

AN APPROACH FOR IMPROVING ACCURACY OF CHANGE DETECTION IN MULTI-TEMPORAL SAR IMAGES

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Abstract: Algorithms of change detection in multi-temporal SAR images have received great interests for recent decades, and been widely applied in natural resource supervision activities. However, these algorithms still expose the limitation of detection accuracy due to inherent presence of speckle noise in SAR images. This paper developed a novel approach of change detection in multi-temporal SAR images of sea surface. The algorithm has increased accuracy of change detection in multi-temporal SAR images of sea surface compared with recent other methods

Keywords: SAR image; Accuracy; Change detection; Multi-temporal image; Speckle noise; Difference image.

1. INTRODUCTION

Remote sensing technology has been applied widely for several decades. Especially, applications of multi-temporal SAR images in detecting abnormal changes on land and sea attracted many practical interests because they are hardly subject to weather effects compared to optical images. An challenge of processing SAR images is speckle noise, but many algorithms have been developed to successfully solve this problem [1-4]. More instantly, solutions to speckle noise can be classified into two types: the supervised [5, 6] and unsupervised ones [7] [8]. For the supervised method group, information of investigated or labeled samples has been known, while the otherwise is true for the unsupervised method group. Therefore, the unsupervised methods are more popular in reality than the supervised ones, in spite of the fact that the latter gives the better description of changes than the former. This paper concerned on the unsupervised method of detecting abnormal changes in SAR images.

In general, multi-temporal SAR image change detection for the unsupervised methods basically includes three steps: (1) image processing, (2) difference image (DI) generation, and analysis of DIs. Geometric correction and registration belongs to the first step and they were assumed to have been completed in this paper. The generation of DIs in second step are performed by two ways: subtracting two multi-temporal images or applying the log-ratio operator to them, in which the latter way is used more widely due to the capability of transforming multiplicative speckle noise into an additive one. There are a variety of DI analysis algorithms. However, they can be classified into four main groups: threshold-based, clustering based, transform based, neural network based methods.

The threshold based methods select an optimal threshold from the DI histogram to classify image pixels into changed and unchanged classes [9-12]. The clustering based methods partition all observations into a certain number of clusters in which each observation belongs to the cluster with nearest mean [13, 14]. Although they are sensitive to noise because insufficient consideration of spatial information, they are more flexible than the threshold methods. Both threshold and clustering based methods are simple in calculation and implementation, but their accuracy are limited and are sometimes used in combination with the other algorithms to

improve the accuracy.

Transform based methods exploit advantages of special transformations such as Principle Component Analysis (PCA) [13], Taselled Cap Transformation [15], Chi-Square Transformation [16], Discrete Wavelet transform [17, 18], Radon transform and Jeffrey divergence [19] and so on to select distinctive and salient regions from the DIs. However, applying transforms to DIs is sometimes a step of coarse processing in complete algorithms of multi-temporal SAR image change detection. It facilitates for later fine processing. In recent years, using artificial neural network in abnormal change detection in SAR images receives great considerations [20, 21] and is applied in the fine processing step to improve accuracy of the detection. In 2018, Gao et al. developed the algorithm of SAR image change detection based on frequency domain analysis and random multi-graphs (FDA-RMG) [22]. In their algorithm, the frequency domain analysis was used to localize coarse changed regions, while random multi-graphs in combination with Fuzzy-C-mean (FCM) [14] algorithm were implemented in the fine changed region classification stage. In 2019, an approach based on Convolutional-Wavelet Neural Networks (CWNN) [23] was also developed by these authors, in which the convolutional-wavelet neural network is used for the fine processing stage.

This paper developed a novel algorithm of change detection in SAR images, which is a combination of the FDA-RMG and CWNN methods. For instance, in the proposed method, the frequency domain analysis is used for the coarse processing stage, while CWNN is performed for the fine processing stage. The remainder of the paper is organized as follows. Section 2 presents the methodology for the proposed method. In Section 3, we present some simulation results to evaluate the proposed algorithm performance in comparison with other algorithms. In Section 4, we draw conclusions from the results of our evaluation and outline areas for future work.

2. METHODOLOGY

The method of FDA-RMG [22] achieves relatively good results of change region detection. Although frequency domain analysis (FDA) was implemented to reduce the effect of speckle noise in the images, detection errors in random multi-graph (RMG) stage are still avoidable because speckle noises in the images have not been completely eliminated by FDA technique. Moreover, the CWNN [23] has been proved as a potential solution to considerably reducing speckle noise for wavelet transform, and improving detection accuracy. Hence, the combination of FDA with CWNN methods can reduce more speckle noise effects, and so possibly enhance detection accuracy in total. That is the basic idea of the proposed algorithm.

This section describes the implementation of the proposed method in detail. The block diagram of the proposed method is shown in figure 1.

Because the proposed algorithm is developed as a combination of the FDA-RMG and CWNN methods. For instance, the proposed algorithm use FDA method

for, it is named as the FDA-CWNN method for convenience. In this block diagram, I_1, I_2 are two multi-temporal images, in which I_2 is the changed version of I_1 . The FDA-CWNN algorithm is implemented through two stages as follows.

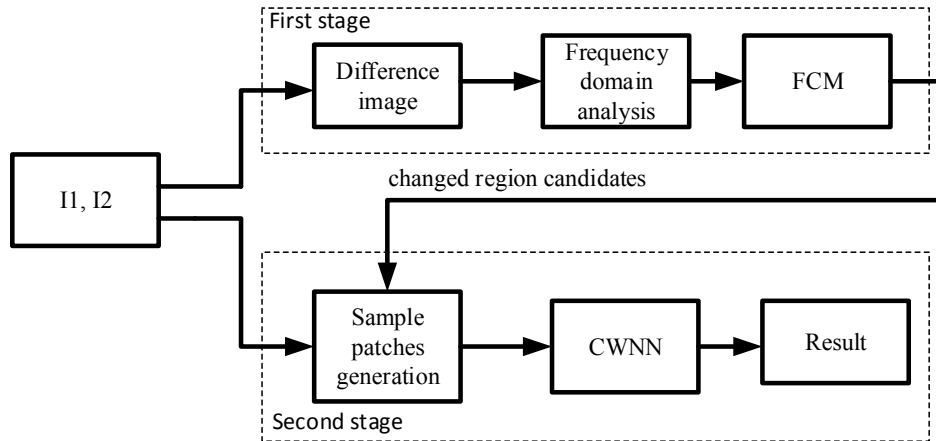


Figure 1. The block diagram of the proposed method.

In the first stage called the coarse processing stage, the difference image is created by using log-ratio operator: $I_D = |Log(I_2 / I_1)|$. Then, frequency domain analysis is performed to receive salient and distinctive regions. At the end of this stage, changed region candidates are selected by FCM algorithm (see details in [14]). For instance, the frequency domain analysis (presented in detail in [22]) was performed by Fourier transform of the investigated images to obtain amplitude and phase spectrums. Then, Gaussian kernel was employed to suppress spikes in the amplitude spectrum of the image. The inverse Fourier transform of the smoothed amplitude spectrum combined with the original phase spectrum was computed to yield the saliency map.

In the second stage called the fine processing stage, the CWNN is utilized to identify changed regions. The inputs of CWNN are image patches including training sample and virtual sample patches created by Sample patches generation block. Virtual samples help to reduce effects of the limited number of training samples. The CWNN was described in detail in [23]. In fact, CWNN is a combination of the dual tree complex wavelet transform (DT-CWT) with the convolutional neural network (CNN). DT-CWT helps to keep low frequency subbands and suppress high-frequency subbands of the images. As a result, some speckle noises are suppressed. In addition, CNN is utilized to train image patches for further change classification.

3. SIMULATION RESULTS

This section compares the results of the proposed method with FDA- RMG [22] and CWNN [23] methods through qualitative and quantitative analysis. The investigated images are shown in figure 2 and 3, which presents the original SAR image in figure 2(a) and the image with a change region marked by the ellipse in figure 2(b). The figure 2(c) show the binary ground-truth image.

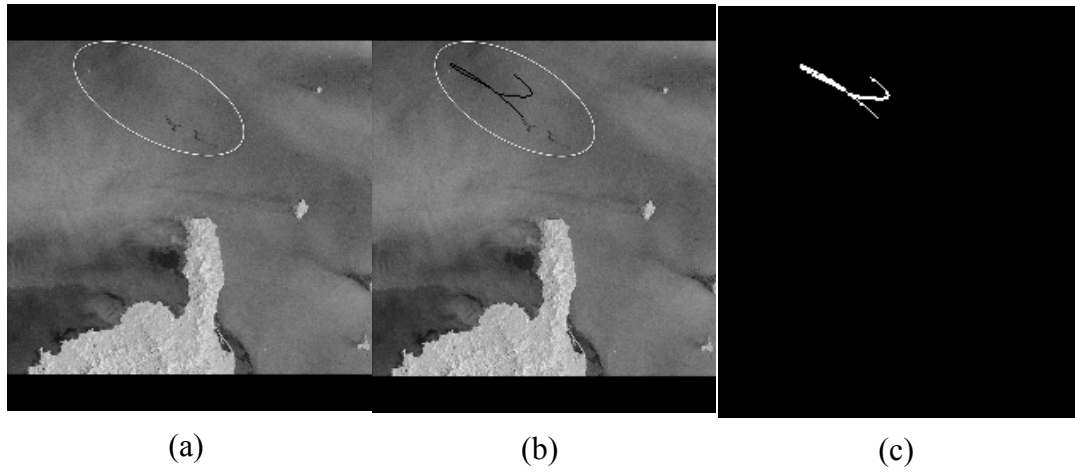


Figure 2. The original image (a) the changed image (b) and binary ground-truth image (c) manually created by combining prior information with photo interpretation.

(the original image from

http://www.esa.int/spaceinimages/Images/2018/10/Oil_spill_spread)

The size of the two investigated images, and the patch size used in the MATLAB simulation were respectively 256x256, and 7x7 pixels. The total training samples utilized in the the simulation were 2000 samples, in which the virtual samples created were 1000.

The qualitative comparison were performed by human vision on the binary change images created by the three methods and binary ground-truth image. The results obtained by the FDA-RMG, CWNN and proposed methods are binary change images respectively shown in figure 3(a), figure 3(b), and figure 3(c). As can be seen in figure 3 in comparison with figure 2(c), the result of the proposed method achieves the higher resolution than the two others.

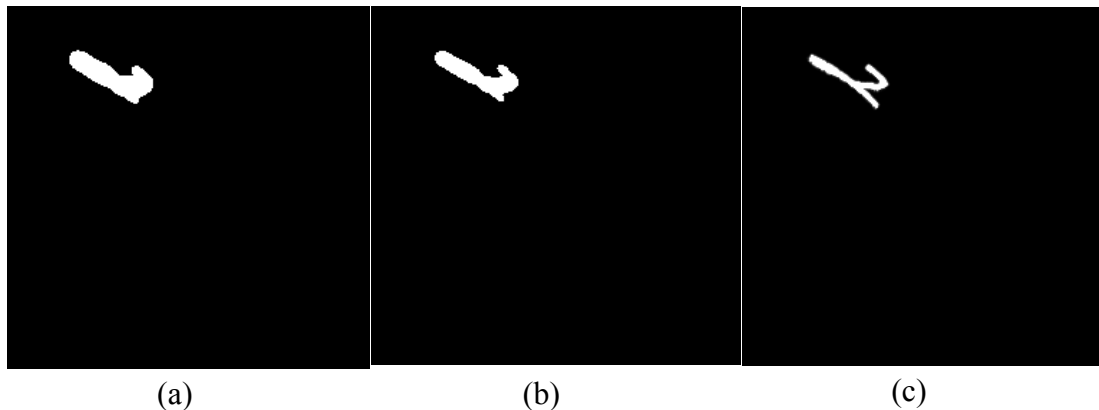


Figure 3. The simulation results of the FDA-RMG method (a), the CWNN method (b), and the proposed method (c).

In addition, the quantitative analysis was performed for the proposed method and

the two other methods by four parameters: false positives (*FP*), false negatives (*FN*s), overall error (*OE*), and percentage correct classification (*PCC*). These parameters are computed based on the pixel-by-pixel comparison between binary change images created by methods and binary ground truth images. More particularly, *FP* is counted as the number of unchanged pixels in the ground truth image but wrongly classified as changed ones, while *FN* is counted as the number of changed pixels in the ground truth image wrongly classified as unchanged ones. The *OE* is summation of *FP* and *FN*: $OE = FP + FN$. Finally, *PCC* is computed as follows.

$$PCC = \frac{Nt - OE}{Nt} \cdot 100\%$$

Where: *Nt* is the total pixels in the ground truth image.

The quantitative results of the three methods are presented in the table 1. This table listed four parameters *FP*, *FN*, *OE* and *PCC* for three algorithms: FDA-RMG, CWNN and the proposed algorithm. Each parameter or each method was computed based on pixel-by-pixel comparison of the binary image in figure 2(c) and each image in figure 3.

Table 1. Quantitive comparison of accuracy for the three methods.

Methods	FP	FN	OE	PCC(%)
FDA-RMG	498	310	708	99,21
CWNN	134	275	409	99,3
Proposed method	130	265	395	99,45

Table 1 shows that for four parameters investigated for the three method, the proposed method achieved the best results. For instance, the proposed method's *FP* is the smallest compared with the two remaining methods, and is approximately 3.5 times less than the FDA-RMG's. In addition, the *OE* of the proposed algorithm is the smallest, and is about 1.5 times less than the FDA-RMG's. As a result, the *PCC* of the proposed algorithm is the highest among the three investigated algorithms, as can be seen in table 1.

4. CONCLUSION

The paper developed the FDA-CWNN method for detecting changes in multi-temporal SAR images based on the combination of the frequency domain analysis based method and the CWNN method. In fact, the proposed method was performed by the coarse-to-fine procedure.

The log-ratio operator was computed on the two images to create the difference image at first. Then, the method of analysing the *DI* on the frequency domain was implemented to obtain salient and distinctive regions. Then, the FCM algorithm was applied to find the changed region candidates. Finally, CWNN method was used to train image samples for change identification. Its training samples also included virtual samples to reduce effects of limited training samples.

Simulation results showed that the proposed method improves accuracy in comparison with recent developed methods. In the near future, we investigate other transforms in combination with deep neural networks to improve accuracy of abnormal change detection in multi-temporal SAR images.

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TÓM TẮT

MỘT PHƯƠNG PHÁP CẢI THIẾN ĐỘ CHÍNH XÁC PHÁT HIỆN SỰ THAY ĐỔI TRONG CÁC ẢNH SAR ĐA THỜI GIAN

Các thuật toán phát hiện sự thay đổi trong các ảnh SAR đa thời gian đã nhận được mối quan tâm lớn trong các thập kỷ gần đây và được ứng dụng rộng rãi trong các hoạt động quản lý, giám sát tài nguyên thiên nhiên. Tuy nhiên, những thuật toán này vẫn bộc lộ hạn chế về độ chính xác phát hiện do sự tồn tại cố hữu của nhiễu đốm trong các ảnh SAR. Bài báo này đề xuất một thuật toán mới về phát hiện sự thay đổi của các ảnh SAR đa thời gian trên mặt biển. Thuật toán này đã cải thiện được độ chính xác về phát hiện sự thay đổi của các ảnh SAR đa thời gian về bề mặt biển so với các thuật toán được phát triển gần đây.

Từ khóa: Ảnh SAR; Độ chính xác; Phát hiện sự thay đổi; Ảnh đa thời gian; Nhiễu đốm; Ảnh sai lệch.

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