IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 11, November 2015

Interactive Segmentation for Change Detection using Fuzzy Local Information C-Means Clustering and SWT in Multispectral Remote-Sensing Images

V. Hima Bindu[1], G. Sreenivasulu[2]

M.Tech (Comm Systems), Dept. of ECE, SVU College of Engineering, Tirupati, Andhra Pradesh, India[1]

Professor, Dept. of ECE, SVU College of Engineering, Tirupati, Andhra Pradesh, India[2]

Abstract: Change Detection is a process that analyzes images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates. In the last decades, it has attracted widespread interest due to a large number of applications in diverse disciplines such as remote sensing, medical diagnosis, and video surveillance. The proposed method is unique in the following two aspects: 1) producing difference images by fusing a mean-ratio image and a log-ratio image and 2) improving the fuzzy local-information c-means (FLICM) clustering algorithm, which is insensitive to noise, to identify the change areas in the difference image, without any distribution assumption. With the development of remote sensing technology, change detection in remote sensing images becomes more and more important. Among them, change detection in synthetic aperture radar (SAR) images exhibits some more difficulties than optical ones due to the fact that SAR images suffer from the presence of the speckle noise. However, SAR sensors are independent of atmospheric and sunlight conditions, which make the change detection in SAR images still attractive. SAR-image change detection is mainly relied on the quality of the difference image and the accuracy of the classification method.

Index Terms: Change detection (CD), mean-ratio image, Fuzzy local-information c-means (FLICM) clustering algorithm.

I. INTRODUCTION

Change detection (CD) is one of the most important applications in remote-sensing technology. **I**MAGE change detection is a process that analyzes images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates. The unsupervised change detection in SAR images can be divided into three steps [1]-[2]:

1) Image preprocessing
2) Producing difference image between the multitemporal images and
3) Analysis of the difference image.

The tasks of the first step mainly include co-registration, geometric corrections, and noise reduction. In the second step, two co-registered images are compared pixel by pixel to generate the difference image. The change detection by using SVM-MRF has a drawback of speckle noise and it confines to only single change areas. For multiple change detection this cannot be incorporated. For this, a novel method FLICM is proposed. In this, the difference image is generated by differencing (subtraction operator) and rationing (ratio operator). These are well-known techniques for producing a difference image. In differencing, changes are measured by subtracting the intensity values pixel by pixel between the considered couple of temporal images. In rationing, changes are obtained by applying a pixel-by-pixel ratio operator to the considered couple of temporal images. However, in the case of SAR images, the ratio operator is typically used instead of the subtraction operator since the image differencing technique is not adapted to the statistics of SAR images and non-robust to calibration errors. In addition, because of the multiplicative nature of speckles, the ratio image is usually expressed in a logarithmic or a mean scale. In the third step, changes are usually detected by applying a decision threshold to the histogram of the difference image.

It appears clearly from the literature that the whole performance of SAR-image change detection is mainly relied on the quality of the difference image and the accuracy of the classification method. In order to address the two issues, in this paper, we propose an unsupervised distribution-free SAR-image change detection approach, we propose an unsupervised distribution-free SAR-image change detection approach which is unique in producing difference images by fusing a mean-ratio image and a log-ratio image, and improving the fuzzy local-information c-means (FLICM) clustering algorithm[3]-[5], which is insensitive to noise, to identify the change areas in the difference image, without any distribution assumption.

Let us consider the two co-registered intensity SAR images and of size, i.e., acquired over the same geographical area at two different times and, respectively. Our objective is aiming at producing a difference image

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 11, November 2015

that represents the change information between the two times; then, a binary classification is applied to produce a binary image corresponding to the two classes: change and unchanged, the proposed unsupervised distribution- free change detection approach is made up of two main phases:
1) Generate the difference image using the wavelet fusion based on the mean-ratio image and the log-ratio image
2) Automatic analysis of the fused image by using an improved fuzzy clustering algorithm.

There was a widespread concern over the logarithm of the ratio image since the log-normal model was considered as a heuristic parametric probability distribution function for SAR intensity and amplitude distributions. With the log-ratio operator, the multiplicative speckle noise can be transformed in an additive noise component. Furthermore, the range of variation of the ratio image will be compressed and thereby enhances the low-intensity pixels. This method have yielded effective results for the change detection in SAR imagery but still have some disadvantage: The logarithmic scale is characterized by enhancing the low-intensity pixels while weakening the pixels in the areas of high intensity; therefore, the distribution of two classes (changed and unchanged) could be made more symmetrical. However, 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. In order to address this problem, an image fusion technique is introduced to generate the difference image by using complementary information from the mean-ratio image and the log-ratio image in this paper. As mentioned in the literature, the information of changed regions reflected by the mean-ratio image is relatively in accordance with the real changed trends in multitemporal SAR images. On the other hand, the information of background obtained by the log-ratio image is relatively flat on account of the logarithmic transformation.

II. SYSTEM ARCHITECTURE:

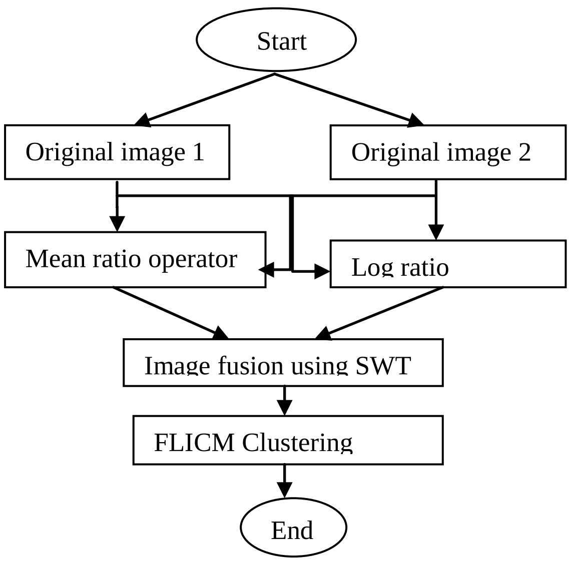

Figure: 1 Flow Chart

1. Ratio Difference image
2. Image Fusion Using SWT
3. FLICM Clustering

1. Ratio Difference Image:

The ratio difference image is usually expressed in a logarithmic or a mean scale because of the presence of speckle noise. With the log-ratio operator, the multiplicative speckle noise can be transformed in an additive noise component. Furthermore, the range of variation of the ratio image will be compressed and there by enhances the low-intensity pixels. The logarithmic scale is characterized by enhancing the low-intensity pixels while weakening the pixels in the areas of high intensity; therefore, the distribution of two classes (changed and unchanged) could be made more symmetrical. However, 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 two source images used for fusion are obtained from the mean-ratio operator and the log-ratio operator, respectively, which are commonly given by

$$\mathbf{X_m = 1 - min\left(\frac{\mu_1}{\mu_2}, \frac{\mu_1}{\mu_2}\right)} \text{ .... } \mathbf{(1)}$$

$$\mathbf{X_l = \left|\log\frac{X_2}{X_1}\right| = |\log X_2 - \log X_1|} \text{ .... } \mathbf{(2)}$$

2. Image Fusion using SWT:

Image Fusion allows one to combine images in a variety of ways. An effective image fusion algorithm should integrate all the relevant information as much as possible. The objectives of image fusion are the following:

i. To combine complementary information from images obtained from a variety of different sensors or from the same sensors
ii. To develop novel ways to use multi sensor, multi resolution, multi spectral imagery from airborne, space borne, ship board or ground-based platform.

The goal of image fusion is to minimize artifacts or distortion in the composite image as a result of fusion. With the rapid growth of advance image processing methodology and availability of variety of sensors, the idea of combining images has become important and has emerged as a new promising research area. A large variety of applications of image fusion is seen in Geo science and remote sensing application where satellite images from different bands and at different resolution is combined to extract more useful information of ground terrain.
Stationary Wavelet Transform (SWT) is similar to Discrete Wavelet Transform (DWT) but the only process of down-sampling is suppressed that means the SWT is translation-invariant. The 2D Stationary Wavelet Transform (SWT)[7] is based on the idea of no decimation. It applies the Discrete Wavelet Transform (DWT) and omits both down-sampling in the forward and up-sampling in their inverse transform. More precisely, it applies the transform at each point of the image and saves the detail coefficients and uses the low frequency information at each level.

DOI 10.17148/IJARCCE.2015.41116

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 11, November 2015

3. FLICM Clustering Algorithm:

The characteristic of FLICM is the use of a fuzzy local similarity measure, which is aimed at guaranteeing noise insensitiveness and image detail preservation. In particular, a novel fuzzy factor G_{ki} is introduced into the object function of FLICM to enhance the clustering performance. This fuzzy factor can be defined mathematically as follows:

$$G_{ki} = \sum_{j\varepsilon N_i} \frac{1}{d_{ij}+1}\left(1-u_{kj}\right)^m \left\|x_j - v_k\right\|^2 \ldots\ldots (3)$$

where the i^{th} pixel is the centre of the local window, the j^{th} pixel represents the neighbouring pixels falling into the window around the i^{th} pixel, and d_{ij} is the spatial Euclidean distance between pixels i and j, v_k represents the prototype of the centre of cluster k, and u_{kj} represents the fuzzy membership of the gray value j with respect to the k^{th} cluster. It can be seen that factor is G_{ki} formulated without setting any artificial parameter that controls the trade off between image noise and the image details. In addition, the influence of pixels within the local window in G_{ki} is exerted flexibly by using their spatial Euclidean distance from the central pixel. Therefore, can reflect the damping extent of the neighbours with the spatial distances from the central pixel. In general, with the application of the fuzzy factor G_{ki}, the corresponding membership values of the no-noisy pixels, as well as of the noisy pixels that is falling into the local window, will converge to a similar value and there by balance the membership values of the pixels that are located in the window. Thus, FLICM becomes more robust to outliers. In addition, the characteristics of FLICM include noise immunity, preserving image details without setting any artificial parameter, and being applied directly on the original image.

By using the definition of G_{ki}, the objective function of the FLICM can be defined in terms of

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} \left[u_{ki}^m \|x_i - v_k\|^2 + G_{ki}\right] \ldots\ldots\ldots\ldots (4)$$

Where represents the prototype value of the k^{th} cluster and represents the fuzzy membership of the j^{th} pixel with respect to cluster, is the number of the data items, and is the number of clusters. C is the Euclidean distance between object and the cluster centre. In addition, the calculation of the membership partition matrix and the cluster centres is performed as follows

$$u_{kj} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_j - v_k\|^2 + G_{ki}}{\|x_j - v_j\|^2 + G_{ji}}\right)^{\frac{1}{(m-1)}}} \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

$$v_k = \frac{\sum_{i=1}^{N} u_{ki}{}^m x_i}{\sum_{i=1}^{n} u_{ki}{}^m} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where the initial membership of partition matrix is computed randomly. Finally, the FLICM algorithm is given as follows.

Step 1) set the number of the cluster prototypes, fuzzification parameter and the stopping condition.
Step 2) Initialize randomly the fuzzy partition matrix.
Step 3) set the loop counter.
Step 4) Compute the cluster prototypes using equation (6).
Step 5) Calculate the fuzzy partition matrix using equation (5).
Step 6) Max $\{U^b - U^{b+1}\} < \varepsilon$ then stop; otherwise, set b=b+1, and go to step 4.

III.RESULT AND DISCUSSION

The output of the FLICM for SAR image is as follows

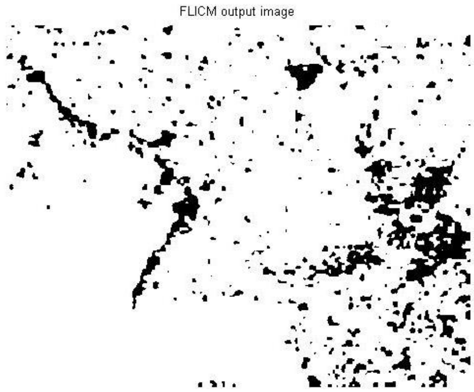

Figure:2 FLICM Output Image

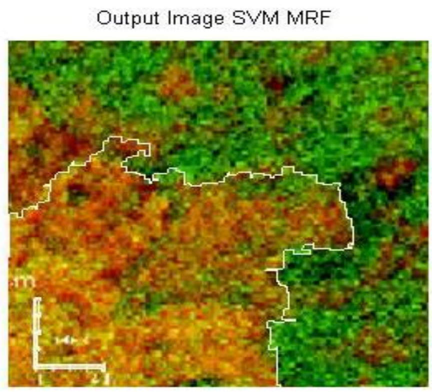

Figure: 3 SVM-MRF Output Image

```
Total Iterations = 31
Image1 Details
MSE
  306.8456

PSNR
   23.2956
```

IV.COMPARISON OF SVM-MRF AND FLICM METHOD

SVM-MRF fails when confronted with images characterized by changes situated in different regions of the DI. Future development of this approach is to extend it to the Multi change case that may characterize the DI. This disadvantage of SVM-MRF can be overcome by the FLICM. The MSE and PSNR values of the proposed method FLICM and previous method SVM [6] are as follows,

Table: 1 Comparison of SVM-MRF and FLICM

ALGORITHM	MSE	PSNR
SVM-MRF	253.6398	24.1226
FLICM	306.8456	23.2956

V.CONCLUSION

In this paper, we have presented a novel SAR-image change detection approach based on image fusion using SWT and an improved fuzzy clustering algorithm, which is quite different from the existing methods. First, for the wavelet fusion approach that we proposed, the key idea is to restrain the background (unchanged areas) information and to enhance the information of changed regions in the greatest extent. The experiment results show that the proposed wavelet fusion strategy can integrate the advantages of the log-ratio operator and the mean-ratio operator and gain a better performance. In SVM only single change is detected where as in FLICM multiple detection is done.

REFERENCES

[1] Robert O. Harger “Synthetic Aperture Radar Fundamentals and Image Processing” EARSEL ADVANCES INREMOTE SENSING, Vol. 2, No. 1-1, 1993
[2] Ashish Ghosh, Niladri Shekhar Mishra, Susmita Ghosh, “Fuzzy clustering algorithms for unsupervised change detection in remote sensing images”, Inform. Sci. (2010),doi:10.1016/j.ins.2010.10.016.
[3] Jerry M. Mendel, "Fuzzy Logic Systems for Engineering: A Tutorial", Proceedings of the IEEE, Vol. 83, No. 3, 1995, pp. 345-377.
[4] F.T. Bujor, L. Valet, E. Trouvk, G. Mauris,Ph. Bolon, “An Interactive Fuzzy Fusion System applied to Change Detection in SAR Images”, Proceedings of the IEEE International Conference on Fuzzy Systems, Vol. 2, 2002, pp. 932-937.
[5] Maoguo Gong, Zhiqiang Zhou and JingjingMa, “Change Detection in Synthetic ApertureRadar Images based on Image Fusion and Fuzzy Clustering”, IEEE Transactions On Image Processing, Vol. 21, No. 4, April 2012,pp. 2141-2151.
[6] F. Melgani and Y. Bazi, “Markovian fusion approach to robust unsupervised change detection in remote sensing images,” IEEE Geosci. Remote Sens. Lett., vol. 3, no. 4, pp. 457–461, Oct. 2006.
[7] Pusit Borwonwatanadelok, Wirat Rattanapitak and Somkait Udomhunsakul, “Multi-Focus Image Fusion based on Stationary Wavelet Transform”, 2009International Conference on Electronic Computer Technology. 978-0-7695-3559-3/09 $25.00 © 2009IEEE.