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Multi Temporal SAR Image Analysis using NSCT Fusion and Supervised Classifier for Change Detection

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ABSTRACT: The project presents change detection approach for synthetic aperture radar (SAR) images based on an image fusion and supervised classifier system. The image fusion technique will be introduced to generate a difference image by using complementary information from a mean-ratio image and a log-ratio image. NSCT (Non- subsampled contourlet transform) fusion rules based on an average operator and minimum local area gradient are chosen to fuse the contourlet coefficients for a low-frequency band and a high-frequency band respectively, to restrain the background information and to enhance the information of changed regions in the fused difference image. For the remote sensing images, differencing(subtraction operator) and ratioing (ratio operator) are well-known techniques for producing a difference image. In differencing, changes are measured by subtracting the intensity values pixel by pixel between the considered couple of temporal images. In ratioing, changes are obtained by applying a pixel-by-pixel ratio operator to the considered couple of temporal images. In the case of SAR images, the ratio operator is typically used instead of the subtraction operator since the image differencing technique is not adapted to the statistics of SAR images. An artificial neural network type multi-layer perceptron or back propagation with feed forward network will be proposed for classifying changed and unchanged regions in the fused difference image. This classifier comes under supervised segmentation which is worked based on training cum classification. The results will be proven that ratioing generates better difference image for change detection, using supervised classifier segmentation approach and efficiency of this algorithm will be exhibited by sensitivity and correlation evaluation.

KEYWORDS: Image fusion, synthetic aperture radar (SAR), Image Segmentation, Non Subsampled Contourlet Transform (NSCT), Log ratio approach, Mean ratio approach, Supervised Classifier.

I. INTRODUCTION

Image change detection is a process that analyzes images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates [1]. In the last decades, it has attracted widespread interest due to a large number of applications in diverse disciplines such as remote sensing, medical diagnosis, and video surveillance. With the development of remote sensing technology, change detection in remote sensing images becomes more and more important. Among them, change detection in synthetic aperture radar (SAR) images exhibits some more difficulties than optical ones due to the fact that SAR images suffer from the presence of the speckle noise. However, SAR sensors are independent of atmospheric and sunlight conditions, which make the change detection in SAR images still attractive. In general, it appears clearly from the literature that the whole performance of SAR-image change detection is mainly relied on the quality of the difference image and the accuracy of the classification method. In order to address the two issues, in this paper, we propose an supervised classifier based SAR-image change detection approach. It is unique in the following two aspects: 1) producing difference images by fusing a mean-ratio image and a log-ratio image, and 2) using Back propagation Feed forward network based algorithm, which is insensitive to noise, to identify the change areas in the difference image and also it consumes less time for classification. In previous works, an unsupervised segmentation method known as spatial fuzzy clustering method is used for change detection. The simulation results prove that using supervised classifier is better in all aspects from the comparison table.

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II. PROPOSED MODEL

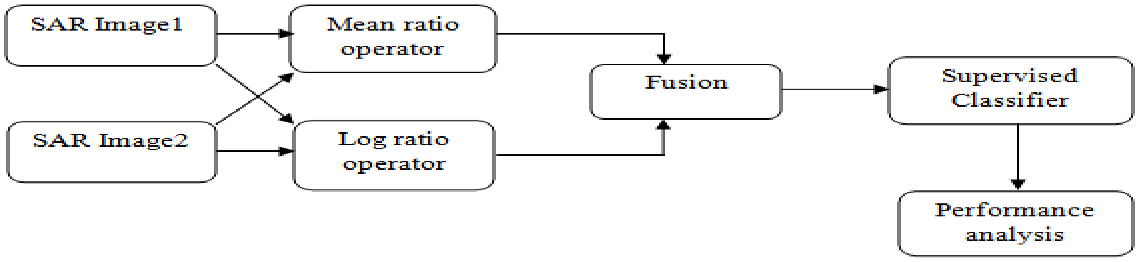

Fig 1.Change Detection

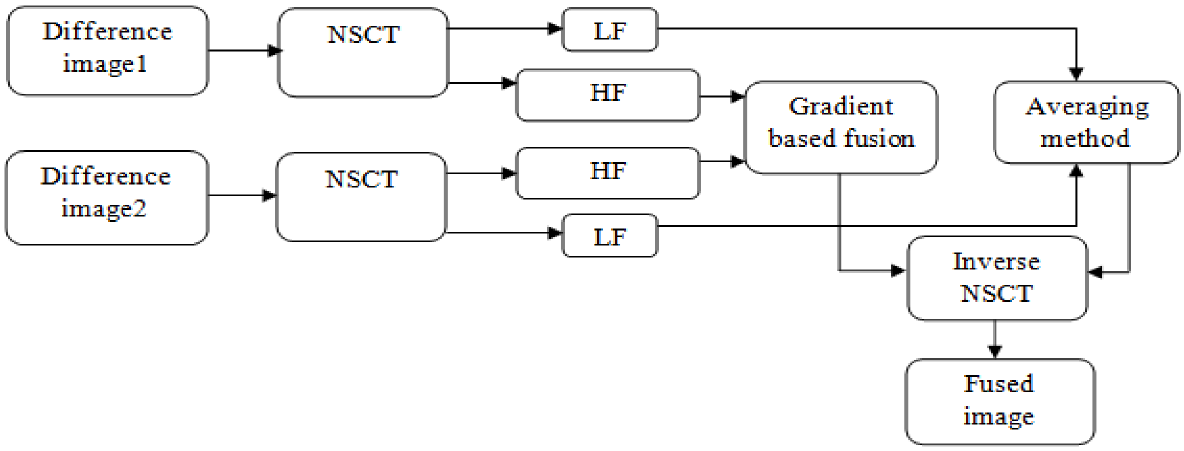

Fig 2. Fusion

A. DESCRIPTION

Change detection approach for synthetic aperture radar images based on an image fusion and a supervised classifier algorithm. The image fusion technique will be introduced to generate a difference image by using complementary information from a mean-ratio image and a log-ratio image.

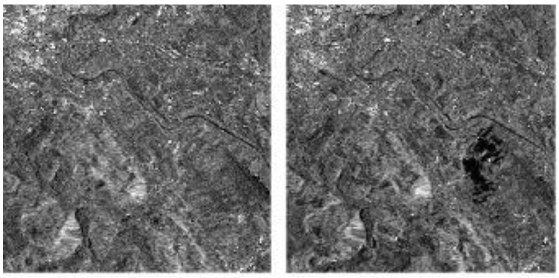

Fig 3. Multitemporal images relating to the city of Bern used in the experiments (a) Image acquired in April 1999 before the flooding. (b) Image acquired in May 1999 after the flooding.

NSCT (Non- subsampled contourlet transform) based fusion involves an average operator and maximum gradient coefficient selection are chosen to fuse low-frequency and a high-frequency band to restrain the background

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information and enhance the information of changed regions in the fused difference image. A supervised classifier algorithm will be proposed for classifying changed and unchanged regions from fused image with performance analysis.

B. DIFFERENCE IMAGE CREATION

Logarithmic scale based difference part will be generated to identify changed and unchanged region and it is weakening the high intensity and enhancing the low intensity pixels. Due to this weakening, there is a possibility of information loss from significant part. So along with this, ratio mean operator and fusion approach is used to reduce this limitation and produce detailed portion from source images for accurate detection of changes.

The difference images are obtained by,

Log ratio approach

$D_1 = |\log X_2 - \log X_1|$ (1)

Where,

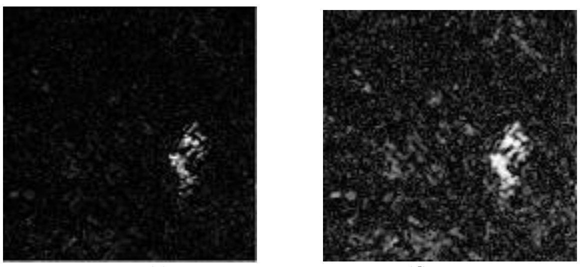
X_2 – Input image1 and X_1 – Input image 2

Mean ratio approach

$D_2 = 1 - \min(u_1/u_2, u_2/u_1)$ (2)

Where,

u_1 – average filtered image1, u_2 – average filtered image2 .



(c) (d)

Fig 4. (c) Log ratio image (d) Mean ratio image

C. NSCT DECOMPOSITION

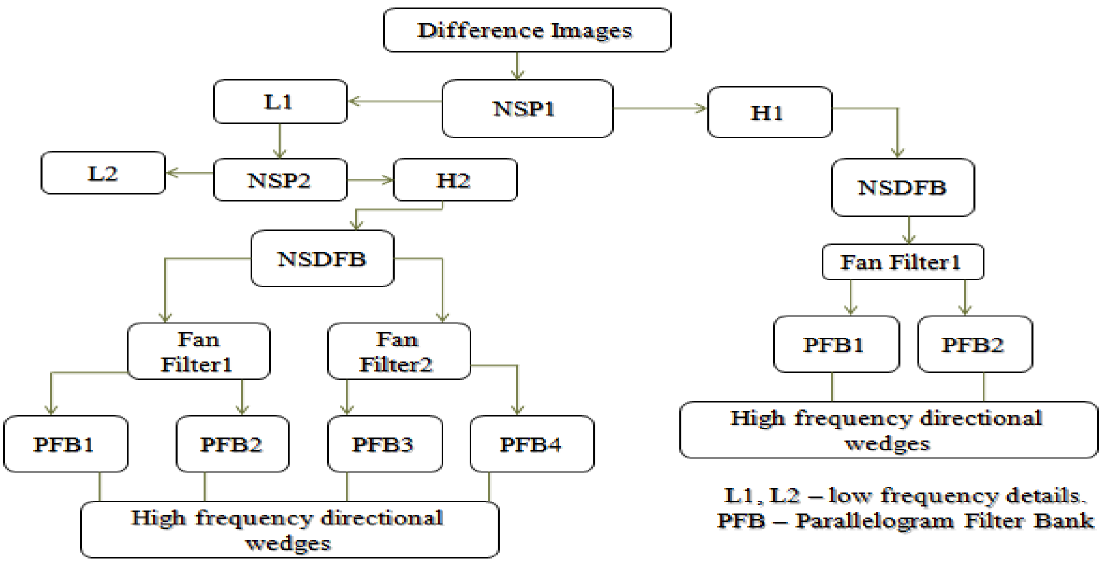


Fig 5. NSCT Decomposition

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NSCT transform is more suitable for constructing a multi-resolution and multi-directional expansions using non-separable Pyramid Directional Filter Banks (PDFB) with small redundancy factor.

NSCT decomposition is to compute the multi scale and different direction components of the discrete images. It involves the two stages such as Non sub sampled pyramid (NSP) and Non sub sampled directional filter bank(NSDFB) to extract the texture, contours and detailed coefficients. NSP decomposes the image into low and high frequency subbands at each decomposition level and it produces n+1 sub images if decomposition level is n.

NSDFB extracts the detailed coefficients from direction decomposition of high frequency subbands obtained from NSP. It generates m power of 2 direction sub images if number of stages be m.

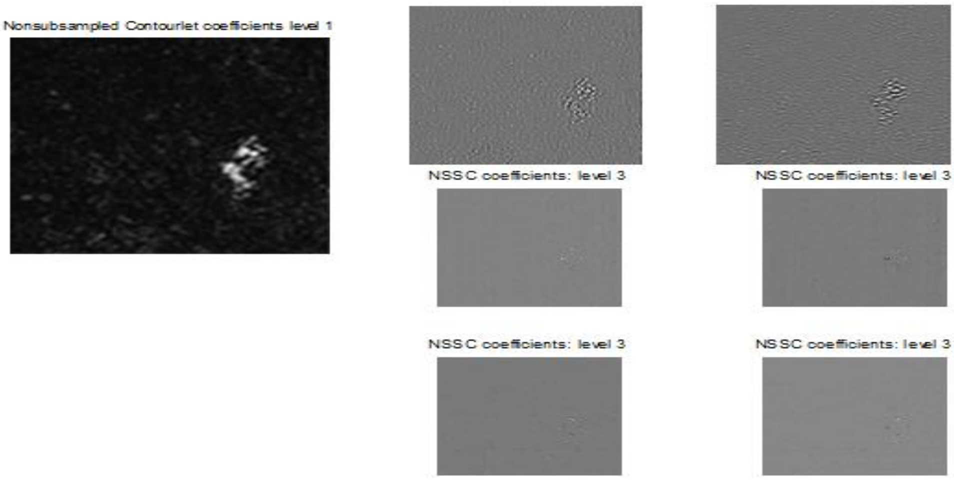

Fig 6. Difference image 1

D. FUSION

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

$$B_F(x,y) = \frac{(B_1(x,y)+ B_2(x,y))}{2} \tag{3}$$

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

FUSION OF HIGH-FREQUENCY COEFFICIENTS

High-frequency coefficients always contain edge and texture features. Suppose C_l^k (x y) is the high-frequency CT coefficients, whose location is (x,y) in the subband of k-th direction at l-th decomposition scale. The region energy is defined as follows:

$$E_l^k(x,y) = \sum_{m,n \in S_{M\times N}} \left(C_l^k(x+m, y+n\,)\right)^2 \tag{4}$$

where $S_{M\times N}$ denotes the regional window and its size is M × N (typically 3×3).

The high frequency coefficients are also fused by evaluating the gradient of the each subband coefficients. The gradient of an image will be defined as,

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$$G = \sqrt{(dzdx^2 + dydx^2)} \tag{5}$$

Where, the dzdx and dydx are the y derivatives and x derivatives obtained by the sobel edge operators.Then these coefficients are fused based on the searching maximum gradient of these two using decision rule.

E. SUPERVISED CLASSIFIER

NEURAL NETWORK

Neural networks are predictive models loosely based on the action of biological neurons. The type of neural network used here is Back propagation with feed forward network for training the samples.

BACK PROPAGATION NETWORK

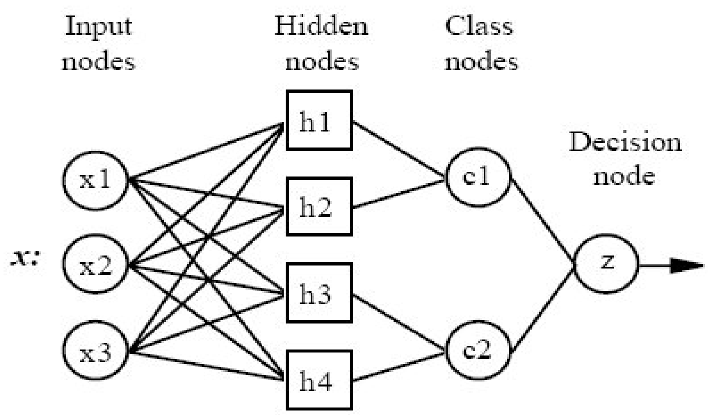

Fig 7. Architecture of a BPN Network

All BPN networks have the following four layers,

INPUT LAYER

There is one neuron in the input layer for each predictor variable. In the case of categorical variables, *N*-1 neurons are used where *N* is the number of categories.

HIDDEN LAYER

This layer has one neuron for each case in the training data set. The neuron stores the values of the predictor variables for the case along with the target value. When presented with the *x* vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma value(s). The resulting value is passed to the neurons in the pattern layer.

PATTERN LAYER / SUMMATION LAYER

For BPN networks there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's category.

DECISION LAYER

For BPN networks, the decision layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

BACK PROPAGATION ALGORITHM

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Consider a network with a single real input x and network function F. The derivative F'(x) is computed in two phases. They are,

FEED-FORWARD

The input x is fed into the network. The primitive functions at the nodes and their derivatives are evaluated at each node. The derivatives are stored.

BACK PROPAGATION

The constant 1 is fed into the output unit and the network is run backwards. Incoming information to a node is added and the result is multiplied by the value stored in the left part of the unit. The result is transmitted to the left of the unit. The result collected at the input unit is the derivative of the network function with respect to x.

STEPS OF THE ALGORITHM

The back propagation algorithm is used to compute the necessary corrections, after choosing the weights of the network randomly. The algorithm can be decomposed in the following four steps:

Step 1: Feed-forward computation

Step 2 : Back propagation to the output layer

Step 3: Back propagation to the hidden layer

Step 4 : Weight updates

The algorithm is stopped when the value of the error function has become sufficiently small.

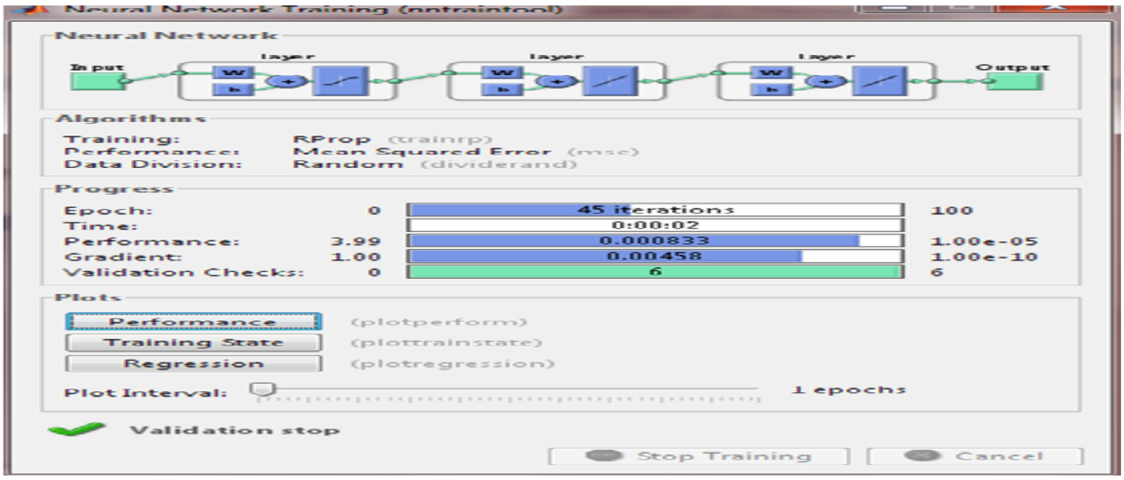

Fig 8 . Neural Network Performance

III. EXPERIMENTAL RESULTS

PEAK SIGNAL TO NOISE RATIO AND MEAN SQUARE ERROR

To establish an objective criterion for digital image quality, a parameter named PSNR (Peak Signal to Noise Ratio) is defined in the following equation.

$$PSNR = 10*\log10\,(255*255/MSE) \tag{6}$$

where MSE (Mean Square Error) stands for the mean-squared difference between the cover-image and the stereo-image. The mathematical definition for MSE is defined as follows,

$$MSE = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(a_{ij} - b_{ij}\right)^2 \tag{7}$$

. The larger PSNR is, the higher the image quality is (which means there is only little difference between the input-image and the fused-image). On the contrary, a small dB value of PSNR means there is great distortion between the input-image and the fused-image.

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Sensitivity: It measures the proportion of actual positives which are correctly identified

Sensitivity = Tp./(Tp + Fn) (8)

Where,
Tp = True Positive: Number of correctly classified pixels as changed region
Fn = False negative: Number of incorrectly classified pixels as changed region

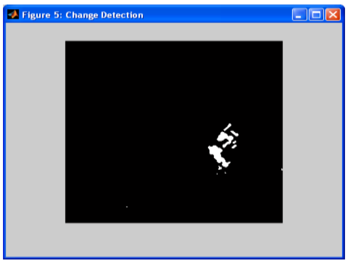

Fig 9. Change detection

Sensitivity: 99.8115 %
Root mean Square Error: 0.0505
Peak Signal to Noise Ratio: 61.0981 dB

Table 1. Comparison Table

PARAMETERS	UNSUPERVISED CLASSIFIER (Existing Method)	SUPERVISED CLASSIFIER (Proposed Method)
SENSITIVITY	99.6058	99.8115
RMSE	0.0725	0.0505
PSNR	59.5304	61.0981

IV. CONCLUSION

The project presented the Change detection approach for remote sensing satellite images based on an image fusion and a supervised classifier for segmentation. Detection of changed region involved the fusion approach for morphing the two images taken at different time to enhance details of changed region from unchanged region. Here, NSCT decomposition was effectively used to extract the smoothing and contour wedges from images to make pixel level fusion with better efficiency. In this type, an averaging rule and gradient detection were utilized. Here, the changes will be detected using supervised classifier from the fused image with less time. The simulated results shown that generated fused image has less error and segmented changed region with better signal to noise ratio, better sensitivity and accuracy compared to the previous method.

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Vol. 4, Issue 5, May 2015

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BIOGRPHY

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