LAND COVER CHANGE DETECTION FOR FULLY POLARIMETRIC SAR IMAGES

Heena Kaldane[1], Varsha Turkar[2], Shaunak De[3], Sanjay Shitole[4], Rinki Deo[5]
[1,4]UMIT, S.N.D.T. Women's University, Mumbai, India
[2]Don Bosco College of Engineering, Fatorda, Goa, India, varshaturkar.iitb@gmail.com
[3]Center of studies in Resources Engineering, Indian Institute of technology, Bombay Maharashtra, India
[5]TERI SAS, New Delhi

Abstract

Land cover change detection is an important application of remote sensing data. Polarimetric Synthetic Aperture Radar (PolSAR) image offers increased potential to detect and monitor changes in land cover over multitemporal images. This paper explores the use of unsupervised Normalize Difference Ratio (NDR) as the change index (CI) followed by supervised thresholding to extract binary mask for changed and unchanged areas. The datasets used for this experiment are UAVSAR fully polarimetric L-band images acquired on two different dates over Hayward, California, USA. The proposed change detection technique is compared with standard supervised techniques. The result indicates that the proposed NDR technique has a higher detection rate than the traditional Differencing techniques and PCCD techniques.

Index Terms— Polarimetry, SAR, change difference algorithms, land use and land cover change.

1. Introduction

Synthetic Aperture Radar (SAR) is capable of imaging though adverse weather conditions and in absence of solar illumination, allowing all-year, day-night operation. It has seen several applications in terrain classification, land cover mapping and dynamic phenomenon observation. Fully-polarimetric SAR (PolSAR) systems encompass the interactions between the electromagnetic wave and the target scatterer in multiple combinations of transmitting and receiving polarization, with most common systems employing H and V polarizations. When compared with single-polarization SAR system, PolSAR data contain inter-channel phase information from radar returns transmitted in two different polarizations, allowing for increased information. With the availability multitemporal data acquisitions, land cover change detection is potentially a major application of collected polSAR data.

Change in land-cover manifests as several variations in observable parameters in multi-temporal SAR images such as backscattering intensity, phase, and other statistical and geometric properties of polarimetric descriptors. [1]. Several studies have demonstrated change detection based on radar backscattering intensity variation, with a majority of these methods being based on differencing operators. This "Difference image (DI)" is obtained by using a difference on the pre- and post-even images corresponding to the changes in land cover. This usually followed by unsupervised thresholding which yields a binary map of change versus no-change classes without the need for a supervised classification stage. Change detection using SAR images are a challenging task due to the image perturbations caused by speckle noise and the difficulty in achieving an optimal co-registration. The speckle, an intrinsic multiplicative noise, often increases the miss-detection and false alarm rates and hence considerably reduces the detection performance. To reduce the effect of multiplicative speckle noise, many authors propose to employ the log-ratio detector (LRD) by performing a logarithm operator on the ratio of local mean. [2]. In [3] have proposed to co-operate these two ratio operators to exploit their complementary information. For unsupervised SAR change detection, generalized Gaussian Model methods have been demonstrated, where change maps are generated by Log Ratio and Generalized Minimum-Error Thresholding [4] & [5]. The second approach for change detection is Post Classification Change Detection (PCCD) technique. In PCCD technique, change is obtained after classification using supervised or unsupervised classifier. The supervised classification for change analysis such as Maximum likelihood and relaxed Wishart distribution are used in [6] and [7]. In [6] a test statistic was introduced which evaluated the covariance measure to derive a probability score for changes in the scene. Recently, machine learning approaches have gained popularity for change detection. The Support Vector Machine classifier is used in [8]. A deep learning based object recognition technique holds great promise in the task of target identification. Deep learning has shown great promise in the task of object recognition over other ma-chine learning techniques [9], [10], with impressive performance in the ImageNet Large-Scale Visual Recognition Challenge [11] such an approach would be reasonably robust to the effects of scale and speckle.

A fully polarimetric image allows the development of several descriptors by different image processing algorithms. For urban change detection, fully polarimetric imagery provides better information of man-made structures than single polarimetric images. [12].This paper focuses on urban change using full polarimetric PolSAR datasets. An open problem with change detection in PolSAR imagery is the lack of accurate and reliable methods capable of performing unsupervised change detection in a completely automatic manner. To overcome this problem, in this paper we have used automatic unsupervised change-detection approach using Normalize Difference Ratio (NDR). A number of polarimetric descriptors were sensitive to changes in land use and cover, and the difference maps (DMs) generated by some carefully selected descriptors produced promising results in distinguishing between areas of increased and decreased intensity [13]. In order to access the effectiveness of the proposed NDR technique, we test traditional differencing methods i.e Difference Image (DI), Mean Ratio Detector (MRD) and Log Ratio Detector (LRD) and PCCD techniques on same datasets.

2. Methodology and Datasets

The data set in this study are major urban land-cover areas and their surroundings in California, USA: Hayward is considered for this study, the cities are heavily urbanized, well planned and have high coverage with airborne polarimetric radar. The dataset chosen is a L band full polarimetric image acquired by NASA's, UAVSAR working at frequency 1.26 GHz. The data used for change detection are acquired on the 3rd March 2016 and 2nd September 2009 over Hayward. Hayward is a city located in Alameda County, California in the East Bay sub region of the San Francisco Bay Area. With a 2014 population of 149,392, Hayward is the sixth largest city in the Bay Area and the third largest in Alameda County. The dataset was multilooked 3 times in range and 12 times in the azimuth direction, resulting in a resolution of 7.2m by 4.9m. Before processing these data sets, preprocessing should be handle. Preprocessing mainly consist of mainly co- registration and speckle filtering. For PolSAR imagery speckle act as a barrier in the analysis, the data set acquired at two different times t1 and t2 are first precisely co-registered and filtered using enhanced Lee filter of window size 5 × 5 in this experiment.

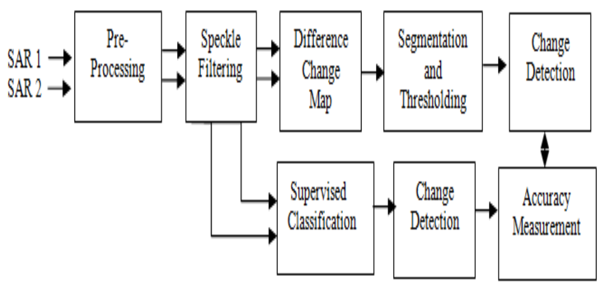


Figure 1: Architecture of Change Detection Algorithm

The framework of the change detection methodology in multi-temporal SAR images is presented in Figure 1.SAR change detection involves four major basics steps: 1. Preprocessing: co-registration and Speckle filtering 2. Change map extraction 3. Threshold Segmentation 4. Accuracy Measurement.

Change Map Generation

The SAR backscattering values at two date's t1 and t2 obtained from co-registered images are used to calculate Normalize difference ratio (NDR). The NDR operator used for generating change map is given as:

$$\text{NDR Change} = \frac{a_2 - a_1}{a_2 + a_1} \qquad (1)$$

where a_2 and a_1 are the SAR backscattered intensity of coregistered data set t_2 and t_1 respectively.

While this metric (NDR) has been previously successfully demonstrated for dual-pol [14] data, the goal of this experiment is to evaluate its effectiveness for full polarimetric data. The difference map using NDR is presented in figure 2.The change maps are also generated using post classification, where experimental data sets are classified using Maximum likelihood classifier separately, after they have been co-registered. Then the classified images are compared and analyzed to form a change matrix which described the mapping of classes between the images. From this matrix, a simple map of change versus no change is extracted.

The threshold value is selected by segmenting the Gaussian distribution in range $\mu \pm N\sigma$. The assumption is that majority of the pixels in the image are unchanged, thus most of the unchanged pixels would be included in the bell-curve segment and the changes would be in the extremeties clipped beyond $N\sigma$. For this dataset we choose N=3, but it can be adjusted according to prior knowledge of the scene. The overall performance of the polarimetric change detector depends on both the quality of the chosen test statistic image and the quality of the thresholding. A binary confusion matrix of change and no change classes is used to estimate the overall accuracy of land cover change.

3. Results and Discussion

The difference map generation using NDR algorithm, along with the change map using DI, MRD, and LRD for the T11 component is shown in Figure 2. Bright areas indicate increase in backscattering intensity (positive change, contruction), whereas dark areas indicate decreased backscattering intensity (negative change, destruction) and the smooth area indicating no change in corresponding images. It is easy to recognize the no-change area in the image with the visual interpretation, which is relatively smooth. This is a good prospect to separate the no-change area in the image. The smooth area is defined as follows. If the

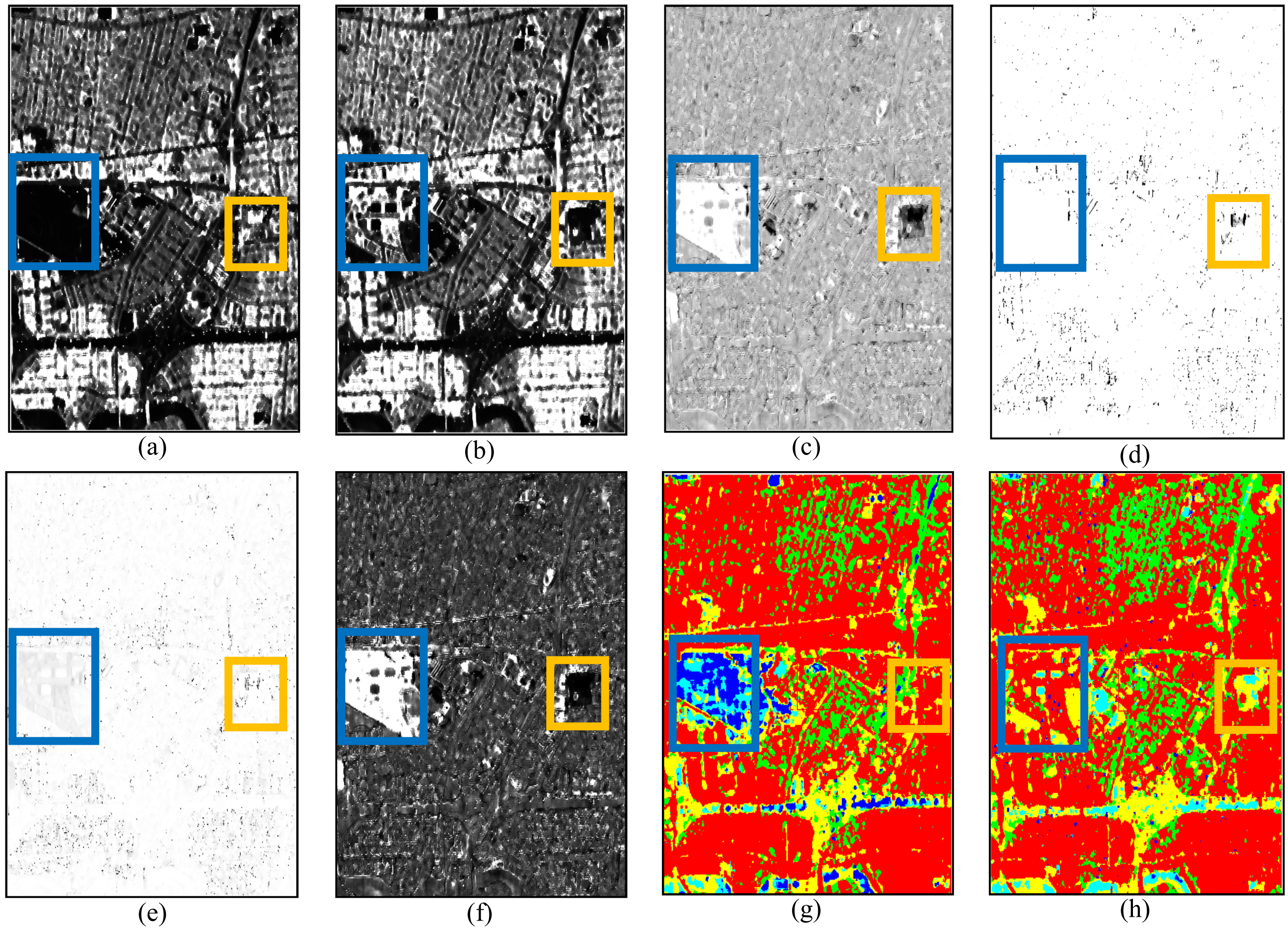
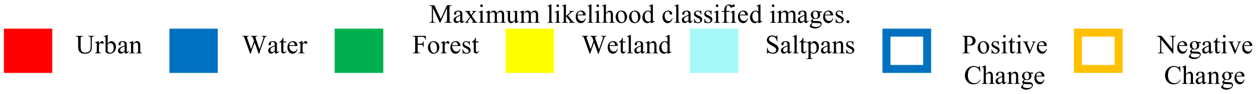


Figure 2: Change Map Generation using various algorithms for UAVSAR L-band full pol images over Hayward City: (a) T11 component, 2009 (b) T11 component, 2016 (c) NDR changes map (d) DI (e) MRD (f) LRD. (g) & (h) Maximum likelihood classified images.



pixel(s) does not have any change, ideally the pre-vent and post-event images should have the same backscattering intensity. However, due to some noises, the backscattering intensity varies slightly; still they have a similar level of intensity. Therefore, the NDR generates a pixel value close to 0 for the no-change area

and that looks smoother than other areas. This change maps are then subjected to binary maps corresponding to the two classes: change and no change by applying thresholding. NDR technique for change detection focused on only change pixels in a particular area independent of any training sets. The accuracy of change analysis obtained by NDR is 88.8% for UAVSAR fully polarimetric data set.

Unlike the ratio operator, the NDR operator generates pixel value from −1 to +1. All no-change pixels are clustered around 0, while all the change pixels are either close to −1 or +1. Therefore, it will give a clear peak for each type. It is clearly observed by visual inspection in figure 2, The smooth change is found using NDR operator compares DI, and ratio operators.

By PCCD technique, datasets are classified using Maximum Likelihood classifier into various classes such as urban, water bodies, forest, wetland and saltpans. The confusion matrix shows image difference in terms of change in respective classes. The negative change found in Forest 7.79%, and in wetland up to 18.69%. Whereas the urban settlement is increases is up to 18.98% and wetland class up to 4.4%. The limitation of post classification is that some of the bare lands are classified as water bodies. The land which is marked as change area was a plane surface in 2009 but that same area is classified as water in figure 2. (g). T11 is highly sensitive to urban change. The similar change is observed in T22 and T33. As the backscatter value is low for plane surface thus, the area is classified as single bunce in the Pauli RGB. For experimental data sets, the classification accuracy obtained by post classification for UAVSAR fully polarimetric images is 68.2% after filtering.

4. Conclusion

In this paper we evaluate the effectiveness of the NDR operator for full pol data. The proposed method is best suited for detection of urban change in fully polarimetric images. NDR is characterized as higher accuracy for change detection upto 88.8%. The NDR operator gives difference between two images and can remove the speckle noise which is more affected in traditional differencing method and ratio operators LRD and MRD .The traditional differencing and PCCD methods have less detection rate compared to the proposed technique. Concerning the limitation of proposed methodology, the care should be taken while selecting the thresholding. The change is not able to detect if it is not statistically significant. The Gaussian threshold is moreover similar to MTEP manual error thresholding. In future the thresholding technique can be improved by region growing algorithm for threshold segmentation.

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