Change Detection Using Spatial Fuzzy c-Means Clustering For VHR Remote Sensing Images

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ABSTRACT :

In this paper, an effective unsupervised change detection technique using spatial fuzzy c- means clustering for VHR remote sensing images is proposed. First, the Gabor wavelets are used to attain the images at multiple scales and rotations, whose maximum magnitude over all rotations in each scale is integrated to form the Gabor feature vector. Then a GWDM image is generated. In GWDM, a local similarity measure MRF neighborhood system is incorporated to obtain the relationship between the neighborhood pixels. The coefficient of variation method is applied to differentiate contributions form different features. Next,improved spatial fuzzy c-means algorithm is incorporated to obtain changed and unchanged results. Finally, the proposed approach demonstrates the effectiveness in the change detection.

Index terms: change detection, Gabor wavelet difference measure(GWDM),local similarity measure, coefficient of variation, spatial fuzzy c-means(SFCM)

I.INTRODUCTION

Change detection technology for remote sensing aims to identify changes occurred on the same geographical area at different times. The usage change detection technology for remote sensing images becomes more and more important. Normally, the supervised and unsupervised are the two types of classification in change detection. In supervised change detection approach, the changed areas are identified and the land-cover transition type can be identified where as in unsupervised approach the changed areas are separated from unchanged ones. The unsupervised change detection approaches are more widely used in many research applications.

The change detection process can be made by dividing into two steps: difference generation and analysis .Image differencing, image regression, image ratio and change vector analysis(CVA) [5]are applied as a in difference generation, while the analysis is performed by following methods such as threshold-based [6], [7] and clustering- based methods [8],[9].With the appearance of very high resolution (VHR) remote sensing images, more detailed ground information can be obtained.

The VHR remote sensing images are more adequate with the spatial information. However, the traditional change detection methods are not sufficient for obtain more amount of spatial information. Several feature based change detection methods are proposed for collecting spatial and contextual information such as line feature [10],shape feature [11],gray level co-occurrence matrix (GLCM) textures [12], and Gabor wavelet features [13]-[15]. Among all proposed methods the Gabor wavelets have strong discriminating power and can accomplish better performance at very low computation cost for change detection [13].Gong et al. [13] proposed to separate irrelevant and noisy elements from Gabor responses for change detection is performed in principal component analysis technique In [14], to extract spatial and contextual features at different scales and orientations Gabor filter was utilized, and a novel post classification change detection method was proposed using this information. In [15], a simple yet effective unsupervised change detection approach was designed for multi temporal synthetic aperture radar images by jointly exploiting the robust Gabor wavelet representation and advanced cascade clustering.

Although effort has been made to improve Gabor feature based methods, practical and effective method needs to be developed. In [15], the Gabor features were extracted from the difference image, which can be obtained using CVA applied to two temporal images. However, a significant quantity of spatial and contextual information contained in VHR images cannot be extracted this way, due to loss of information in the differencing process. In addition, the pixel wise difference measure (i.e., CVA) is not suitable for Gabor wavelet features due to lack of spatial correlation. Therefore, an effective difference measure based on Gabor features is proposed based on extracted Gabor features from original images.

The data clustering Fuzzy c-means clustering algorithm (FCM) was introduced by Ruspin[1969],developed by Dunn [1973], generalized by Bezdek [1981].The FCM algorithm and its derivatives have been used successfully in many applications, such as pattern recognition, classification, data mining, and image segmentation. FCM allows pixels to belong to multiple clusters with varying degree of membership. The neighborhood pixels possess nearly the same features of data. Hence, for image classification the spatial relationship between neighboring pixels is an important characteristic. However, the spatial information in the images is not fully utilized in traditional FCM algorithm. The membership weighting of each cluster is changed after the cluster distribution in the neighborhood is considered. A new method is proposed in which the weighting membership of each cluster is changed after Cluster distribution. The proposed GWDM-SFCM reduces the errors and improves the effectiveness in the change detection technique.

The remaining part of the paper is organized as follows: Section II describes proposed approach. Section III provides experimental results. Section IV presents conclusion.

II. PROPOSED CHANGE DETECTION APPROACH FOR VHR IMAGES

A. Problem formulation

Let X1 and X2 be two multispectral images acquired in same geographical area at two different times. It is assumed that the two images have the same size of M1 X M2 which have been and radio-metrically corrected and co-registered. Thus, by performing image differencing for the two images using Gabor wavelet the difference image D is generated.

The two VHR remote sensing image have abundant spatial and contextual information, but the difference image has little.A siginificant amount of structural information was lost in the differencing process. As a result, many features included in the original images cannot be extracted and applied for change detection. Then there is a necessity for Gabor wavelet prior to pixel wise differencing. The pixel wise difference measure (i.e., CVA) is not suitable for images including the strong spatial correlation inside the features. As shown in Fig. 2(c) the difference image generated by CVA is shown .According to traditional methods, this region will be directly classified into an unchanged class. However, this result is not completely correct because the two temporal feature image chips were not coincident. To address the aforementioned, the Gabor wavelet difference measures provided which gathers more amount of spatial and contextual information from the VHR images. After difference generation, the analysis in change selection clustering algorithm is proposed. The conventional fuzzy c-means does not fully utilize the spatial information. To overcome this, spatial fuzzy c-means is proposed in this letter. In this proposed approach initially Gabor wavelet features are extracted from the multi temporal images. Then Gabor wavelet difference measure is applied to generate difference image. Finally spatial fuzzy c-means clustering algorithm is proposed.

B. Gabor wavelet feature extraction

Gabor wavelets have been extensively applied to image analysis due to their biological relevance and computational properties. wavelet transform with

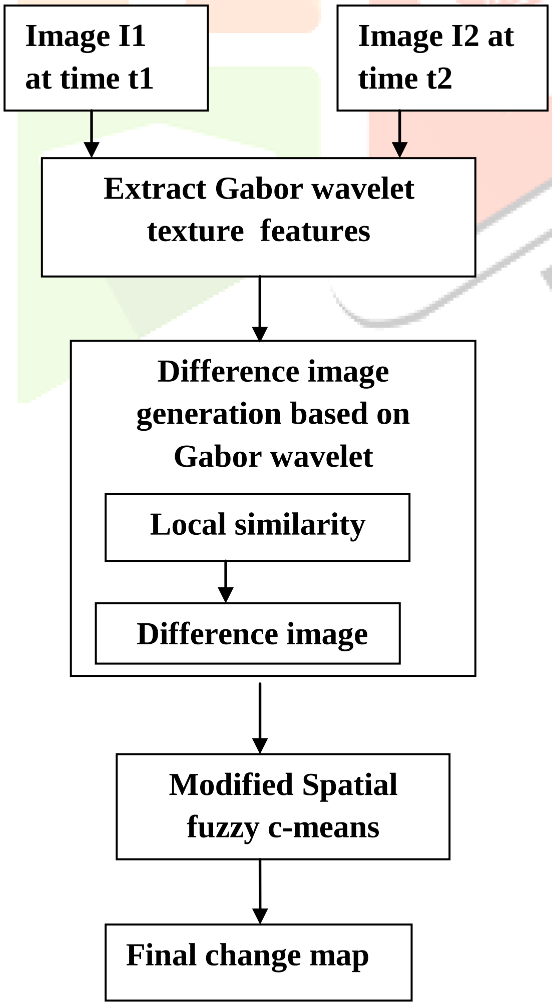


Fig.1: Proposed framework for change detection

Gabor function is considered for Gabor wavelet. Now, consider the Gabor function which is 2-D,

$$\varphi(a,b) = \exp(2\pi j W_a) - \left[\sqrt{R} + log(2\pi\sigma_a\sigma_b)\right] \qquad (1)$$

Where, σ_a and σ_b denotes the standard deviation of Gabor function along the axis x and y named as (a,b) respectively. W represents the frequency bandwidth of wavelet and $j=\sqrt{-1}$.

Applying Fourier transform, it is represented as

$$F(u,v) = \exp\left\{\frac{v^2}{\sigma_v^2} - \frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2}\right]\right\} \quad (2)$$

Where, $\sigma_u=1/2\pi\sigma_x$ and $\sigma_v=1/2\pi\sigma_y$

A Gabor filter is generated with proper scale and rotations for the 2-D Gabor wavelet φ(x,y)

$$\varphi_{so}(a,b) = \gamma^{-m} F(x,y)$$

$$\gamma > 1, m, n = integer \quad (3)$$

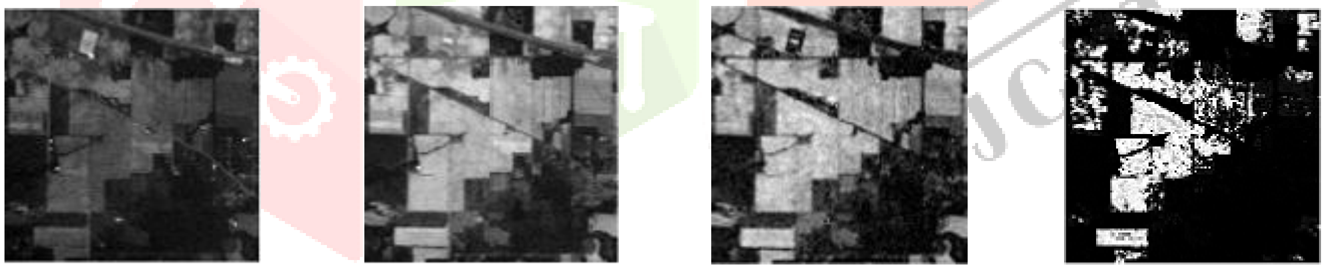
Where,

$\theta = \frac{o\pi}{n}$,k is the total number of orientations,o Є [0,n-1] ,γ^{-m} is the scale factor s Є[0,m-1],s is the number of scales the parameters of the Gabor wavelet are set as

$$\gamma = \frac{\exp(-f_{max}\, f_{min})}{m-1} \quad (4)$$

Where f_{min} and f_{max} are minimum and maximum center frequencies respectively. Given an image I(x,y) its 2-D Gabor wavelet transform can be defined as

$$G_{so}(x,y) = \int I(x1,y1)\varphi_{so} * (x-x1, y-y1)dx \ (5)$$



(a) **(b)** **(c)** **(d)**

Fig.2 (a) First input image **(b)**Second input image **(c)**CVA image **(d)** CVA-FCM image

C.Gabor-wavelet based difference measure

After Gabor feature extraction, the GWDM is defined to generate the difference image. In, GWDM, based on the MRF neighborhood system between two temporal Gabor features, a local similarity measure p_{so}(I1,I2) is designed and formulated as

$$p_{so}(I1,I2) = \frac{1}{(t_{so}(I1,I2)^2} \quad (6)$$

$$t_{so}(I1,I2) = h.f_{so}^{(I1,I2)}{}_{o}(x,y) + \sum_{(x,y)\in u} f_{so}^{(I1,I2)}(x,y) \quad (7)$$

Where t_{so}(I1,I2) denotes the variation index between two temporally corresponding Gabor feature regions at scale s and orientation o. $f_{mso}^{(I1,I2)}(x,y)$ presents Gabor wavelet features for two images I1 and I2 at two different times respectively.(x,y) denotes the position of the target pixel in the image.u defines the MRF neighborhood system ar centered at the target pixel denotes the distance between the target pixel and its neighboring pixels. Using the local similarity images at scale and orientation are generated from the temporal Gabor wavelet features. In order to display the contributions of different Gabor features, CVM is utilized which is a weight determination method is proposed.

(x-1,y-1)	**(x-1,y)**	**(x-1,y+1)**
(x,y-1)	**(x,y)**	**(x,y+1)**
(u+1,y-1)	**(u+1,y)**	**(x+1,y+1)**

(a)

$\sqrt{2}$	**1**	$\sqrt{2}$
1	**(x,y)**	**1**
$\sqrt{2}$	**1**	$\sqrt{2}$

(b)

Fig.2 (a) Neighborhood system centered at (x,y) **(b)** Distance between the center pixel (x,y) and its neighborhoods

The weights are calculated using CVM coefficient of variation.The Gabor features at scale s and orientation o, μ_{so} and σ_{so} are the mean value and the standard deviationare calculated. Then, the difference image can be generated as

$$D(I1, I2) = \sum_s^m \sum_o^n \frac{V_{so}}{p_{so}\,(I1,I2)} \quad (8)$$

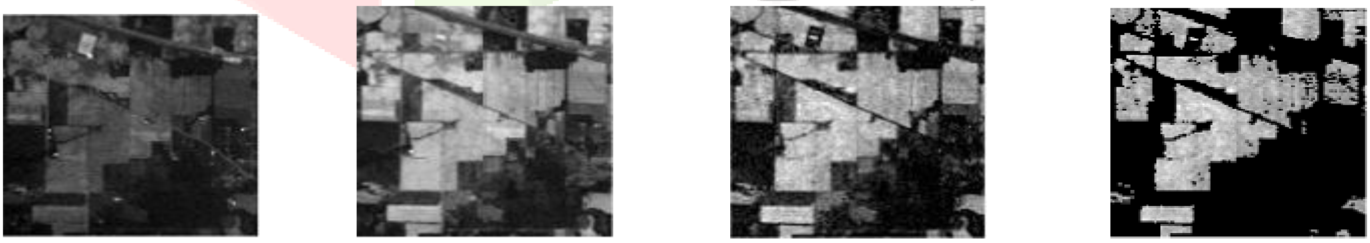
Where V_{SO} is the ratio of the standarad deviation to the mean.

In this way, the difference image is obtained using GWDM as shown in Fig.3(c).

D. segmentation of the Difference(SFCM)

Once the difference image has been generated, change detection processing is needed to classify the changed pixels and unchanged pixels by segmenting the difference image. Fig.3(d) shows the GWDM-FCM which is generated after difference measure and fuzzy c-means. The conventional FCM clustering algorithm is sensitive to noise and simply falls into local minimum value. To overcome these disadvantages, the spatial information was considered. For this the spatial function is defined as follows:

$$s_{ij} = \sum_{k \in NB\,(pj)} u_{ik}$$



(a) **(b)** **(c)** **(d)**

Fig.3: (a) First input image (b)Second input image (c)GWDM image (d)GWDM-FCM

$NB(p_j)$ represents a square area with pixel p_j as the center of the spatial domain. Similar to the membership function s_{ij} represents the membership which the p_j belongs to the ith cluster center. The value of spatial functions is larger when the pixels around a certain point belong to the same cluster. The membership function and spatial function are combined is shown as following:

$$u'_{ij} = u_{ij}^{p} s_{ij}^{q} \Big/ \sum_{K=1}^{Q} u_{kj}^{p} s_{kj}^{q}$$

P and q are two important parameters in the function. The spatial function in the cluster domain simply improve the original membership whereas the clustering results remains unchanged. However, equation(5) can reduces the weight of noise pixels by highlighting its neighboring pixels. Therefore, it is easy to resolve the pixels in noise area or points misclassified of defective area.

III. EXPERIMENTAL RESULTS AND ANALYSIS

To demonstrate the performance of the proposed method, comparisons between the proposed algorithm and traditional change detection algorithms were implemented. Because, CVA is the most popular difference image generation method and can provide more detailed change information[2],it was selected to compare with the GWDM. For the difference image segmentation method. FCM cluster algorithm was adopted to compare[ ].To take the advantage of the spatial information in the image segmentation GWDM-FCM is compared with the GWDM-SFCM.

Besides the visual interpretation, three objective metrics .i.e., false alarm rate (P_f),missed detection rate(P_m) and total error rate (P_t) are adopted for qualitative assessment. Specifically, P_f =FA/Nuc x 100% and P_m=MD/NC x 100% in which (FA) false alarm detection measures the number of the unchanged pixels that are detected as the changed, while (MD) missed detection refers to that of the changed pixels that are detected as the unchanged. The summation of both missed detected and false alarm forms Total error such that P_t=(FA+MD)/(N_U+N_c) x 100% where N_u and N_c denoting the total number of unchanged and changed pixels in the ground truth change map.

A. Description of the Data sets and experiments setup

The two images of size 128 x128 pixels are acquired from the very high resolution satellite as shown in Fig.4(a) and fig.4(b) which has a spatial resolution is 2.4m.

In Gabor wavelet feature extraction, some parameters were implemented using default parameters, such as U_l=0.05, U_h=0.4, S=4, K=6. In the improved SFCM cluster algorithm, the initial membership probability was randomly generated with uniformly distributed values in (0,1),c=3, m=3, ϵ=1e-5, and the maximum number of iterations was 200.

Fig.2(c),2(d) and 3(c),3(d) show the change detection results using CV-FCM, GWDM-FCM and the proposed method GWDM-SFCM have better visual change detection results and with fewer error pixels.

As shown in table I the CVA-FCM, GWDM-FCM and the proposed methods in change detection performance. Specifically, for GWDM-SFCM improved to 22.667%, 47.509% and 27.67% GWDM-FCM, and CVA-FCM respectively. In addition, the proposed GWDM-SFCM method provides better performance than GWDM-FCM. This indicates that the proposed cascade scheme is helpful for discriminating changed and unchanged pixels, and is more accurate than traditional methods.

(a) **(b)** **(c)** **(d)**

Fig.4(a) first input image **(b)** second input image (c)GWDM image (d) GWDM-SFCM

Table I: Comparing results with CVA-FCM,GWDM-FCM,GWDM-SFCM

Method	**Missed detection**		**False alarm**		**Total error**	
	Pixels	**P_m**	**pixels**	**P_f**	**Pixels**	**P_t**
CVA-FCM	180	31.73	5199	3.46	5379	47.50
GWDM-FCM	164	36.88	5993	2.74	6157	27.97
GWDM-SFCM	172	37.34	6117	2.62	6424	22.66

IV. CONCLUSION

A novel change detection technique based on Gabor wavelet features with spatial fuzzy c-means is proposed and implemented for VHR remote sensing images in this letter. The proposed algorithm extracts Gabor wavelets features from two temporal VHR images before the differencing process to obtain spatial and contextual information. A GWDM based on MRF and CVM is then proposed and used to generate and used to generate the difference image. For change detection technique in the analysis clustering based FCM algorithm is applied to segment images into clusters with similar spectral properties. In this it mainly utilizes distance between the cluster centers and pixels to compute the membership function. Hence, the neighboring pixels in an image are highly correlated where clustering becomes inaccurate. By, using spatial relationship between the pixels the clustering becomes accurate which is seldom utilized in FCM.

In this paper, we proposed a spatial FCM that includes the spatial information into the membership function to develop the segmentation results. For obtaining cluster distribution statistics the membership functions of the neighboring centers on a pixel in the spatial domain are specified. These statistics are transformed into a weighting function and incorporated into the membership function. This neighboring effect reduces the number of error pixels. The new method was tested on very high resolution remote sensing images and evaluated by using various cluster validity functions. Preliminary results showed that the effect of error rate was considerably less with the new algorithm than with the conventional FCM.

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