Fuzzy Clustering with a Modified MRF Energy Function for Change Detection in Synthetic Aperture Radar Images

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Abstract: In this paper, we put forward a novel approach for change detection in synthetic aperture radar (SAR) images. The approach classifies changed and unchanged regions by fuzzy c-means (FCM) clustering with a novel Markov random field (MRF) energy function. In order to reduce the effect of speckle noise, a novel form of the MRF energy function with an additional term is established to modify the membership of each pixel. In addition, the degree of modification is determined by the relationship of the neighborhood pixels. The specific form of the additional term is contingent upon different situations, and it is established ultimately by utilizing the least-square method. There are two aspects to our contributions. First, in order to reduce the effect of speckle noise, the proposed approach focuses on modifying the membership instead of modifying the objective function. It is computationally simple in all the steps involved. Its objective function can just return to the original form of FCM, which leads to its consuming less time than that of some obviously recently improved FCM algorithms. Second, the proposed approach modifies the membership of each pixel according to a novel form of the MRF energy function through which the neighbors of each pixel, as well as their relationship, are concerned. Theoretical analysis and experimental results on real SAR datasets show that the proposed approach can detect the real changes as well as mitigate the effect of speckle noises. Theoretical analysis and experiments also demonstrate its low time complexity.

Keywords: Fuzzy Clustering, Image Change Detection, Markov Random Field (MRF), Synthetic Aperture Radar (SAR).

I. INTRODUCTION

Image change detection, which means detecting regions of change in images of the same scene taken at different times, is of widespread interest due to a large number of applications in diverse disciplines, such as remote sensing [2]–[10], medical diagnosis[11][12], and video surveillance. Especially, when a natural catastrophe strikes, an effective and efficient change detection task appears critical when lives and properties are at stake. The images that are generated by synthetic aperture radars (SARs) are of great use due to their independence of atmospheric and sunlight conditions; therefore, they have become valuable and indispensable sources of information in change detection. Generally speaking, change detection in SAR images is the process of the analysis of two co registered SAR images that are acquired over the same geographical area at different times. Such analysis is unsupervised when it aims to discriminate between two opposite classes (which represent unchanged and changed areas) with no prior knowledge about the scene (i.e., no ground truth is available to model the classes) [4]. As is mentioned in [2], the procedure of change detection in SAR images can be divided into three steps: 1) image preprocessing; 2) generation of a difference image (DI) from multi-temporal images; and 3) analysis of the DI. Geometric correction and registration are usually implemented in the first step to align two images in the same coordinate frame. Here, we emphasize on the second and third steps. It is important to cope with speckle noise. Were there no or little noise pollution in the two SAR images, it would be fairly easy for the change detection process. Unfortunately, however, the way of originating SAR images is so special that they are usually corrupted by speckle noise, and its existence makes it rather difficult to discern the two classes.

Therefore, utilizing a relatively primary approach will not be capable of undertaking the analysis so well. To overcome the defect inherently characterizing in SAR images, in many literatures, researchers have tried to utilize different kinds of algorithms to reduce the corruption of the speckle noise. In the DI-generation step, the log-ratio operator is often used because of its robustness and non sensitiveness to speckle noise. In addition, the DI-analysis step in fact can be looked on as the process of image segmentation, and two conventional methods, the threshold method and the clustering method, have been widely used. In the threshold method, some essential models are usually established to search for the best threshold to divide the DI into two classes, and in the clustering method, we do not need to establish a model; therefore, it seems to be more convenient and feasible. One of the most popular clustering methods for image segmentation is the fuzzy c-means (FCM) algorithm,
which can retain more image information than hard clustering in some cases. In the standard FCM algorithm, a function that is related to the membership and dissimilarity is minimized in each iteration process, and the function is what is usually referred to as the objective function. Being able to retain more information from the original image, FCM has robust characteristics for ambiguity. However, the standard FCM algorithm is very sensitive to noise since it considers no information about spatial context. In recent years, many researchers have incorporated the local spatial and local gray-level information into the original FCM algorithm to compensate for this defect of FCM. Some novel approaches were developed, and the utilization of the spatial context was embodied basically in the modification of the objective function.

In, Cai *et al.* proposed the fast generalized FCM algorithm (FGFCM) for image segmentation which incorporates the spatial information, the intensity of the local pixel neighborhood, and the number of gray levels in an image. FGFCM can significantly reduce the execution time by clustering on gray-level histogram rather than on pixels; meanwhile, it is less sensitive to noise to some extent because of the introduction of local spatial information. In, Krindis and Chatzis proposed a robust fuzzy local information C-means clustering algorithm (FLICM) for image segmentation. The characteristic of FLICM is the use of a fuzzy local similarity measure which is aimed to guarantee noise insensitiveness and image detail preservation. In particular, a novel fuzzy factor is introduced into its objective function to enhance the clustering performance. Recently, we proposed an improved FLICM to classify changed and unchanged regions of the change detection problem. The reformulated FLICM (RFLICM) incorporates the information about spatial context by adding a new fuzzy factor into its objective function for the purpose of enhancing the changed information and reducing the effect of speckle noise.

It was emphasized on the modification of the objective function. In, another way of utilizing the spatial context was proposed for a spatiotemporal fuzzy-control system. In, the spatially constrained fuzzy c-means (SCFCM) method is presented by both adding some terms in the objective function and modifying the way to compute the clustering centers. The SCFCM method achieved some excellent results in its intended realm. Ju and Liu applied FCM to human-hand motion recognition by introducing a new dissimilarity function. In, Coletta *et al.* offered some augmentation of FCM algorithms used to cluster distributed data by arriving at some constructive ways of determining essential parameters of the algorithms and forming a set of systematically structured guidelines. The objective function was also exhibited in a modified appearance by adding some terms with a few parameters involved. A Markov random field (MRF) serves as an opportune tool to introduce information about the mutual influences among image pixels in a powerful and formal way. In, Chatzis and Varvarigou proposed a novel fuzzy objective function regularized by Kullback–Leibler divergence information. Their algorithm was facilitated by the application of a mean-field-like approximation of the MRF prior. In, Markov spatial constraint field and the fuzzy segmentation information resulting from FCM are fused. In, FCM with the MRF was applied in wavelet domain for image segmentation. Its label field of image was characterized by the MRF. The modified objective function with locally spatial constraint was introduced by the initial label of different scale wavelet coefficients.

Following the work mentioned above, in this study, we propose an SAR image change detection approach based on the FCM algorithm by adding the MRF with a novel form of energy function. The proposed approach (known as MRFFCM for short) does not improve FCM by modifying the objective function as in the aforementioned literature. Instead, it focuses on the modification of the membership to reduce the effect of speckle noise. It is of computational simplicity in all the steps involved, and its objective function can just return to the original form of FCM which leads to it being less time consuming than that of some obviously recently improved FCM algorithms. It modifies the membership of each pixel by introducing the information provided by the spatial context, i.e., the neighbors of the central pixel, as well as their interrelationship, are concerned in the process of using the MRF. What is more, theoretical analysis and experimental results show that the new approach not only does well in reducing the effect of speckle noise but has low time complexity as well. The rest of this paper is organized as follows: Section II Literature Survey. Section III describes the Proposed Methodology. Experimental results on real multi-temporal SAR images are described in Section IV. Finally, conclusions are drawn in Section V.

**II. LITERATURE SURVEY**

The performance of the proposed system mainly depends on the quality of difference image (DI) & accuracy of the classification method. Two conventional methods for difference image analysis are 1) Threshold method, 2) Clustering method. In the threshold method, some essential models are usually established to search for a best threshold to divide DI into two classes. E.g.: minimum-error thresholding algorithm (K&I), expectation maximization (EM) algorithm. Advantages of this approach are that it is simple and effective tool to separate objects from the background. But this approach Lack objective measures to assess the performance. Noise, ambient illumination, busyness of gray levels within the object and its background, inadequate contrast etc complicate the thresholding operation. Also improper thresholding causes blotches, streaks etc on the resulting image. But in the clustering method, we don’t need to establish a model, so it seems to be more convenient and feasible. One of the most popular clustering methods for image segmentation is the fuzzy c-means (FCM) algorithm, which can retain more
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image information than hard clustering in some cases. In the standard FCM algorithm, a function that is related to the membership and dissimilarity is minimized in each iteration process, and the function is what is usually referred to as the objective function. Being able to retain more information from the original image, FCM has robust characteristics for ambiguity.

However, the standard FCM algorithm is very sensitive to noise since it does not consider any information about spatial context. Later many researchers have incorporated the local spatial and local grey level information into the original FCM algorithm to compensate this defect of FCM. In 2002 M. Ahmed, S. Yamany, N. Mohamed proposed FCM_S which incorporated the local spatial and local grey level information into the original FCM algorithm. Advantages of this approach are, it was proven to be effective for image segmentation and it enhances their insensitivity to noise. Problem with this approach is that it still lacks enough robustness to noise and outliers especially in absence of prior knowledge of the noise. In their objective functions there exists a crucial parameter α which is selected generally through experience. Also the time of segmenting an image is dependent on the image size. Later in 2007 Chen and Zhang developed FGFCM (fast generalized fuzzy c-means clustering algorithms). It incorporates the spatial information, the intensity of the local pixel neighborhood and the number of grey levels in an image. Use a new factor as a local similarity measure & remove the empirically-adjusted parameter of previous algorithm.

Now the segmenting time is only dependent on the number of the gray-levels. Also this algorithm is relatively independent of the types of the noise and the value of new factor can be automatically determined. But still FGFCM has a crucial parameter „a” which is usually obtained using trial-and-error method. In 2010 S. Krinidis and V. Chatzis proposed FLICM (fuzzy local information c-means clustering algorithm). It uses a fuzzy local similarity measure which aimed at guaranteeing noise insensitiveness and image detail preservation. Here a novel fuzzy factor G is used to improve clustering performance. It can automatically determine the spatial and gray level relationship it improves the image segmentation performance, it is free of the empirically adjusted parameters, and also this algorithm is relatively independent of the types of noise. Balance among image details and noise is automatically achieved. In 2012 Maoguo Gong et al proposed RFLICM (Reformulated FLICM) which improved the performance of FLICM. Complementary information from the mean-ratio image and the log-ratio image is utilized to fuse a new difference image.

In RFLICM It introduces a new Reformulated factor as a local similarity measure to make a trade-off between image detail and noise. It incorporates the information about spatial context in a novel fuzzy way for the purpose of enhancing the changed information and to reduce the effect of speckle noise. This is relatively insensitive to probability statistics model. It provides accurate detection of foreground changes by fusing log ratio and mean ratio image. It is less sensitive to noises. Also FLICM is able to incorporate the local information more exactly. In, authors proposed another clustering method where they used a new way for utilizing the spatial context for spatiotemporal fuzzy-control system. This SCFCM method was developed by both adding some complicated terms in the objective function and modifying the way to compute the clustering centers. In, the authors developed new approach by fusing Markov spatial constraint field and the fuzzy segmentation information resulting from FCM. Later in, FCM along with MRF was used in wavelet domain for the purpose of image segmentation. Later they proposed MRFFCM (Markov Random Field FCM).

In order to reduce the effect of speckle noise, a novel form of MRF energy function with an additional term is established to modify the membership of each pixel. And the degree of modification is determined by the relationship of the neighborhood pixels. Approach focuses on modifying the membership instead of modifying the objective function. It is computational simple in all the steps involved. Its objective function can just return to the original form of FCM, which leads to its less time consumption than that of some recently improved FCM algorithms obviously. Also this approach modifies the membership of each pixel according to a novel form of MRF energy function through which the neighbors of each pixel as well as their relationship are concerned with. In this work we propose a new framework for change detection in SAR images. Here first we produce a difference image by applying Contourlet image fusion on mean ratio and log ratio image. Then we apply MRFFCM algorithm on fused difference image to classify changed and unchanged region.

III. PROPOSED METHODOLOGY

Image change detection is the process of identifying the changes between images of the same scene taken at different times. Change detection in SAR images is the process of the analysis of two co-registered SAR images acquired over the same geographical area at different times. Such analysis is unsupervised when it aims to discriminate between two opposite classes which represent unchanged and changed areas without any prior knowledge about the scene. It consists of 3 steps: 1) Image preprocessing 2) Producing difference image between the SAR images 3) Analysis of the difference image. The tasks of the first step mainly include co registration, geometric corrections, and noise reduction. Image registration is the process of transforming different sets of data into one coordinate system. Data may be multiple photographs, data from different sensors, times, depths, or viewpoints. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurements. Image Geometry Correction (often referred to as Image Warping) is the process of digitally
manipulating image data such that the image’s projection precisely matches a specific projection surface or shape. In the second step, two co-registered images are compared pixel by pixel to generate the difference image. In the DI-generation step, the logarithmic operator is characterized by enhancing the low-intensity pixels while weakening the pixels in the areas of high intensity therefore, the information of changed regions that is obtained by the log-ratio image may not be able to reflect the real changed trends in the maximum extent because of the weakening in the areas of high-intensity pixels.

The underlying idea of the optimal difference image is that unchanged pixels exhibit small values, whereas changed areas exhibit larger values. Mean-ratio shows the changed region but it doesn’t enhance it. Result is better than that of log ratio operator. In order to address this problem, in this paper we use Contourlet image fusion technique to generate fused difference image by fusing log-ratio and mean-ratio image for better change detection. In the third step a Fuzzy clustering algorithm is used for classifying changed and unchanged regions in the difference image. The algorithm used is MRFFCM (Markov Random Field Fuzzy C-Means). Markov random field (MRF) serves as an opportune tool to introduce information about the mutual influences among image pixels in a powerful and formal way. MRFFCM does not improve FCM by modifying the objective function instead; it focuses on the modification of the membership to reduce the effect of speckle noise. It is of computational simplicity in all the steps involved, and its objective function can just return to the original form of FCM which leads to its less time consumption than that of some recently improved FCM algorithms obviously. It modifies the membership of each pixel by introducing the information provided by the spatial context; the neighbors of the central pixel as well as their interrelationship are concerned in the process of using MRF. Fig 1 shows the overall change detection process.

IV. EXPERIMENTAL RESULTS
A. Test of the Parameter R
The first experiment is a test of $R$, which stands for the number of subintervals that the closed interval $[0, 1]$ is divided into. It is selected as the test parameter because it is related to both the accuracy of the final result and the amount of storage. We want to know whether it is worthwhile to get a more accurate result by sacrificing the storage in the memory. In this experiment, $R$ ranges from 10 to 100 and is of some discrete values. The three datasets are experimented on, and the deliberate and cogent criterion $KC$ is employed here. The results are shown in Fig. 2. It is quite clear from the three curves that when the value of $R$ is less than 20, the value of $KC$ varies conspicuously, whereas when it is larger than 30, the value nearly stays constant in both of the datasets. At the same time, it is noticed that the higher the value of $R$, the more the storage space occupied in the memory. Therefore, it is not necessary that $R$ be selected as so high a value. Hence, upon a comprehensive analysis, it is appropriate to select $R$ as a moderate value, say 30. The value of $R$ in the experiments is 30.

![Fig.2. Testing curve of the parameter $R$ on the three datasets](image)

![Fig.3. Final maps of the Bern dataset generated by (a) FCM; (b) FLICM; (c) RFLICM; (d) MRFEM; (e) MRFSM; (f) MRFN; and (g) proposed MRFFCM.](image)
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B. Results on the Bern Dataset

The results of the main experiment and the six comparison experiments are exhibited in two ways: The final maps in figure form and the criteria in tabular form. Fig. 3 shows the final maps of the experiments on the Bern dataset, and Table I list the values for evaluation. In the table, the results of the novel approach are written in bold. Fig. 3 and Table I show that for the original FCM, some vital changed regions are not detected (appearing as a high value of \( FN \)). It proves that the use of the information provided by the neighbors positively affects the results in this scenario. The two methods, FLICM and RFLICM in which the objective function is modified, do generate better results than FCM due to their conspicuous high values of \( KC \). The results are even better than those by MRFEM, MRFSM, and MRFN. However, the result of the proposed approach outperforms all the compared algorithms in both \( PCC \) and \( KC \). In Fig. 3(d), many white noise spots that do not actually exist emerge on the black background, which is due to MRFEM in which all the memberships of the neighbors are counted.

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\begin{array}{cccccc}
\text{TABLE I. VALUES OF THE EVALUATION} \\
\text{CRITERIA OF THE BERN DATASET} \\
\hline
\text{Algorithm} & \text{FP} & \text{FN} & \text{OE} & \text{PCC} & \text{KC} & \text{T/s} \\
\hline
\text{FCM} & 190 & 349 & 539 & 0.9941 & 0.7464 & 10.6 \\
\text{FLICM} & 724 & 84 & 808 & 0.9911 & 0.8045 & 137.6 \\
\text{RFLICM} & 723 & 61 & 784 & 0.9913 & 0.8132 & 139.4 \\
\text{MRFEM} & 6390 & 26 & 6416 & 0.9292 & 0.2436 & 63.4 \\
\text{MRFSM} & 651 & 45 & 696 & 0.9923 & 0.7576 & 66.1 \\
\text{MRFN} & 1756 & 36 & 1792 & 0.9802 & 0.5471 & 54.9 \\
\text{MRFFCM} & \text{364} & \text{47} & \text{411} & \text{0.9955} & \text{0.8413} & \text{73.9} \\
\end{array}
\]

Therefore, the new membership should be considerably influenced by the adjacent points polluted by noise. Without using the pixels which do not belong to the same class as the central one, MRFSM and MRFN appear to be much better than MRFEM. These two experiments distinguish the useful information from the useless (even adverse) information to some extent. With an additional term, MRFFCM appears more effective as is seen from both the figure and the table. In Table I, \( FN \) and \( FP \) of MRF FCM do not exhibit the best, whereas \( PCC \) and \( KC \), both of which serve as an overall evaluation, are the best. It is worth noting that although the values of \( PCC \) in FCM and MRFFCM are very similar, those of \( FN \) and \( OE \) differ remarkably. Besides, the values of \( KC \), which serves as a more cogent criterion than \( PCC \), are of large discrimination. In addition, the computational times of FLICM and RFLICM are nearly twice as long as that of the methods in which the MRF are involved. These results demonstrate that applying the MRF to FCM is less time-consuming and verify our qualitative analysis of time complexity. The results indicate that the novel approach, indeed, is capable of improving detecting accuracy effectively and do not engender a high time complexity.

C. Results on the Ottawa Dataset

The results of the experiments on the Ottawa dataset are shown and listed in Fig. 4 and Table II. For the Ottawa dataset, Fig. 4 and Table II show that the proposed MRFFCM also obtains the best values of \( FP \), \( FN \), \( OE \), \( PCC \), and \( KC \), for it adds an additional term which can adjust the probability automatically in the light of \( n_{i \in \partial j} \). This number may be even more indispensable from the fact that the value of \( KC \) of MRFN is larger than that of MRFSM. In addition, the fact that the value of \( KC \) of MRFFCM is larger than that of MRFN illustrates that modifying probability by the number of pixels is also of effectiveness. To sum up, the proposed approach will fit the two situations where the changed area appears centralized (the Bern dataset) and scattered (the Ottawa dataset), and it also verifies its relatively far-ranging applicability.

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\begin{array}{cccccc}
\text{TABLE II. VALUES OF THE EVALUATION} \\
\text{CRITERIA OF THE OTTAWA DATASET} \\
\hline
\text{Algorithm} & \text{FP} & \text{FN} & \text{OE} & \text{PCC} & \text{KC} & \text{T/s} \\
\hline
\text{FCM} & 422 & 2319 & 2741 & 0.9730 & 0.8935 & 12.3 \\
\text{FLICM} & 2608 & 369 & 2977 & 0.9707 & 0.9052 & 156.2 \\
\text{RFLICM} & 2381 & 469 & 2850 & 0.9719 & 0.9075 & 161.3 \\
\text{MRFEM} & 5397 & 298 & 5695 & 0.9439 & 0.8133 & 77.0 \\
\text{MRFSM} & 2855 & 487 & 3342 & 0.9671 & 0.8833 & 77.9 \\
\text{MRFN} & 2642 & 414 & 3056 & 0.9699 & 0.8929 & 63.5 \\
\text{MRFFCM} & \text{1636} & \text{712} & \text{2348} & \text{0.9769} & \text{0.9151} & \text{83.8} \\
\end{array}
\]

D. Results on the Yellow River Dataset

Unlike the Bern or Ottawa dataset, the influence of speckle noise on the image acquired in 2009 is much greater than the one acquired in 2008 since the two images considered are single look image and four-look image. It represents a more complicated situation to assess the effectiveness of the proposed approach. Moreover, there is
no ground-truth image provided for the whole Yellow River Estuary dataset to quantitatively evaluate the effectiveness of the proposed change detection methods.

Hence, only a visually analysis is available to analyze the change detection results. Fig.5 illustrates the change detection results that are obtained by different approaches. Due to the large size of the original images (7666×7692), the detailed information in such small pages cannot be clearly exhibited, which is hardly able to verify the effectiveness of our proposed method. Therefore, the results of the selected area are given in Fig.6 and Table III. Fig.5, Fig.6, and Table III show that for the Yellow River dataset, many white spots appear in the final map generated by FCM, which is listed as a high value of FP in Table III. These white spots are eliminated to different degrees by modifying FCM. FLICM and RFLICM have reduced the value of FP to a large degree at the cost of a high time complexity (listed as great time consumption). The methods with the MRF are low in time complexity, and the proposed MRFFCM is the best, which verifies the effectiveness of the new algorithm.

V. CONCLUSION
In this paper, a novel change detection approach specifically toward the analysis of multi-temporal SAR images has been presented. This approach is based on the universal utilized FCM algorithm and the MRF model. After generating the DI through the log-ratio operator, we add the MRF method in the procedure of FCM. The approach is of novelty in that the form of the energy function is altered by utilizing not only the memberships but
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also the number of the same class of neighborhood pixels. Thus, we are able to decide whether the central pixel locates in a homogeneous region or a heterogeneous region. Great emphasis is put on the establishment of the additional term. By adding the term, the modified membership can be adjusted automatically according to both the membership and the number of the same class of neighborhood pixels. The well-known LSM is applied to get the relationship the membership and the adjusting parameter. The effectiveness is tested through four comparison experiments on three real SAR datasets. This novel approach is basically built on the mathematical analysis such as the knowledge of elementary function and LSM. The new approach does not consider the use of any prior knowledge about the scene but consider only the use of the gray level intensity and, therefore, is an unsupervised approach. In general, the main advantages of our change detection approach can be concluded as 1) superiority in reducing speckle noises (as the membership to each pixel is determined by two important factors comprehensively, and it has been validated by the experimental results), and 2) computational simplicity (the calculation of each step only includes the computation of some elementary functions, and theoretical analysis and experiments have demonstrated its low time complexity). In either scientific experiments or engineering practice, these advantages will play an indispensable role.

VI. REFERENCES


