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Building Change Detection on Multi-Temporal VHR SAR Image Based on Second Level Decomposition and Fuzzyrule

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Abstract: In this paper, building change detection technique of multi temporal VHR SAR images based on second level wavelet transforms. The proposed method fuses absolute difference and change vector analysis image using fuzzy rules. Using complementary information from second level wavelet decomposition and log ratio image the image fusion technique will be produced to create a difference image. Using clustering algorithm the changed and unchanged regions from the fused difference image will be classified. For upgrading the changed information and reducing the effect of speckle noise, it assimilates the details about spatial context in a novel fuzzy way. To produce difference image, differencing and rationing are widely known method for the remote sensing images. Changes are measured in differencing by deducting the potency values pixel by pixel among the considered couple of temporal images. The fused image highlights the changed areas while suppress unchanged areas in rationing; changes can be achieved by applying pixel by pixel ratio operator to the considered couple of temporal images. Ratio operator is typically used in SAR images instead of subtraction operator. The results will be proven using spatial fuzzy clustering approach and effectiveness of this algorithm will be shown by sensitivity and correlation evaluation.

Keywords: SAR Images, 2nd level decomposition, fuzzy rule log-ratio features and building change detection.

I. INTRODUCTION

Monitoring of urban areas is of great importance for several applications such as urban planning, cadastral map updating, environmental monitoring, and disaster assessment and so on. The uncensored synoptic view and the repeat pass nature of satellites render them an ideal platform from where acquiring information about human settlements. Nonetheless, the huge amount of data acquired from the satellite sensors requires the development of automatic algorithms that can process the data and extract the desired information without any manual processing or ground truth information. In the last decades a new generation of satellite sensors has been operated, which can regularly acquire very high geometrical resolution (VHR) images i.e., images having a resolution of a meter or less. The increasing availability of such data allows the analysis of urban areas at a detail level never reached before resulting in the possibility of detecting buildings individually .Very High geometrical Resolution SAR images are more diversified than high or medium resolution data Objects which are considered similar from a semantic point of view (e.g., buildings) show a signature that is non uniform at high spatial resolution because of the scattering contributions from sub-objects (e.g., facade and roof in a building). Furthermore, on the one hand the side-looking illumination required by SAR systems leads to phenomena such as layover, shadow and multi-path signals which are very pronounced in urban areas.

II. PROBLEM FORMULATION

To generate the difference images to enhance details about changes between source images is the first step of this process. To obtain difference images in logarithmic and mean scale rationing will be performed. It is highly resilient to speckle noise. To identify changed and unchanged region Logarithmic scale based difference part will be generated and it is weakening the high intensity and enhancing the low intensity pixels. Information loss is possible from significant part due to this weakening. For accurate detection of changes ratio means operator and fusion approach is used so that the limitation is reduced and produce detailed portion from source images. Using two source images the sub band images are obtained from first level decomposition.

These are used for morphing process to get the detail enhanced changed region from unchanged region. Here, we use the pixel level fusion method for this process. By averaging rule the low frequency sub bands of two difference image will be fused and by using gradient measurement high frequency sub bands will be fused to select the desired coefficients. To reconstruct the fused image and to evaluate the parameters between input and fused image fused two different frequency sub bands are inverse transformed. Using first level wavelet decomposition we can get draw backs on Contrast information loss due to averaging method; Maximizing approach is sensitive to sensor noise; Spatial distortion is high; Loss edge details because of down sampling.

A. Discrete wavelet transform: first level

Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas of the image respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2D-DWT output images Straight forward convolution implementation of 1D-DWT requires a large amount of memory and large computation complexity. An alternative implementation of the 1D-DWT, known as the lifting scheme, provides significant reduction in the memory and the computation complexity.

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\, \psi^{*}_{(a,b)}(x)\, \mathrm{d}x$$

Mathematically

Where the * is the complex conjugate symbol and function ψ is some function. This function can be chosen arbitrarily provided that it obeys certain rules.

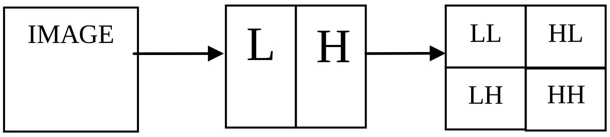

Fig:1 Wavelet Decomposition on first level Flow Process

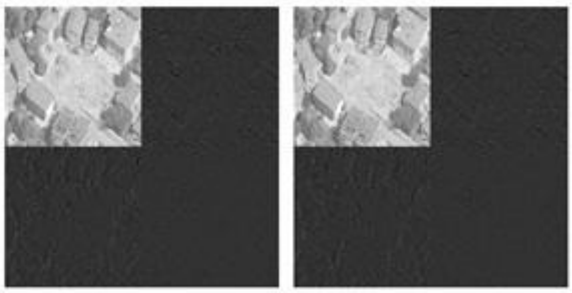

Fig: 2 Wavelet Decomposition on first level process for both input images

Fig: 3 Input Images on 3years (2012) back and current year (2015) image

On the other hand, the appearance of a ground object depends on radar system parameters (i.e., wavelength, polarization, pulse length, incidence angle, look direction, etc.), surface feature properties (e.g., dielectric constant) and environmental variables (e.g., ground water content). On top of these aspects, SAR images are corrupted by speckle noise.

III. Proposed Method

Structural details. It describes the textures and edges in various directions as it is a shift and rotation invariant transform. 2nd level Wavelet Transform decomposes an image into low and high frequency sub bands. Low/high frequency sub bands are contains coarsest and finest details. The sharpness of the image details found from high frequency sub bands in six different directions and it is directionally selective. The real and complex band coefficients are applied to modify by shrinkage method and LF's are kept same. Under transformed domain, to restore coefficients from high frequency bands shrinkage rule is used. Shrinkage approach is used to remove the highly contaminated high frequency sub bands with random noise which affects edges and texture of the image. The robust median estimator and signal variance are used to estimate the threshold. To remove the noise the coarsest details will be kept same and finest details are applied for shrink process and finally the restored components will be reconstructed with inverse second level wavelet to get the resultant images.

A. Discrete wavelet transforms second level

In our proposed method for speckle reduction. In this model, a noisy image is decomposed into four 7 sub bands in wavelet domain (2 level wavelet transform). The low frequency sub band contains the low frequency coefficients (structural components with noise) and high frequency sub bands contain the high frequency coefficients (texture components with noise) that can be easily eliminated using Anisotropic Diffusion method. The proposed method is compared with previous methods as applied to simulated and nuisance parameters ie, mean square error and peak signal to noise ratio will be evaluated for performance evaluation

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2D-DWT output image.

We can use multiple levels of wavelet transforms to concentrate data energy in the lowest sampled bands. Specifically, the LL sub band can be transformed again to form LL2, HL2, LH2, and HH2 sub bands, producing a two-level wavelet transform. An (R-1) level wavelet decomposition is associated with R resolution levels numbered from 0 to (R-1), with 0 and (R-1) corresponding to the coarsest and finest resolutions.

The straight forward convolution implementation of 1D-DWT requires a large amount of memory and large computation complexity. An alternative implementation of the 1D-DWT, known as the lifting scheme, provides significant reduction in the memory and the computation complexity. Lifting also allows in-place computation of the wavelet coefficients. Nevertheless, the lifting approach computes the same coefficients as the direct filter-bank convolution

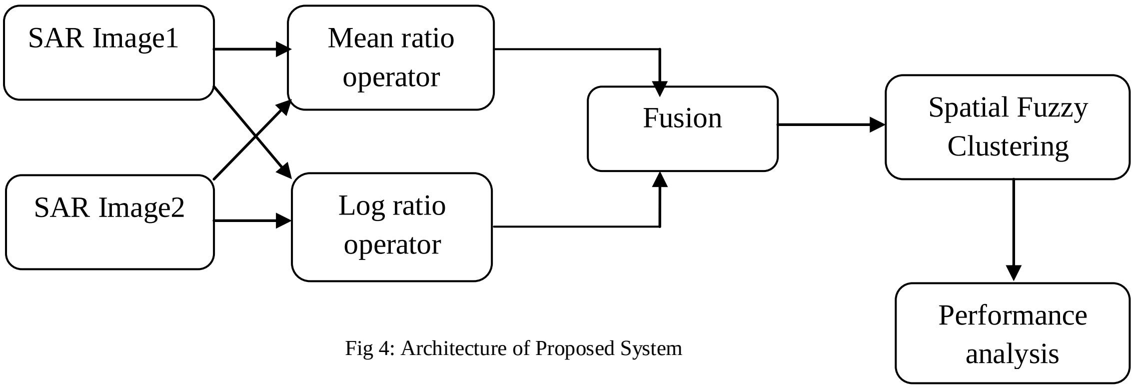

Fig 4: Architecture of Proposed System

IV. KERNEL WEIGHTED FUZZY CLUSTERING

Fuzzy clustering plays an important role in solving problems in the areas of pattern recognition and fuzzy model identification. A variety of fuzzy clustering methods have been proposed and most of them are based upon distance criteria. One widely used algorithm is the fuzzy c-means (FCM) algorithm. It uses reciprocal distance to compute fuzzy weights. A more efficient algorithm is the new FCFM. It computes the cluster center using Gaussian weights, uses large initial prototypes, and adds processes of eliminating, clustering and merging. In the following sections we discuss and compare the FCM algorithm and FCFM algorithm.

Spatial Fuzzy C Means method incorporates spatial information, and the membership weighting of each cluster is altered after the cluster distribution in the neighborhood is considered. The first pass is the same as that in standard FCM 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 the spatial function is computed from that. The FCM iteration proceeds with the new membership that is incorporated with the spatial function. The iteration is 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 by J. C. Bezdek [2]. The idea of FCM is using the weights that minimize the total weighted mean-square error:

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

$$\Sigma_{(k=1,K)} (w_{qk}) = 1$$

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

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.

$$J_m(U, V; X) = \sum_{k=1}^{n} \sum_{j=1}^{c} u_{ik}^m \|x_k - v_i\|_A^2, \quad 1 < m < \infty \quad (5)$$

Where=[v1,v2, ...vc]^T is a vector of unknown cluster prototypes. The value of uik represents the membership of the data point xk from the set X= [x1,x2,.....xn] with respect to the ith cluster. The inner product defined by a norm matrix A defines a measurement of similarity between a data point and the cluster prototypes, respectively. A non degenerate fuzzy –partition of is X conveniently represented by a matrix U=u[ik]. The weighting exponent controls the extent of membership shared by c clusters.

It has been shown by Bezdek [20] that if for all and and , then could be minimized at where

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m}, \quad \text{for } 1 \le i \le c,$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|_A^2}{\|x_k - v_j\|_A^2} \right)^{\frac{1}{m-1}}}, \quad \text{for } 1 \le i \le c \quad \text{an} \quad 1 \le k \le n.$$

Algorithm (Fuzzy -Means):

Step-1: Input the number of clusters c, the weighting exponent, and error toleranceType equation here.

Step-2: Initialize the cluster centre, for 1 ≤i≤ c

Step – 3: Input data X= {x1, x2, ...xn}

Step-4: Calculate the c cluster centres {vi(l)} by (6)

Step-5: Update U(l) by (6)

Step-6: If $||lu^{(l)}$-$u^{(l-1)}|| > \epsilon$,l=l+1 and return to step 4: otherwise, stop

The computational complexity of original K-means algorithm is ***O(ndk),*** where n is the total number of objects, k is the number of clusters, and d is the dimensions of datasets.

- Change detection approach for synthetic aperture radar images based on an image fusion and a spatial fuzzy clustering 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.
- A spatial fuzzy clustering algorithm will be proposed for classifying changed and unchanged regions from fused image with performance analysis.

PSEUDOCODE FOR K MEANS

Algorithm: Original K-means(S, k), S= {x_1, x_2... x_n}.

Input: The number of clusters k and a dataset containing n objects x_i.

Output: A set of k clusters C_j that minimize the squared-error criterion

.

Begin

1. m=1;

2. initialize k prototypes; //arbitrarily chooses k objects as the initial centers.

3. Repeat

for i=1 to n do
Begin
for j=1 to k do
Compute $D(X_i, Z_j) = |X_i, Z_j|$;//$Z_j$is the center

of cluster j.
if $D(X_i, Z_j)$ = min{ $D(X_i, Z_j)$ } then
$X_i \in C_j$;

end;// (re)assign each object to the cluster based on the mean

if m=1 then

$$J_c(m) = \sum_{j=1}^{k} \sum_{X_i \in C_j} |X_i - Z_j|^2$$

m=m+1;
for j=1 to k do

$$Z_j = \frac{1}{n_j} \sum_{i=1}^{n_j} x_i^{(j)}$$; //(re)calculate the mean value of the objectsfor each cluster

$$J_c(m) = \sum_{j=1}^{k} \sum_{X_i \in C_j} |X_i - Z_j|^2$$; //compute the error Function

4. Until $J_c(m) - J_c(m-1) < \zeta$ End

The computational complexity of original K-means algorithm is ***O(ndk),*** where n is the total number of objects, k is the number of clusters, and d is the dimensions of datasets.

- Change detection approach for synthetic aperture radar images based on an image fusion and a spatial fuzzy clustering 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.
- NSCT (Non- sub sampled contour let 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 information and enhance the information of changed regions in the fused difference image.
- A spatial fuzzy clustering algorithm will be proposed for classifying changed and unchanged regions from fused image with performance analysis.

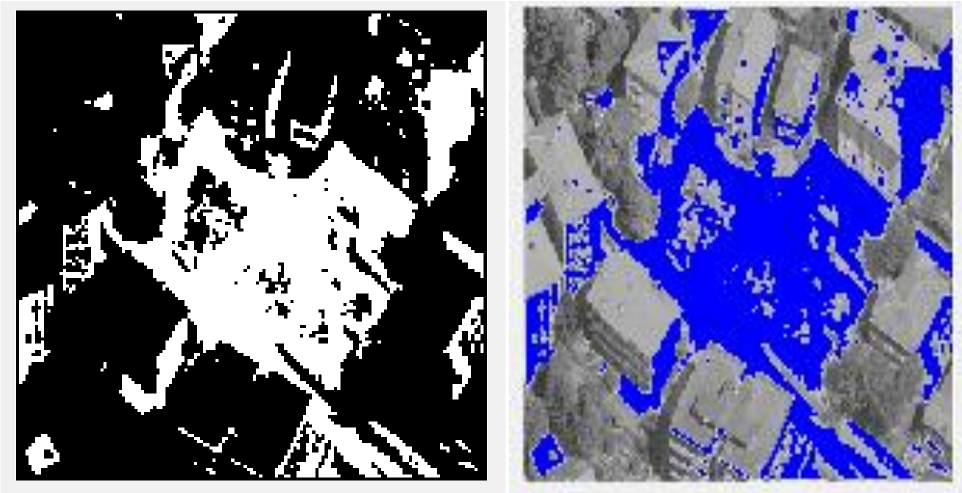

Fig: 5 the output of scene changed area and scene changed detection

V. CONCLUSION

In this paper an approach to building change detection in multi temporal VHR SAR images has been proposed that detects changes by distinguishing between new and demolished buildings and also the pixel counts of scene changed area . The approach is based on two concepts: (i) the extraction of information on changes associated with increase and decrease of backscattering at the optimal building scale; and (ii) the exploitation of the expected backscattering properties of buildings to detect either new and fully demolished buildings with their grade of reliability. From this modeling new and destroyed buildings can be identified by a pattern made up of an area of both increase and decrease of backscattering with specific spatial properties and a specific alignment. In order to extract the changes associated with increase and decrease of backscattering, the proposed approach makes use of a multi scale representation of the multi temporal information. This allows a detection of changes at the optimal building scale. This means that the changes smaller than the selected building scale are rejected while the changes related to building size are made homogeneous. This information is used to identify the candidates to be changed buildings. The building candidates are analyzed in order to properly detect the new or destroyed building.

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