminating, clustering and merging. In the following sections, the comparison of FCM algorithm and FCFM algorithm is discussed.

Spatial Fuzzy C Means Clustering method describes the spatial information, and the membership weighting of each cluster which should be altered or changed after the cluster distribution in the neighborhood. The first pass is the same as that in standard FCM.

This is to calculate the membership function in the spectral domain. In the second pass, the membership information of each pixel is mapped to the spatial domain. And also the spatial function is computed from that. The FCM iteration which is incorporated with the spatial function proceeds with the new membership.

The process of iteration will be stopped when the maximum difference between cluster centers or membership functions at two successive iterations is less than a least threshold value.

The fuzzy c-means (FCM) algorithm was introduced.The idea of FCM is based on the weights that minimize the total weighted mean-square error:

$$J(w_{qk}, z^{(k)}) = \Sigma_{(k=1,K)} \Sigma_{(k=1,K)} (w_{qk}) \| x^{(q)} - z^{(k)} \|^2$$

$$\Sigma_{(k=1,K)} (Wqk) = 1 \text{ for each } q$$

$$w_{qk} = (1/(D_{qk})^2)^{1/(p-1)} / \Sigma_{(k=1,K)} (1/(D_{qk})^2)^{1/(p-1)}, \; p > 1 \qquad (3)$$

The FCM allows each feature vector to belong to every cluster with a fuzzy truth value (between 0 and 1), which is computed using Equation (4).

The algorithm assigns a feature vector to a cluster according to the maximum weight of the feature vector over all clusters.

Algorithm Flow

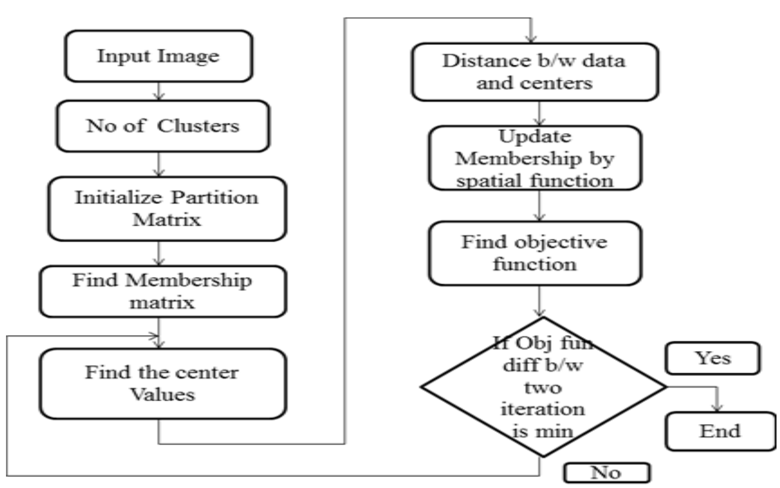

Figure 9: Flow chart for SFCM Method.

Initializing the Fuzzy Weights should be done first in order to compare the FCM with FCFM. Our implementation allows the user to choose the initialized weights using feature vectors or randomly. The process of initializing the weights using feature vectors assigns the first K_{init} (user-given) feature vectors to prototypes. Aftrt it then computes the weights.

Standardize the Weights over Q is done next. During the FCM iteration, the computed cluster centers get closer and closer. To avoid the fast convergence and always grouping into single cluster, we use

$W[q, k] = (w[q, k] - w_{min})/(w_{max} - w_{min})$ (4)

Where w_{max}, w_{min} are maximum or minimum weights over the weights of all feature vectors for the particular class prototype. Eliminating Empty Clusters is the next step. After the fuzzy clustering loop we add a step to eliminate the empty clusters this step is put outside the fuzzy clustering loop and before the calculation of modified XB validity. Without the elimination of empty clusters, the minimum distance of prototype pair used in Equation may be the distance of empty cluster pair. We call the method of eliminating small clusters by passing 0 to the process. Only then it will eliminate the empty clusters. After the fuzzy c-means iteration, for the purpose of comparison and to pick the optimal result, we add Step 9 to calculate the cluster centers and the modified Xie-Beni clustering validity κ :

The Xie-Beni validity is a product of compactness and separation measures Ashish Ghosh et al [10]. The compactness-to-separation ratio ν is defined by Equation (5).

$\nu = \{(1/K)\sum_{(k=1,K)}\sigma_k^2\}/D_{min}^2$ (5)

$\sigma_k^2 = \sum_{(q=1,Q)} w_{qk} \| x^{(q)} - c^{(k)} \|^2$ (6)

D_{min} is the minimum distance between the cluster centers.

The Modified Xie-Beni validity κ is defined as

$\kappa = D_{min}^2 / \{\sum_{(k=1,K)}\sigma_k^2\}$ (7)

The variance of each cluster is calculated by summing over only the members of each cluster rather than over all Q for each cluster, which contrasts with the original Xie-Beni validity measure.

$$\sigma_k^2 = \sum_{\{q:\ q \text{ is in cluster } k\}} w_{qk} \| x^{(q)} - c^{(k)} \|^2 \qquad (8)$$

The spatial function is included into membership function as given in Equation

$$u'_{ij} = \frac{u_{ij}^p h_{ij}^q}{\sum_{k=1}^{c} u_{kj}^p h_{kj}^q} \qquad (9)$$

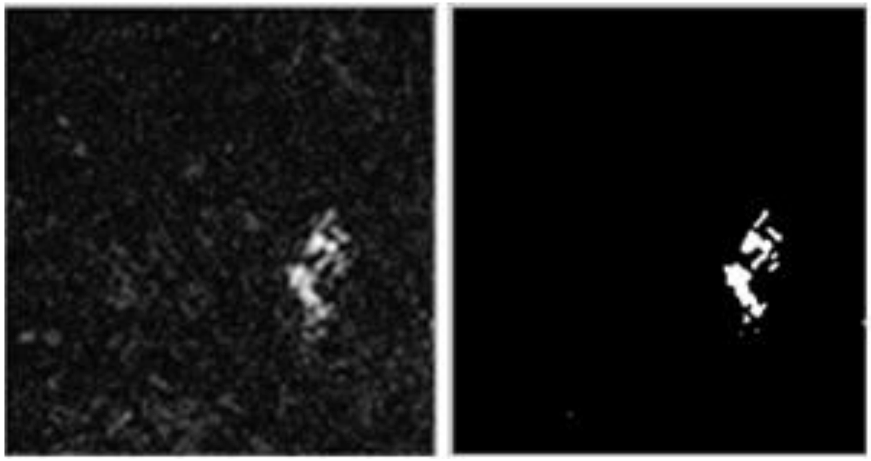

Figure 10: NSCT fusion Image and SFCM SAR Change detection.

V. Result Analysis

In this section we report some experimental results. These results illustrate the performance of the proposed approach. The experiments were performed under windows and MATLAB software running on a desktop machine.

Quality Measurement

The pixel Quality of the reconstructed image is measured in-terms of Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) ratio. The MSE is often called as reconstruction error variance σ_q^2. K.Srilatha et al [1].The MSE error between the original image f and the reconstructed image g at decoder is formulated as:

$$MSE = \frac{1}{MXN} \sum_{j,k} (f[j,k] - g[j,k]) \quad (10)$$

Here, the sum over j, k denotes the sum overall pixels in the image.

N is the number of pixels in each image. The Peak Signal-to-Noise Ratio is defined as the ratio between signal variance and reconstruction error variance. Consider two images having 8 bit pixel in terms of decibels (dB). The PSNR between these two images is given by:

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \quad (11)$$

Usually, when PSNR value is 20 dB or greater than 20 dB, then the original and the reconstructed images are virtually in-differentiable by human eyes.

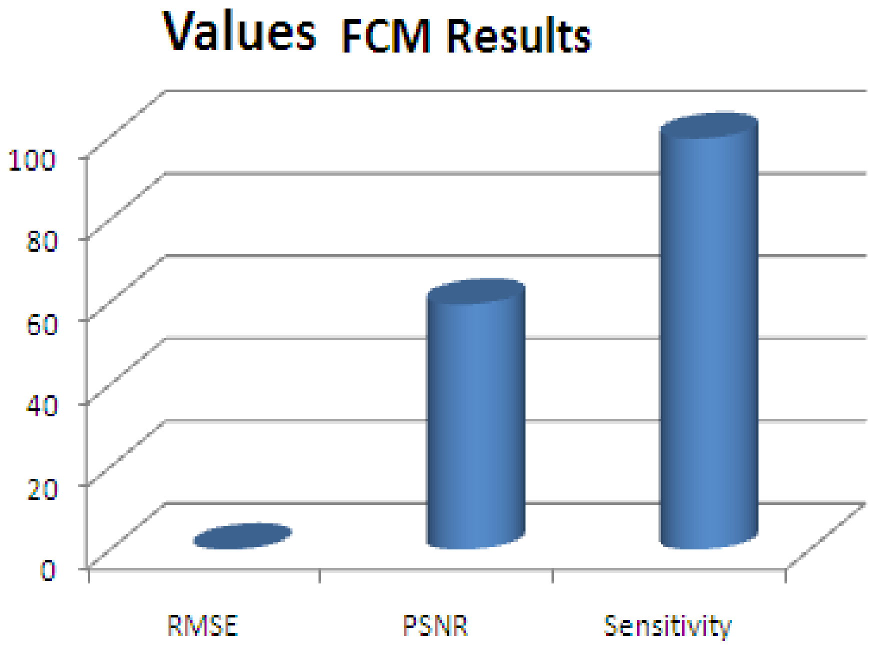

Figure 11: Result analysis for Proposed Method.

		EXISTING METHOD(Pixel Concatenation)	PROPOSED METHOD(NSTC and SFCM)
Sensitivity		99.4784	99.6058
Accuracy		73.7733	85.7851
PSNR		58.7358	59.5304

Table 1: Comparison of methods.

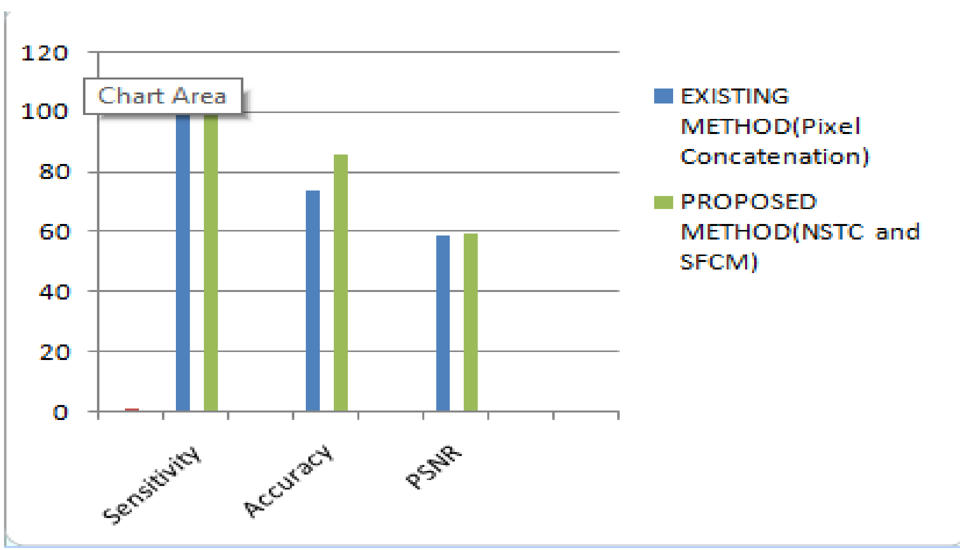

Figure 12: Result analysis of NSCT with Pixel Concatenation.

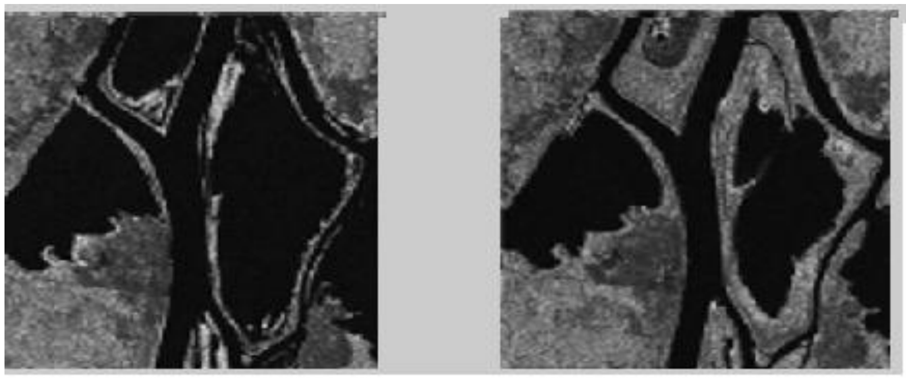

Figure 13: Input images.

Figure 14: Output image.

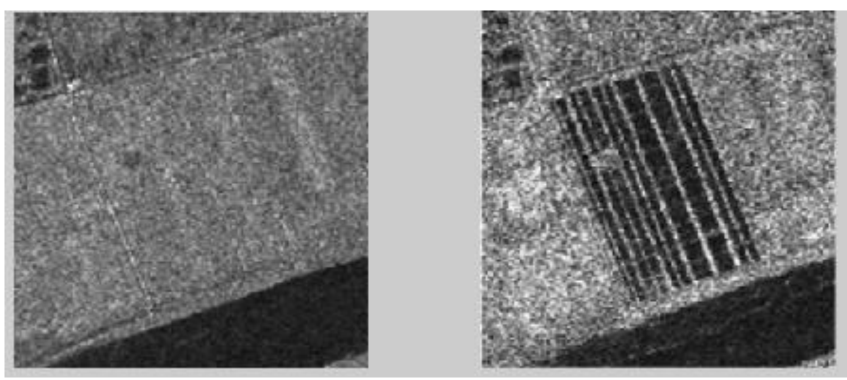

Figure 15: Input Images.

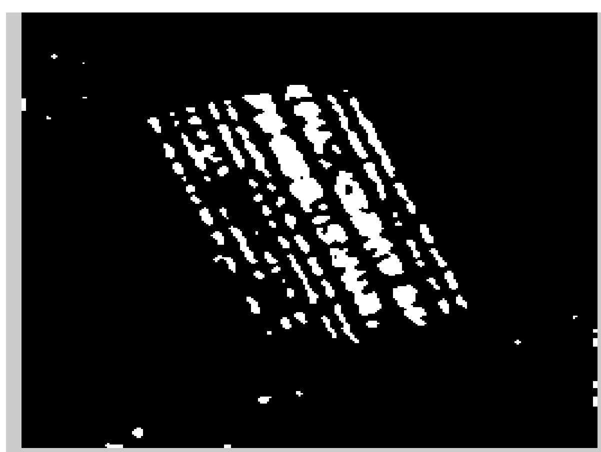

Figure16: Output image.

VI. Conclusion

The paper presents the Change Detection approach for remote sensing satellite images based on an image fusion and a spatial fuzzy clustering algorithm. This change detection in specific region involves the fusion approach for morphing the two images taken at different time. This is taken to enhance the details of changed region from unchanged region. In this paper, decomposition of NSCT was effectively used to extract the smoothing and contour wedges from images to make pixel level fusion which provides better efficiency. An averaging rule and gradient detection were utilized in this paper. The changes will be detected using SFCM (Spatial Fuzzy c means Clustering) from the fused image. This detection can be done with less time. The simulated result shows that generated fused image has less error than the existing methods and also has better signal to noise ratio for segmented changed region. Better sensitivity and accuracy are also the major fact for this proposed method.

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