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Disclose Variation in Synthetic Aperture Radar Images Adopting Fuzzy Clustering Along with Higher-order MRF Energy Function and Wavelet Denoising Technique - A Detailed Survey

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***Abstract* -In this paper we put forward a unique access to disclose variation in synthetic aperture radar (SAR) images. In this approach we classify the changed and unchanged region by the help of the fuzzy c-means (FCM) clustering along with the use of a Higher-order Markov random field (MRF). It is important to cope with speckle noise so we use a form of the Higher-order MRF along with an additional term that is the Bayesian denoising technique to reduce the speckle noise found in the SAR images. In this we use two approaches for the detection of change in synthetic aperture radar images. First, we use the log-ratio operator for getting the difference image. Secondly, with the help of FCM and the higher-order MRF we detect the change in the SAR images. We also apply the Wavelet denoising technique to reduce the speckle noise. The main advantage of the proposed method is its superiority in reducing speckle noises and its computational simplicity.**

Keywords: Log Ratio, Fuzzy C Means Clustering (FCM), Higher-Order Markov Random Field (MRF), Wavelet Bayesian Denoising Technique, Synthetic Aperture Radar (SAR).

I INTRODUCTION

The detection of the variation in the same image taken in different time is of great interest due to its large application in the current world. The changes can happen due to many reasons. It's well said that the Earth's surface is in constant motion [14]. So the surface of the earth also experience different types of changes as the time change. The change can be due to the environmental disasters like earthquake, volcanic eruption, flood etc. so the detection of these changes had a wide range of application in this current world. The Synthetic-aperture radar (SAR) is a type of radar image which can be used to create images of objects, such as landscapes [20]. In this paper we propose a method to find the difference between the two SAR images that has been taken in two different times. In this method we don't have any prior knowledge about the scene.

The main steps that are involved in disclosing the variation in the SAR can be classified into 3 steps. In the first step we preprocess the image. Then we try to obtain a difference image (DI) form the multi temporal images. Later we analyses the DI that had been obtained. It is very important to deal with the speckle noise. If there is any scope of noise or error then it will affect the change detection in a negative in way. But the real fact is that the SAR images are usually obtained in a corrupted form. So the rate of speckle noise is very high.

To reduce the rate of speckle noise we first generate the DI of the two images [14], by the help of the log-ratio operator. Along with the generation of DI operator we also use the process for image segmentation with the help of the two improved method, that is the threshold method and clustering method. In the threshold method we need to establish a model for finding the threshold for the classification of the images. But in the clustering method we do not need to establish a model. So, by the help of the FCM clustering we retain more image information. We also use the Higher- Order MRF along with the FCM for the better results. To reduce the speckle noise we use the Wavelet Bayesian denoising technique also.

The paper later explains about the literature survey in the Section II. The Section III gives the descriptions of the methodology that is being used in the change detection of the SAR images. Later in the Section IV there is the description of the dataset used. Finally we conclude with Section V.

II LITERATURE SURVEY

This paper deals with the change detection of the synthetic radar image (SAR) before and after a time period. In this paper we use the log ratio operator to find the Difference Image (DI). These DI can be found by the help of the mean ratio operator but the log ratio operator is used because it is simpler. There have being many methods found for the detection of the change in the synthetic radar image (SAR). The change in multi temporal synthetic aperture radar images [2] can be found by the measuring the local statistics of the image between two dates. The local statistics is found by using a cumulant-based series expansion, which determines probability density functions in the neighbourhood of each pixel in the image. Hidden

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Markov random field (HMRF) models [3] are also widely used for image segmentation, as they can be used in problems where a spatially constrained clustering scheme is used. Fuzzy c-means (FCM) clustering has also been successfully applied in several image segmentation applications. This can be used for obtaining excellent robustness. An HMRF model [3] is a stochastic process created by an MRF, in this state sequence can be inferred only through a random field of observations.

There are many methods to find the variation in image and various methods for image clustering. Fuzzy c means is one such method used. In this paper we use the fuzzy c mean method because it gives high precision than the other image clustering methods. There can be various variations that can be used for the FCM. Fuzzy Local Information C-Means (FLICM) is such a method. In this method [4] we incorporate the local spatial information and grey level information in a novel fuzzy way. The main feature of FLICM is the use of a fuzzy local (both spatial and grey level) similarity measure, which help to reduce the noise and preserve the image detail.

There are many methods for detecting the change detection in the images by unsupervised distribution-free method [5]. In this the image fusion technique is used to create a variation in image by the help of combined information from the mean-ratio image and a log-ratio image. This method uses the information about the spatial context in the fuzzy way for enhancing the changed information and decreasing the effect of speckle noise. Another variant of the widely used Fuzzy C-Means (FCM) algorithm that supports clustering data distributed across different sections [6]. Some of the methods are named as collaborative and parallel fuzzy clustering.

The other technique used for advanced FCM is applying spatial constraints [7][21] with the algorithm. But this method has its own limitation like it takes more time and the complexity is very high. Image change detection is widely used in applications such as robot vision, object recognition, geographical imaging and medical imaging. So this method can be used as an application of change detection.

In this paper we introduce a method called MRF energy function in the Fuzzy C-Means clustering algorithm to improve the robustness. It is a powerful tool that can be used for the implementation. The use of a pixel-level MRF [8] makes the clustering deficient to deal with images with enhanced texture patterns. But we can find many modified version of MRF energy function. Region level MRF is such an advanced method of Markov Random Field [8]. This method acts an important role in explaining large-range difference of macro textures. In this paper we consider the complexity of image features; a region-level mean template is also created to improve the relationships between the neighbouring regions. But this method has being proved as a better method than the four state-of-the-art competitors.

The change detection of the SAR images can also be done by the help of another technique called hybrid conditional random field (HCRF) model [9]. This is an advanced technique used nowadays. In this method we construct the statistics of the log-ratio image which has been derived from the two-temporal SAR images into conditional random field model. In this we use the Gamma distribution (GΓD) for finding the log-ratio value[19]. This had its own limitations so it is not widely used. Another method that was introduced is DWT Based Image Fusion & RFLICM Clustering [10]. In this we use the clustering method called RFLICM. The main advantage of this method is that it can be used for the noise removal and speckle noise can be removed is an effective way.

III METHODOLOGY

As said before in the introduction we initially find the DI of the SAR images by the help of the log-ratio operator. In this if we have two coregistered SAR image, then let I1 = {I1 (h, l), $1 \leq h \leq A$, $1 \leq l \leq B$}, and I2 = {I2 (h, l), $1 \leq h \leq A$, $1 \leq l \leq B$}. Now by the use of the log-ratio operator we find the DI of the image, i.e. IX = {IX (h, l), $1 \leq h \leq A$, $1 \leq l \leq B$}. After this we analyse the DI that is been obtained.

A. Concepts involved in the usage of FCM along with the Markov Random Field.

By the help of the log- ratio operator we are able to differentiate between the changed and unchanged image areas. This basically deals with the image segmentation process. Clustering is the process of dividing data elements into classes or clusters so that items in the same class are as similar as possible, and items in different classes are as dissimilar as possible. Depending on the nature of the data and the purpose for which clustering is being used, different measures of similarity may be used to place items into classes, where the similarity measure controls how the clusters are formed. The usage of FCM helps to cluster these images. FCM is a well-known and popular method used nowadays.

The FCM algorithm attempts to partition a finite collection of n elements X= {x1... xn} into a collection of c fuzzy clusters with respect to some given criterion. Given a finite set of data, the algorithm returns a list of C cluster centers C= {c1,…,cn} and a partition matrix is used in the FCM called as W, which is between the interval [0,1]. Fuzzy c-means has been used widely as a very important tool for image processing in clustering objects in an image.

In order to reduce the effect of speckle noise, we propose a novel form of the energy function of the Higher-order MRF to modify the membership of the FCM algorithm instead of modifying the objective function. Therefore, the MRF can be utilized to consider the spatial context and, thus, to enhance the traditional FCM algorithm without engendering much time complexity. We can test the complexity so as to obtain improved results. Here using the higher order MRF function help to reduce the speckle noise present in the image dataset.

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B. Brief description of the Markov Random Field.

In general, an image $I = \{I(h, l), 1 \leq h \leq A, 1 \leq l \leq B\}$ itself can be viewed as a field, and each pixel of image is an element. If we consider ∂ as a neighbourhood system lying on the field and if $p(x)$ is an MRF with respect to the new neighbourhood system ∂j, then,

$$p(x_j \,|x_{I-\{j\}}) = p(x_j \,|x_{\partial j}) \;\forall j \in I$$

where $j = (h, l)$ denotes the position of a certain element in the field, and $x_{I-\{j\}}$ means the property of the whole elements in the field except the pixel j. Fig.1 helps to get the description of this concept.

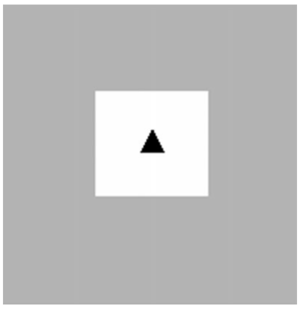

Fig. 1. Example of how the MRF energy function deals with the spatial context.

C. Hypergraph based reduction for higher order binary Markov Random Field.

This method is used as the extension of the MRF energy function. In this we use the help of higher order reduction technique [30]. The basic concept behind this method is that the clique structure of an MRF is a hyper graph. Usually in the MRF function we take a term one at a time. So the complexity is very high in this method. Not only that this is more efficient in the first-order terms only [31]. So it's really important to get a method for the higher order terms[32]. In this proposed method we have used the method of reducing many terms at once. So we know that for n binary variables each of which appear in terms with k other variables, at worst we produce the complexity of non-sub modular terms. In this we also consider a local completeness property and find that it can work in an effective method in even this computer vision problem like the image fusion etc.

The basic principle behind this method is the reduction of the multi linear polynomial with higher order terms to quadratic form. The main 2 steps involved in this technique are firstly we eliminate all higher order positive terms with the common sub set to a single variable. In the second step all the higher order terms now have negative coefficient. We reduce them term-by-term.

D. Wavelet Bayesian Denoising Technique

We have already seen that the rate of speckle noise in the SAR images is very high as it is independent of sunlight and other atmospheric conditions.

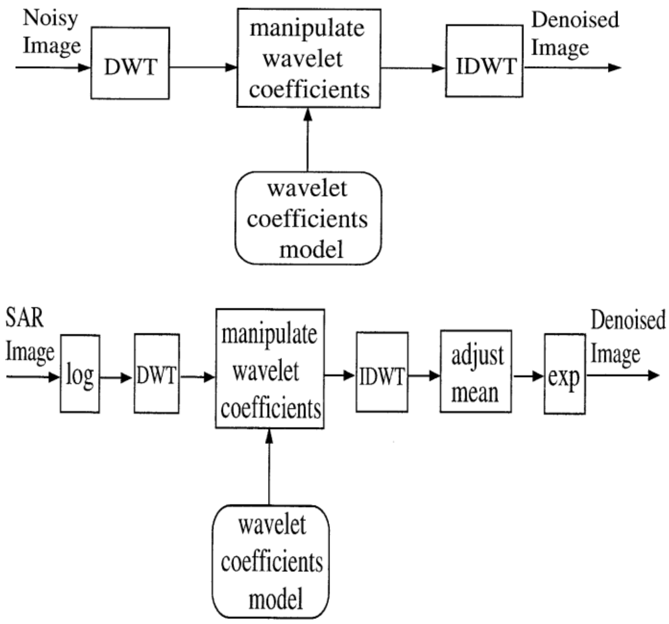

Fig. 2. The wavelet denoising procedure. (a) Additive noise model; (b) multiplicative noise model.

So we also consider a method to reduce the speckle noise in this method. So we develop a spatially adaptive speckle-reduction algorithm by fusing the wavelet Bayesian denoising technique [29] with an image regularization procedure based on Markov random fields. Usually most of the denoising techniques are designed to operate on images with additive random noise, speckle noise in a SAR image is multiplicative in character, but by applying a logarithmic transformation to the SAR image, we can convert it into an image with additive noise. We also use the Expectation–Maximization algorithm is used to estimate hyper parameters and specify the mixture model, and the iterated conditional modes method is implemented to optimize the state configuration.

The overall review of the methods used in the change detection of the SAR images help in the effective finding of the changes in the SAR images taken in same place at different time. Here we start with the log ratio operator, then moving to the FCM clustering along with Higher Order MRF energy function. We also use the help of the Wavelet Bayesian denoising method for finding the speckle noise in the image and for the effective removal of the noise in the SAR images.

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IV DATASET DESCRIPTION

We mainly use 3 dataset for the experiments. The dataset used are Bern dataset, Ottawa dataset and Yellow River dataset. The dataset are collected of two difference time.

The first dataset is called the Bern dataset, it has the representation section (301x301) of two SAR images acquired by the (Fig. 3) European Remote Sensing 2 satellite SAR sensor over an area near the city of Bern, Switzerland, in April and May 1999.

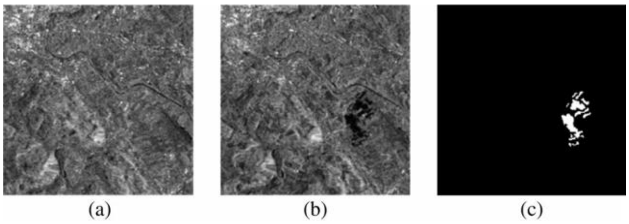

Fig. 3. Bern dataset. (a) Image acquired in April 1999. (b) Image acquired in May 1999. (c) Ground-truth image

The second dataset used is the Ottawa dataset. It has a section (290 x350) of two SAR images over the city of Ottawa by RADARSAT SAR sensor. They were provided by the (Fig. 4) Defence Research and Development Canada, Ottawa. This dataset contains two images in May and August 1997.

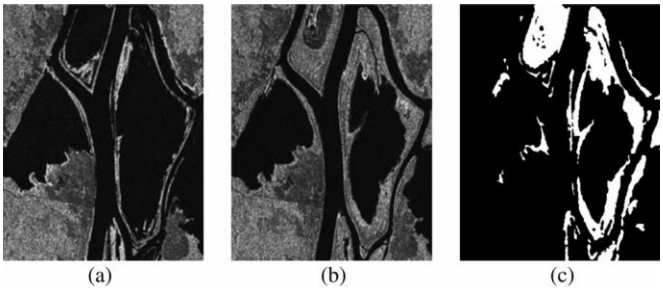

Fig. 4. Ottawa dataset. (a) Image acquired in May 1997. (b) Image acquired in August 1997. (c) Ground-truth image

The third dataset that is collected is the Yellow River dataset that consists of two SAR images acquired by Radarsat-2 at the region of the [Fig. 5] Yellow River Estuary in China in June 2008 and June 2009.

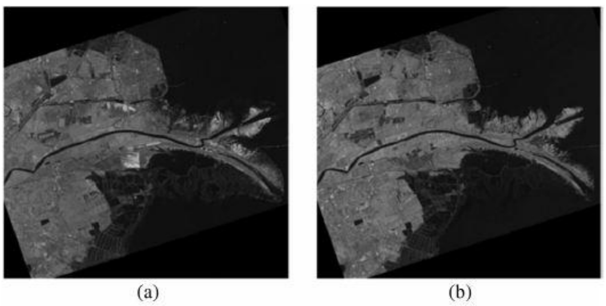

Fig. 5 Yellow River dataset. (a) Original image acquired in 2008. (b) Original image acquired in 2009.

This is the description about the datasets used in this experiment.

V CONCLUSION

In this paper we disclose the variation in the synthetic aperture radar (SAR) images by the help of Fuzzy c-means (FCM) clustering along with the help of Higher-order Markov random field (MRF) as an energy function. Initially we generate the difference image (DI) with the help of the log-ratio operator and then analyse the DI. Later we add the Higher-order MRF procedure into the FCM and find the change in the images. We also apply a Wavelet Bayesian denoising technique to reduce the speckle noise that is present in the SAR images. Here we mainly concentrate in the synthetic radar images (SAR).

In this paper we use mainly 3 dataset, i.e. Bern dataset, Ottawa dataset and yellow river dataset. The method is widely used and has got many advantages. The main advantage of this method is that it can be used to reduce the speckle noise and the method is computationally simpler.

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VII REFERENCE

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