Unsupervised Change Detection on SAR Images using Markovian Fusion

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ABSTRACT

In this paper, we present a novel unsupervised change detection approach in temporal sets of synthetic aperture radar (SAR) images using Markovian fusion. This method is carried out within a Markovian framework which combines two different change detection algorithms to achieve noise removing and spatial information preserving at the same time. This approach is composed of two steps: 1) two change maps are generated by two distinctive but complementary approaches respectively; 2) final results are achieved by fusing the two change maps within a Markovian framework. In the first step, two different thresholding algorithms are selected to get two change maps aimed at speckle noise removing and spatial contexture preserving respectively; In the second step, a solution to fusion the two change maps through a Markov random field framework is proposed. The minimization of energy function is carried out through iterative conditional mode (ICM) algorithm because of its simplicity and moderate computation-consuming. Experiments results obtained on a SAR data set confirm the effectiveness of the proposed approach. It shows that the fusion approach based on MRFs model is a promising way of achieving robust unsupervised change detection.

Keywords: Unsupervised change detection, data fusion, MRFs, iterative conditional mode (ICM), synthetic aperture radar (SAR) images.

1. INTRODUCTION

Change detection is one of the most important applications of the remote sensing technology and it plays a more and more important role in a variety of fields [1]-[2]. Usually, Change detection aims at discerning areas of change on two registered remote sensing images acquired in the same geographical area at two different times. Two main approaches, supervised and unsupervised, are used to detect the change. The former is based on supervised classification methods, which require the availability of a ground truth in order to derive a suitable training set for the learning process of the classifiers. The latter performs change detection without any additional information besides the raw images considered. The effective unsupervised change-detection method is fundamental in many applications in that the suitable ground-truth information is not always available.

Synthetic aperture radar (SAR) sensors hold a strong potential for change detection studies, especially

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thanks to the insensitivity of SAR imagery to atmospheric conditions and cloud cover issues. Hence, change detection on SAR images is expected to play a relevant role, with respect to ecological and environmental monitoring applications or to disaster prevention and assessment. However, SAR images are less exploited in unsupervised change detection [3]-[6]. This lack can be explained by the following reasons: 1) image modality with the presence of speckle inherent to sensors; 2) difference of incidence angle of the acquisitions; 3) the difference of the images produced by different generation of radar sensors [7].

Usually, change detection on SAR images is based on a three-step procedure: 1) image despeckling; 2) pixel-by-pixel comparison of two images; and 3) image thresholding. In the first step, the aim of despeckling is removing speckle noise and preserving spatial contexture information simultaneously. As we know, speckle noise in SAR images often degrades the quality of the SAR images and makes change detection harder. In the past ten years, many algorithms have been developed to suppress speckle noise. Such as, Lee filter, Frost filter, Kuan filter, etc.. Unfortunately, most of those methods reduce the speckle at the expense of degrading the image resolution and the geometrical details. One of the possible reasons for such kind of case is that much more statistical characteristics information that should be considered is not considered at all. In the second step, when SAR images are concerned, the ratio operator is widely used in SAR images due to the operator well-suited to SAR imagery according to the multiplicative nature of speckle [7][8]. In the third step, the problem of image thresholding can be viewed as an image binarization problem, which discriminate the “change” from the “no-change” classes in the difference image [9]. In [10], two automatic techniques based on the Bayes theory for the analysis of the difference image are proposed. One allows an automatic selection of the decision threshold maximizing the over all change-detection error under the assumption that pixels in the DI are spatially independent. In [8], under the generalized Gaussian (GG) assumption, the changes are identified by analyzing the log-ratio image according to the modified Kittler–Illingworth (KI) threshold selection criterion. In [11], the observed multitemporal images are modeled as MRFs in order to search for an optimal image of changes by means of the a posteriori probability (MAP) decision criterion and maximum the simulated annealing (SA) energy minimization procedure. This approach has been extended in [3] by using a fuzzy HMC (f-HMC) model which combines both statistical and fuzzy approaches to address the unsupervised change detection task in the SAR context. However, all those thresholding techniques seem that it’s difficult to remove speckle noise and preserve spatial contexture information simultaneously using a single method.

The fusion approach has been studied extensively in the literature to solve challenging classification problems [12]. In [9], it’s proven that the results achieved by Markovian fusion approach are either better or comparable to those of the best single thresholding algorithm of the ensemble. MRFs has its unique merits to carry out the fusion task: 1) MRFs represent a mathematically well-founded framework; 2) MRFs allow to implement a complex but effective image analysis at a global scale; 3) MRFs are useful to model the spatial-contextual information included in the neighborhood of each pixel.

In this paper, we propose a fusion approach within a Markovian framework which combines two different change detection algorithms to achieve noise removing and spatial information preserving at the same time. This approach is composed of two steps: 1) two change maps are generated by two distinctive but complementary approaches respectively; 2) final results are achieved by fusing the two change maps within a Markovian framework. Fig. 1 illustrates the general diagram of the proposed approach.

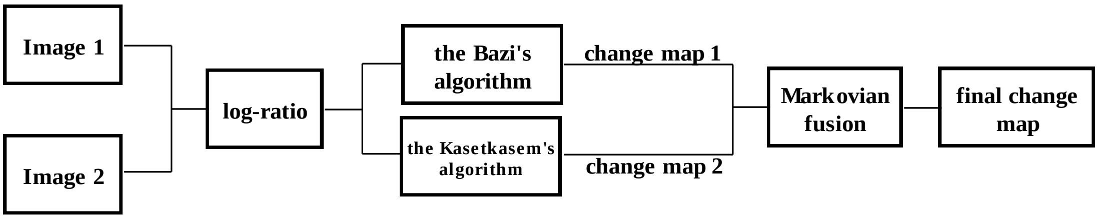


Fig. 1. the flowchart of the proposed approach

The main contribution of the work is proposing a novel approach and achieving noise removing and spatial information preserving on SAR images change detection simultaneously. The paper is organized as follows: Section II introduces the general formulation of the problem. Section III describes the two distinctive but complementary change detection algorithms selected to generate the final change detection map. The datasets used are presented in Section IV, which also contains a description of the experiment results obtained on a bidate set of SAR images. Finally, conclusions and perspectives are drawn in Section V.

2. PROBLEM FORMULATION

Let us consider two georeferenced and coregistered SAR intensity images $X1=\{X1(i, j), 1\leq i\leq I, 1\leq j\leq J\}$ and $X2=\{X2(i, j), 1\leq i\leq I, 1\leq j\leq J\}$ acquired over the same geographical area but at two different time t1 and t2, respectively. Our aim is to generate a change detection map that represents changes that occurred on the ground between the acquisition dates. The change detection problem can be viewed as binary classification problem where each pixel is mapped into the set $\Omega=\{\omega_U, \omega_C\}$ of possible labels. The conventional methods for supervised change detection on SAR images generally focus on either despeckling or spatial information preserving. However, it's not always possible to get the best change detection map by a single algorithm for a given difference image, because: 1) In most situation, ground truth is not available, so it’s quite difficult to represent the prior knowledge of the scene; 2) It’s not easy to fully utilize all the information contained in images; 3) An algorithm that may appear the best for one image may be a complete failure for another. A possible approach to solve this problem is to fuse the results provided by an ensemble of different thresholding algorithms, which produce two change maps emphasizing particularly on different peculiarities contained in the difference image, especially those peculiarities may complementary. In this way, we will be able to exploit more peculiarities of the difference image, so the final decision map will be more robust than with a single change detection method. Therefore, to a certain extent, the algorithms adopted may play the decision role of the final change map. To construct the ensemble, two change detection algorithms which emphasize on different peculiarities of the difference image and are is the beneficial supplement to each other are elaborately selected. The two thresholding algorithms are introduced as follow:

In [8], Bazi etc. proposed a closed-loop process change-detection approach made up of a controlled adaptive filtering preprocessing and an automatic analysis of the log-ratio image for generation of a change map based on the Kittler-Illingworth (KI) threshold selection criterion [13]. One of the most important novelties in this approach is that the author proposes to identify the optimal number of despeckling filter iterations automatically by analyzing the behavior of the modified K&I criterion to optimize the effects of the filtering process on the change-detection accuracy. This step avoids the use of empirical methods for the selection of the number of filter iterations and may maximize the separability between changed and unchanged classes. However, three problems need to be examined carefully. Firstly, the computational complexity of the proposed approach can be reduced significantly using some small tricks. The most time-consuming phase is related to speckle filtering, because the method for searching the optimal number of filtering iterations is still an exhaustion method. Secondly, the algorithm does not take full advantage of all the information present in the speckle. As we know, the iterative filtering also reduces the amount of information present in the speckle, so with the reducing of speckle, the information present in the speckle is destroyed seriously. Thirdly, the modified KI threshold selection criterion used in this paper is derived under the generalized Gaussian assumption for modeling the distributions of changed and unchanged classes. However, in fact, the statistical characters of the distributions of changed and unchanged classes do not accurately match the assumption and one can expect that a mixture of two Gaussian distributions could not be precise in reconstructing the statistical behavior of the two classes in the log-ratio image. Under this situation, the sophisticated spatial contextual information undoubtedly can't be exploited sufficiently.

Kasetkasem's algorithm [11] is a Markov Random Field (MRF) approach to unsupervised change detection based on a technique exploiting the maximum a posterior (MAP) algorithm for the estimation of the density functions associated with both change and unchanged pixels in the difference image. The MRF models characterize the statistical correlation of intensity levels among neighboring pixels more accurately than pixel-based models and a new ICD algorithm based on an MRF model that employs the MAP criterion is developed, which is the main contribution of the work. Unfortunately, the whole work is founded on the assumption that the SAR images can be modeled as the summation of a noiseless image satisfying MRF properties and the additive Gaussian noises with mean zero and covariance matrix $\sigma^2 I$. Consequently, this approach is sensitive to speckle noise. A large value of noise variance yields a high error rate, because noise overwhelms the information in NIMs and the dependence of intensity levels between two highly noisy images becomes insignificant.

3. MARKOVIAN FUSION APPROACH

3.1 MRF Fusion Model

MRF has long been recognized as an accurate model to fuse multiple sources of information successfully and it also allows to completing a complex but effective image analysis at a global scale. Let's consider two sets of random variables, X={$0 \le x_{mn} \le L-1$, m=0,1,…, M-1, n=0, 1,…, N-1} and Y={$y_{mn} \in \{\varphi_U, \varphi_C\}$ }corresponding respectively to the scalar M×N difference image with L possible gray levels generated from a couple of SAR multitemporal images and the desired change detection map. We here suppose that the random variables Y are conditionally independent with respect to X and that the distribution of each y_{mn} conditional on X is equal to its distribution conditional on x_{mn},

$$P(X_n = x_n \mid X_1 = x_1, ..., X_{n-1} = x_{n-1}) = P(X_n = x_n \mid X_{n-1} = x_{n-1}).$$

In other words, we deal with the problem of merging change maps $M_1=\{\omega_{C1}, \omega_{U1}\}$ and $M_2=\{\omega_{C2}, \omega_{U2}\}$ provided by two change detection algorithms mentioned above. Our goal consists in applying the maximum a posteriori probability (MAP) decision criterion to get a label set of M=={ω_C, ω_U}. By adopting the MRF approach, the fusion implies the definition of local mass functions of the individual pixels and of the interactions among pixels in the appropriate neighborhoods. Let us define the neighbor system of the pixel with coordinates (i, j) as N(i, j) = {(i, j)+ (g, h) | (g, h)∈N}, where N is a second-order spatial neighborhood system. The Markov modeling of the conditional distribution of the pixel label M(i, j), given the pixel labels elsewhere, is expressed as:

$$P(Y(i,j) \mid M_1(i,j), M_2(i,j), (i,j) \in N(g,h)) = \frac{1}{Z}\exp[-U(M_i)/T] \qquad (1)$$

Where, U is the energy function, Z is a normalizing factor, and T is a constant. The maximization of (1) is equivalent to the minimization of $U(M_i)$, which is given by:

$$U(M_i) = E_{data}(Y_{mn}, M_{mn}) + E_{co}(\ ) \qquad (2)$$

Under the Markovian framework, the total energy function $U(\bullet)$ can be rewritten in terms of the local energy function. Where $E_{data}(Y_{mn}, M_{mn})$ represents the correlation of intensity levels between the individual pixel Y(m, n) in final change map and the pixel M(m, n) in difference image, and $E_{con}(Y_{mn})$ describes the potential function of the interactions among pixels in the appropriate neighborhoods.

3.2 Energy Functions formation

The details of $E_{data}(Y_{mn}, M_{mn})$ and $E_{con}(Y_{mn})$ are expressed in the follow relationship:

$$E_{data}(Y_{mn}, M_{mn}) = \sum_{l=1}^{2} \sum_{(g,h)\in M_l(m,n)} \exp(-(M_l(m,n) - \overline{T})) \bullet \delta_k(Y(m,n), M_l(g,h)) \qquad (3)$$

Where $\delta_k(\bullet)$ is the indicator function, and is defined as:

$$\delta(y_{mn}, y_{gh}) = \begin{cases} 1, if \ \ y_{mn} = y_{gh} \\ 0, \quad otherwise \end{cases} \qquad (4)$$

$\overline{T} = (T_1 + T_2)/2$ is the average threshold value.

$$E_{con}(Y_{mn}) = \sum_{(g,h)\in Y(m,n)} \delta_k(Y(m,n), Y(g,h)) \qquad (5)$$

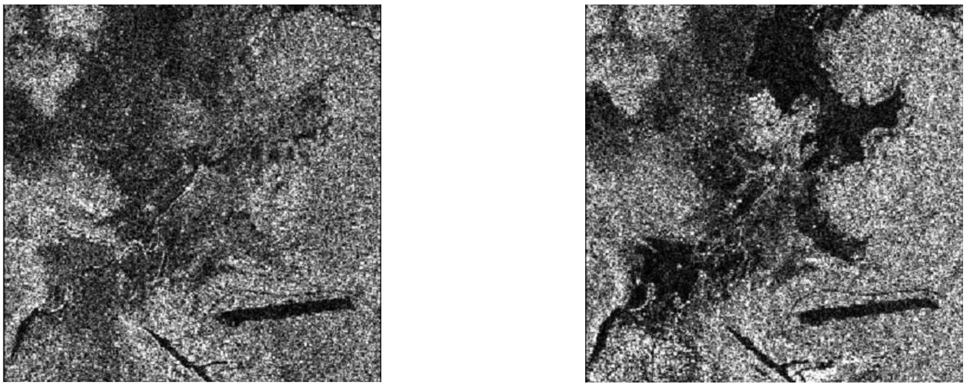
Where {g, h} represents the four clique types, associated with the vertical pairs, horizontal pairs, left-diagonal pairs and right-diagonal pairs, respectively.

The minimization of energy function E_{mn} can be carried out by means of different algorithms: the most popular being the simulated annealing (SA) algorithm, the maximizer of posterior marginal (MPM) algorithm, and the iterative conditional modes (ICM) algorithm (Besag, 1986). In this paper, the ICM algorithm is adopted because of its simplicity and moderate computation-consuming. In this way, the peculiarities of the two different change detection algorithms can be exploited synthetically and complementarily, and a more robust change-detection map will be reached.

4. EXPERIMENT

4.1 Dataset description

In order to testify the validity of the novel approach, we selected a region (coverage about 4 by 4 km) from the original images (coverage about 60 by 60 km). The original images are the JERS SAR channel 1 images with pixel sizes of 12.5m, which were taken on November 23, 1992 and February 19, 1993 respectively in the airport at Cooinda, Kakadu National Park, Australia [14]. The images are georeferenced and coregistered. In our experiment, the selected area is 320 pixels by 320 lines. The corresponding images are shown in Figure 2.



（a） （b）

Fig.2. The JERS SAR images related to the airport at Cooinda, Kakadu National Park, Australia. (a)Image acquired on November 23, 1992. (b)Image acquired on February 19, 1993.

4.2 Experimental results

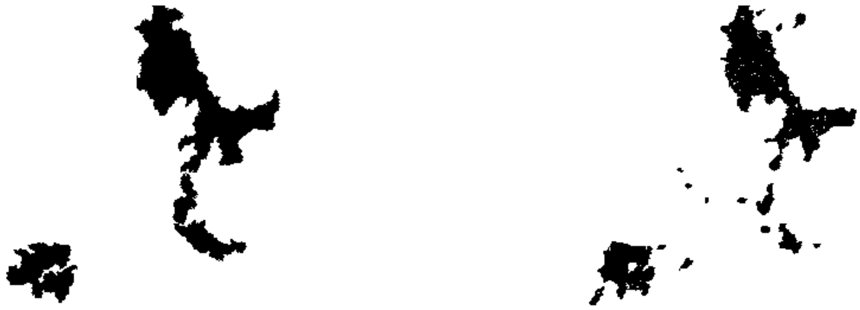
The accuracy of the results are evaluated in terms of: 1) error rate (PE); 2) false alarm rate (PF); 3) missed alarm rate (PM). All these measures are reported in Table 1. We compare our MRF fusion approach with the two algorithms, the Bazi's algorithm and the Kasetkasem's algorithm, assembled within our Markovian framework.

Table 1.Results achieved by the proposed MRF fusion approach, the Bazi's algorithm and the Kasetkasem's algorithm.

method	MRF fusion	Bazi	Kasetkasem
P_E	3307	3398	5202
P_F	513	615	2266
P_M	2794	2783	2936

The quantitative comparison in Table 1 confirms that the results obtained from the proposed approach are better or comparable to the results gained by the assembled two single algorithms. This is also shown by the maps obtained by the proposed Markovian Fusion approach depicted in Fig. 3. Figure 3(a) shows that the filtering preprocessing used in the Bazi's algorithm can reduce the speckle significantly, but the final change map is also blurred. It can be seen clearly that the map's edge details loss badly, which is the inevitable product of the filtering preprocessing. One of the possible reasons for such kind of case is that much more locally statistical information that should be considered is not considered at all. Figure 3(b) shows that the Kasetkasem's algorithm makes good use of the statistical correlation of intensity levels among neighboring pixels, but it's so sensitive to speckle noise that the change map is spoiled by the speckle. Figure 3(c) illustrates that the proposed Markovian fusion framework can take full advantages of peculiarities from the both algorithms assembled. The final change map shows that the speckle noise is reduced remarkablely and the edge details are preserved finely. It proves that the proposed fusion approach based on MRFs model is a powerful way of achieving robust unsupervised change detection.

(a) (b)



(c) (d)

Fig. 3. Ground-truth map and change maps obtained by the proposed Markovian Fusion approach and the Bazi's algorithm, the Kasetkasem's algorithm. (a) The Bazi's algorithm. (b) The Kasetkasem's algorithm. (c) The proposed Markovian Fusion approach. (d) The Ground-truth.

5. CONCLUSION AND DISCUSSION

In this paper, we present a novel unsupervised change detection approach in temporal sets of SAR images using Markovian fusion. This method is carried out within a Markovian fusion framework which combines two different change detection algorithms to achieve noise removing and spatial information preserving at the same time. The proposed approach is capable of capturing the good peculiarities from the both combined thresholding algorithms. Therefore, the approach can not only reduce the speckle competently but also retain the homogeneous areas and the edge details capably. Experiments results obtained on a SAR data set confirm the effectiveness of the proposed approach.

The main innovation of this paper lies in the formulation of the unsupervised change detection problem within a Markovian fusion framework. Within this framework, the contradiction between the speckle remove and the spatial contexture information preserving is unified and robust unsupervised change detection is achieved. The reasons are that: 1) the adopted two different change detection algorithms are complementary which enable to achieve noise removing and spatial information preserving at the same time; 2) MRF is an accurate model to describe a variety of image characteristics, and the statistical correlation of intensity levels among neighboring pixels can be exploited; 3) the proposed MRF fusion approach is capable of capturing the best peculiarities from the two complementary change detection algorithms.

Future lines of research may be related to: 1) more sophisticated thresholding algorithms can be adopted to get better intermediate maps so that the final change maps will be more reliable; 2) more accurate model can be developed which may make the algorithm more universal; 3) fuzzy set theory may be introduced to reach a satisfactory reliability level in the context of SAR images change detection.

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