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Survey on Change Detection in SAR Images with Image Fusion and Image Segmentation

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ABSTRACT

In this paper the pilot survey of the different image processing techniques and different core decision rules to detect change in Synthetic Aperture Radar images is carried out. Change detection in SAR images is much more difficult than that of optical images due to the existence of speckle noise and the complex mixture of terrain environment. Change Detection is identifying the differences between images of same area acquired during different instances. Its wide applications are positioning and hazard assessment of earthquake area, monitoring of crop growth conditions, detecting of urban land use. Typically change detection in SAR images is divided in two different modules first is Generating difference image and second one is Detection of change in difference image, hence in this paper we are discussing various methods to generate difference image, Image fusion techniques along with the change detection algorithm.

Keywords: Synthetic Aperture Radar (SAR), difference image, image fusion, image change Detection algorithms.

I. INTRODUCTION

The detection of changes occurring on the earth surface by using multitemporal remote sensing images is one of the most important applications of remote sensing technology. This depends on the fact that, for many public and private institutions, the knowledge of the dynamics of either natural resources or man-made structures is a valuable source of information in decision making. In this context, change-detection applications related to environmental monitoring, agricultural crop survey, urban and rural studies, and forest monitoring the satellite and airborne remote sensing sensors had proven its usefulness. Usually, change detection involves the analysis of two co-registered remote sensing images acquired over the same geographical area at different time instances. Such an analysis is called unsupervised when it aims at discriminating between two opposite classes without any prior knowledge about the scene. In the analysis of multitemporal remote sensing data acquired by (optical) multispectral sensors, various automatic and unsupervised change-detection methods have been developed and described in the literature.

Unsupervised Change Detection in SAR images can be divided into different modules such as image pre-processing, Producing difference image between the multitemporal images, and analysis of the difference image [2]. In first step, to pre-process the images include co-registration, geometric corrections, and noise reduction. In the second step, two co registered images are compared pixel by pixel to generate the difference image. For the remote sensing images, differencing and rationing are well known techniques for producing a difference image [10]. In differencing, changes are measured by subtracting the intensity values pixel by pixel between 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. In addition, because of the multiplicative nature of speckles, the ratio image is usually expressed in a logarithmic or a mean scale. In the third step, to detect the changes a decision threshold to the histogram of the difference image is usually applied.

To determine the threshold in an unsupervised manner several Threshoulding methods like Otsu, the Kittler and Illingworth minimum-error Threshoulding algorithm (K& I), and the Expectation Maximization (EM) algorithm are proposed in the literature. Taking the speckle noise and the correlation of nonstationarities in two multitemporal SAR images into account Zheng et al. [3] proposed a new approach for change detection in multitemporal synthetic aperture radar images. Considering about the existence of speckle noise, the local statistics in a sliding window are compared instead of pixel by-pixel comparison.

In the case of space borne synthetic aperture radar (SAR) imagery, change detection techniques have been developed for the temporal tracking of multiyear sea-ice floes using Seasat SAR observations. Change detection techniques for SAR data can be divided into several categories, each corresponding to different image quality requirements. In a first category, changes are detected based on the temporal tracking of objects or stable image features of recognizable geometrical shape. Absolute calibration of the data is not required, but the data must be rectified from geometric distortions due to differences in imaging geometry or SAR processing parameters, and the accurate spatial registration of the multidate data is essential. Combining information acquired from multiple sensors has become very popular in many signal and image processing applications. In the case of earth observation applications, the fusion of the data produced by different types of sensors provides a complementary which overcomes the limitations of a specific kind of sensor. User has to use the available archive images or the first acquisition available after an event of interest. Both image registration and change detection techniques consists of comparing two images reference image and secondary image, acquired over the same landscape scene at two different dates.

Usually, the reference image is obtained from an archive and the acquisition of the secondary image is scheduled after an abrupt change, like a natural disaster. In the case of the change detection, the goal is producing an indicator of change for each pixel of the region of interest. This indicator of change is the result of applying locally a similarity measure to the two images. This similarity measure is usually chosen as the correlation coefficient or other statistical feature in order to deal with noisy data.

II. METHODOLOGIES

The goal of a change detection algorithm is to detect significant changes while rejecting unimportant ones. Sophisticated methods for making this distinction require detailed modelling of all the expected types of changes for a given application and integration of these models into an effective algorithm. In next subsection various processing steps are described which are used in order to make the change detection decision.

A. Fusion Of Multitemporal Sar Images:

In SAR images the additive noise model is no longer valid. For active sensor images the commonly adopted noise model is multiplicative. The direct consequences that the difference operator becomes poorly effective. Let us consider two multilook intensity SAR images. It is possible to show that after subtraction the statistical distribution of the resulting image depends on both the relative change between the intensity values in the two images and a reference intensity value (i.e., the intensity at t1 or t2). This leads to a higher change-detection error for changes occurred in high-intensity regions of the image than in low-intensity regions. Although in the past the difference operator was used with SAR data , the aforementioned behavior is an undesired effect that renders the difference operator intrinsically not suited to the statistics of SAR images. To overcome this problem the ratio operator was introduced in the SAR multitemporal image comparison at feature level literature. The ratio operator demonstrated to be more effective because its distribution depends only on the relative change in the average intensity between the two dates and not on a reference intensity level. Moreover it is possible to prove that the distribution of the ratio image depends on the true change in the radar cross section. Thus changes are detected in the same manner both in high- and low-intensity regions. Moreover rationing allows to reduce common multiplicative error components which are due to both multiplicative sensor calibration errors and to the multiplicative effects of the interaction of the coherent signal with the terrain geometry, as far as these components are the same for images acquired with the same geometry. In the literature, the ratio image is usually expressed in a logarithmic scale. With this operation the distribution of the classes of interest in the ratio image becomes more symmetrical and the residual multiplicative speckle noise can be transformed in an additive noise component. Thus the log-ratio operator is typically preferred when dealing with SAR images. In the Kullback–Leibler (KL) divergence was used as change index. The divergence is a function of two probability densities characterizing a random variable that describes the image behaviours in the local neighbourhood of the analyzed pixel. If the probability densities are similar (no change), the Kullback-Leibler divergence has a small value otherwise the value is high.

More recently the multiscale/resolution concept has been introduced in the multitemporal image analysis. This need emerged because of the complexity of SAR data and because of the intrinsic multiresolution information available in the images acquired by the new generation high spatial resolution sensors. To properly model multiscale/resolution information different approaches have been used either before or after applying fusion at feature level according to the operators listed above. Among the others we recall the Wavelet decomposition, the Contourlet transform, and the local similarity measures computed on varying windows size or multiscale segments. The multiresolution analysis had a step forward when very high spatial resolution images become available leading to the development of methods based on objects, primitives extraction and modelling suitable for modelling the high level semantic information available in VHR images. However polarimetric SAR data can be considered for multitemporal fusion as well. When dealing with polarimetric SAR the comparison operators listed above have been used after extracting specific features like: i) the backscattering coefficient ii) Cloude decomposition (or H-a decomposition) , iii) Polarimetric signatures (i.e., a by-product of polarimetry synthesis) or the polar azimuthal polarimetric signature[6].

Table 1. Summary of the most widely used comparison operators

Technique	**Feature vector fk at the ti me tk**	**Comparison operator**
Image differencing	fk =Xk	XLR=f2-f1
Image rationing	fk =Xk	XR =f2/f1
Log-ratio	fk =Xk	XLR=logf2-logf1
Kullback- Leibler distance	fk =Xk	KL(f1 | f2)= ∫log[p(f1)/p(f2)]p(f1)

B. Concurrent Self-Organizing Maps For Supervised Change Detection In Remote Sensing:

This paper [7] proposes two approaches to change detection in bitemporal remote sensing images based on concurrent selforganizing maps (CSOM) neural classifier. The first one performs change detection in a supervised way, whereas the second performs change detection in an unsupervised way. The supervised approach is based on two steps: 1) concatenation (CON); and 2) CSOM classification. CSOM classifier uses two SOM modules: 1) one associated to the class of change; and 2) the other to the class of no-change for the generation of the training set. The unsupervised change detection approach is based on four steps: 1) image comparison (IC), consisting of either computation of difference image (DI) for passive sensors or computation of log-ratio image (LRI) for active sensors; 2) unsupervised selection of the pseudotraining sample set (USPS) 3) concatenation (CON) and 4) CSOM classification. The proposed approaches are evaluated using two datasets. First dataset is a LANDSAT-5 TM bitemporal image over Mexico area taken before and after two wildfires, and the second one is a TerraSAR-X image acquired in the Fukushima region, Japan, before and after tsunami. Experimental results confirm the effectiveness of the proposed approaches. Experimental results confirm the effectiveness of the CSOM based supervised/unsupervised change detection methods when compared with standard MLP-NN, RBF-NN, and SVM in terms of OA, Kappa accuracy, and error rate.

C. Image Fusion And Fuzzy Clustering:

This paper[8] Image fusion technique is used to generate difference image by collecting information from Log ratio image and Mean ratio image. In order to intensify the information of changed regions and suppress the background information, Contourlet fusion rules are chosen to fuse the contourlet coefficients. For classifying changed and unchanged regions a reformulated FLICM (Fuzzy Local Information c-means) is proposed. This method reduces the effect of speckle noise because it is insensitive to noise. Experimental observations, obtained on real multi-temporal SAR images by the Reformulated FLICM clustering algorithm exhibited low error rate.

In this paper, they have presented an unsupervised approach based on contourlet fusion and fuzzy clustering for change detection in SAR images. In order to restrain the unchanged areas and enhance the changed areas, fusion approach is used. Among the fusion methods, the limitation of wavelet transforms is capturing the geometry of image edges. So in this paper, contourlet transform is used because it can capture the intrinsic geometrical structure which is key in visual information. they show that, this method can provide fused image with better visual quality. In addition to that difference image produced in this method is better than that of fused difference image generated by Discrete wavelet Transform, Mean ratio and log ratio. The fused image obtained by Contourlet Transform can preserve much information of edges and textures of SAR images. The experiment results also show that the proposed contourlet fusion strategy can integrate the advantages of the log ratio operator and the mean-ratio operator and gain a better performance. The change detection results also shows that the RFLICM algorithm gives better result as compare to FLICM.

D. Image Fusion And Kernel K-Means Clustering:

In this paper [9], a novel method for unsupervised change detection in synthetic aperture radar (SAR) images based on image fusion and kernel K-means clustering is proposed. Here difference image is generated by performing image fusion on mean-ratio and log-ratio image and for fusion discrete wavelet transform is used On the difference image generated by collecting the information from mean-ratio and log-ratio image, kernel K-means clustering is performed. In kernel K-means clustering, non-linear clustering is performed, as a result the false alarm rate is reduced and accuracy of the clustering process is enhanced. The aggregation of image fusion and kernel K-means clustering is seen to be more effective in detecting the changes.

In order to improve the accuracy of the binary change map, the data samples obtained by fusing the log-ratio and mean-ratio images are projected to a higher dimensional feature space, in which a linear algorithm can be applied to separate the changed and unchanged pixels. Mapping to the feature space is done by using kernel functions. The kernel function compute the similarity between training samples S using pair-wise inner products between mapped samples. Kernel K-means clustering algorithm is applied on the data samples of the fused image in order to perform non-linear clustering. The kernel techniques allows linear evaluation of data in higher dimensional feature space, which results in nonlinear clustering of data samples present in the input space.

E. Dual Ratio Operator And Wavelet Fusion:

This paper [10] 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. SWT (Stationary Wavelet transform) fusion rules based on an average operator and minimum local area Energy are chosen for a low-frequency band and a high-frequency band, respectively to restrain the background information and enhance the information of changed regions in the fused difference image. For the remote sensing images, differencing (subtraction operator) and rationing (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 rationing, changes are obtained through application of ratio operatoron pixel-by-pixel 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. In this paper Back propagation with feed forward network is used 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 proven that rationing generates better difference image for change detection using supervised classifier segmentation approach and efficiency of this algorithm exhibited by sensitivity and Peak signal to noise ratio evaluation.

Table 2. Summary of the Literature survey

SR. NO	AUTHOR & YEAR	DIFFERENCE IMAGE GENERATION TECHNIQUE	IMAGE FUSION TECHNIQUE	CLASSIFIER /METHOD	DATA SET USED / SAT / YEAR	MISSED ALARM RATE (%)	OVERALL ACCURACY	APPROACH
1	Victor-Emil Neagoe, Radu-Mihai Stoica,Alexandru-Ioan Ciurea,Lorenzo Bruzzone,Frances	log-ratio operator	NA	concurrent self-organizing maps (CSOM) neural classifier	Mexico Dataset , Landsat-5 , year 2000 & 2002	6.92	97.78	Unsupervised

	ca Bovolo, 2014							
2	Biao Hou, Qian Wei,Yaoguo Zheng,Shuang Wang,2014	Gauss-log ratio and log-ratio	Nonsubsampled contourlet trans-form (NSCT)	simple k-means clustering	Yellow River china , Radarsat-2 , June-2008 & 2009	33.55	90.67	Unsupervised
3	Hire Gayatri Ashok, D. R. Patil , 2014	mean ratio and log ratio	Contourlet Image Fusion	Reformulated FLICM Clustering Algorithm	Bern data set, European Remote Sensing 2 satellite , April-may 1999	2.31	96.77	unsupervised
4	K. Venkateswaran , N. Kasthuri, Arathy.C.Haran. V, 2013	mean-ratio and log-ratio	discrete wavelet transform	kernel K-means clustering	Bern data set, European Remote Sensing 2 satellite , April-may 1999	NA	94.357	unsupervised
5	M.Adithyan, R.Arul Pandi, A.Ramesh , J.Venkatesen ,2016	mean-ratio and log-ratio	Stationary Wavelet transform	back propagation with feed forward network	Bern data set, European Remote Sensing 2 satellite , April-may 1999	NA	NA	Supervised
6	Lu Jia,Ming Li,Peng Zhang,Yan Wu,Lin An,and Wanying Song,2016	subtraction and ratio opera-tion	multiple wavelet fusion kernel (MWF kernel)	minimum Euclidean distance in the kernel space	Gloucester flood dataset, Nov1999-Oct2000	1.4	96.06	unsupervised

III. CONCLUSIONS

The change detection algorithm most actively used in two application domains those are remote sensing and video surveillance, and their approach to the problem are often quite different. We have attempted to survey the recent state of change detection in SAR images. Based on different parameters such as Difference image generation Technique, Image fusion technique, type of classifier/method used, data set used, missed alarm rate, overall accuracy it is found that concurrent self-organizing maps (CSOM) neural classifier [7] gives high detection rate and a low false-alarm rate simultaneously.

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