Integrating NSCT Image Fusion with Spatial Fuzzy Clustering for Multi Temporal Image Change Detection

M. Sornam[1], Muthu Subash Kavitha[2], R. Cheryal Percy[1]
[1]*Department of Computer Science, University of Madras, Chennai, India*
[2]*Department of Nuclear Medicine, Kyungpook National University School of Medicine and Hospital, Daegu, Korea*

***Abstract*—**This study proposed a change detection approach by integrating non-subsampled contourlet transform (NSCT) image fusion with spatial fuzzy clustering (SFC) model on remote sensing satellite images. The proposed study involved four phases. In first phase, input images are decomposed into approximation and detail coefficients using NSCT. In second phase, an average operator and maximum gradient coefficient Gradient is used to select pixels from the approximation and detail coefficients for generating the approximation and detail coefficients of the fused difference image. In third phase, inverse NSCT is adopted to reconstruct the fused image. Finally, SFCM and morphological operation was applied to detect the changes on the fused image. The proposed change detection method was performed on satellite radar images of yellow river estuary. Performance measures were used to compare the efficiency of the proposed approach over *k*-means algorithm in determining the changes on the fused images. The experimental results suggested that the proposed method outperforms the conventional method in terms of visual and quantitative error rate analysis.

Keywords*—*NSCT; spatial; fuzzy cluster; morphological; gradient; coefficient

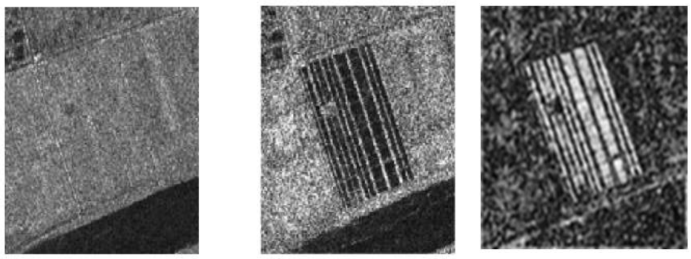
I. INTRODUCTION

The advancements in various remote sensing platforms have resulted in the generation of huge amounts of satellite images. The recent formation of satellite images are quite often multispectral or hyper spectral data [1]. It is important to arrange, sort, query and browse useful information on these image databases. Generally in all the application domains the quality of the output greatly depends on the quality of the segmented satellite images. Several image segmentation techniques have been proposed for the evaluation satellite images [1, 2, 3]. The segmentation methods are classified as edge or contour detection based [4, 5] region-based [6] and stochastic model based approaches. Several studies proposed some mimic algorithms on the basis of behavior of honey bees [7, 8]. Owing to simplicity and flexibility of image enhancement, multi scale decompositions (MSD) based fusion approaches were applied [9]. Furthermore wavelet transform model was considered as the one of the most popular approximation image fusion technique, because of the retrieval of joint information representation from the spatial-spectral domain. However wavelets are able to capture only limited directional information. Contour-let transform was showed that it can efficiently capture the intrinsic geometrical structure for visual information [10]. In addition it provides various and flexible number of directions at each scale. This study focuses integrating NSCT image fusion with SFC model for detecting changes on the multi temporal image. In order to assess the effectiveness of the proposed technique we applied performance metrics for image change detection. Furthermore the performance of the proposed SFC based change detection model was compared with that of k-means algorithm.

II. PROPOSED METHODOLOGY

A. Experimental Dataset

The data set is a pair of two SAR images with 3m resolution acquired by Radarsat-2 at the region of yellow river estuary in China in June 2008 and June 2009 as shown in *Fig. 1(a)* and *(b)*, respectively. These images showed vegetation areas (paddy field) and included different levels of strong noises. The combination of sensory data from multiple sensors provides more reliable and accurate information. The ground truth map is shown in Figure. 1(c) which is generated based on the prior information of the picture interpretation based on the input images from *Fig.1* (a) and 1(b).



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

Fig.1. Satellite radar images of yellow river estuary acquired (a) in 2008 (b) in 2009 (c) ground truth

B. Image Change Detection

The proposed image change detection approach on satellite radar images involved various methods as shown in *Fig. 2.*

C. NSCT Based Image Fusion

The image fusion technique is introduced to generate a difference image by using complementary information from source images as shown in *Fig.3*. Furthermore it is a method of combining relevant information from two or more images into a new single image [11]. It has been successfully employed in image enhancement, de-noising and fusion. Most of the fusion approaches are based on the combinations of the MSDs of the source images. In order to improve the fusion performance and avoid the discontinuity in the transition zones between focus and defocus, new image fusion rules for low and high pass sub band coefficients were developed. It is based on the technique of focused region detection and selection principles. NSCT based fusion involves an average operator and maximum gradient coefficient to fuse low-frequency and a high-frequency band, which restrain the background information and enhance the information of the changed regions in the fused difference image. NSCT is a kind of multi-scale and multi-direction computation framework of the discrete images. It involves two stages such as non-sub sampled pyramid (NSP) and non-subsampled directional filter bank (NSDFB) to extract textures, contours and detailed coefficients. NSP decomposes the images into low and high frequency sub bands at each decomposition level. It produces n+1 sub images in the *n* decomposition level. NSDFB extracts the detailed coefficients from directional decomposition of high frequency sub bands which is obtained from NSP. It generates *m* power of two directions of sub images at *m* number of stages.

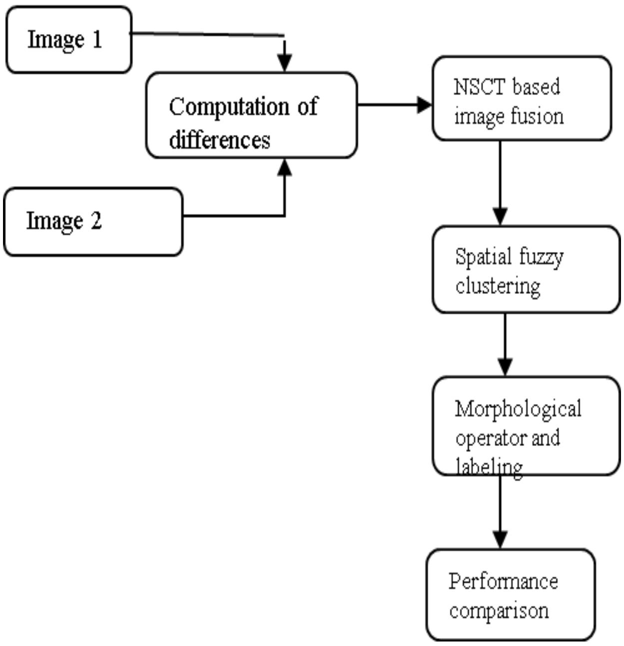


Fig. 2. Block diagram of the proposed image change detection method

D. Spatial Fuzzy Clustering Model

Spatial fuzzy clustering is adopted in this study for classifying the changed and unchanged regions from the fused images. It is an effective method for analyzing the relevant information from huge number of data. Traditional fuzzy c-means (FCM) algorithm groups data into each by using memberships [12, 13]. FCM is an iterative algorithm that minimized the cost function defined as follows:

$$Q = \sum_{i=1}^{J} \sum_{i=1}^{c} u_{in}^{m} \left\| x_n - v_i \right\|^2 \quad (1)$$

where u_{in} represents the membership of pixel x_n in the *n*th cluster, v_i is the *i*th cluster center and *m* is constant. The cost function is minimized when pixels close to the centroid of their clusters are assigned high membership values. The pixels with data far from the centroid are assigned low membership vaues. The spatial relationship of an image is important in clustering [14]. But it is not considered in a traditional FCM algorithm. Hence incorporating spatial information into an FCM is useful to minimize image noise, artifacts and thus image segmentation is improved. To utilize the spatial information, a spatial function is incorporated into membership function

$$u_{in}^{'} = \frac{u_{in}^{t} g_{in}^{r}}{\sum_{p=1}^{c} u_{pj}^{t} g_{pj}^{r}} \quad (2)$$

where t and r controls the relative importance of both functions. This procedure is a two-pass process at each iteration. In the first pass, FCM calculate the membership function in the spectral domain. In the second pass, the membership information of each pixel is mapped to the spatial domain, and the spatial function is retrieved from that. The iteration is stopped until the difference between two cluster centers at two successive iterations is less than a user defined threshold at 0.04.

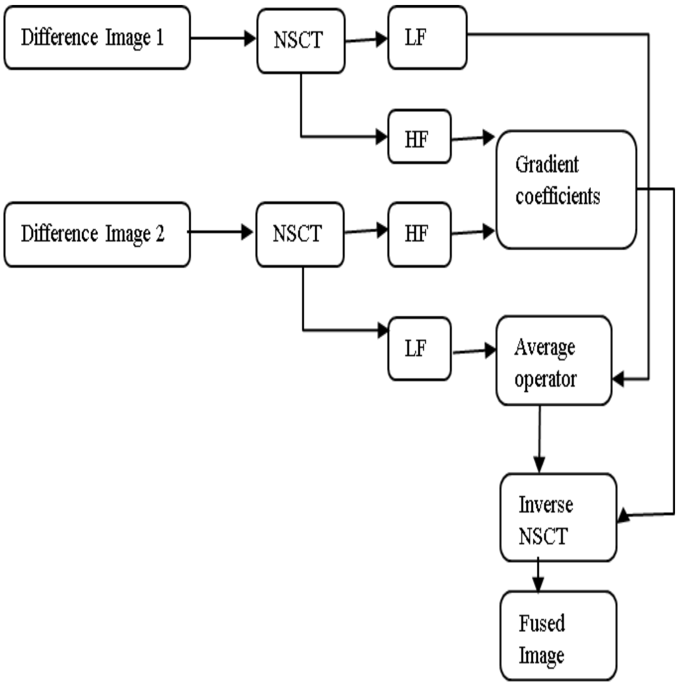


Fig.3. Block diagram of the reconstruction of the fused image using NSCT model

E. Morphological operation and labeling

It is a collection of non-linear operations related to shape or morphology of the image features. We applied erosion operator with small (2×2) square structuring elements, which shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. Finally connected component labeling was used for visualizing the changes on the fused images as shown in *Fig.4*.

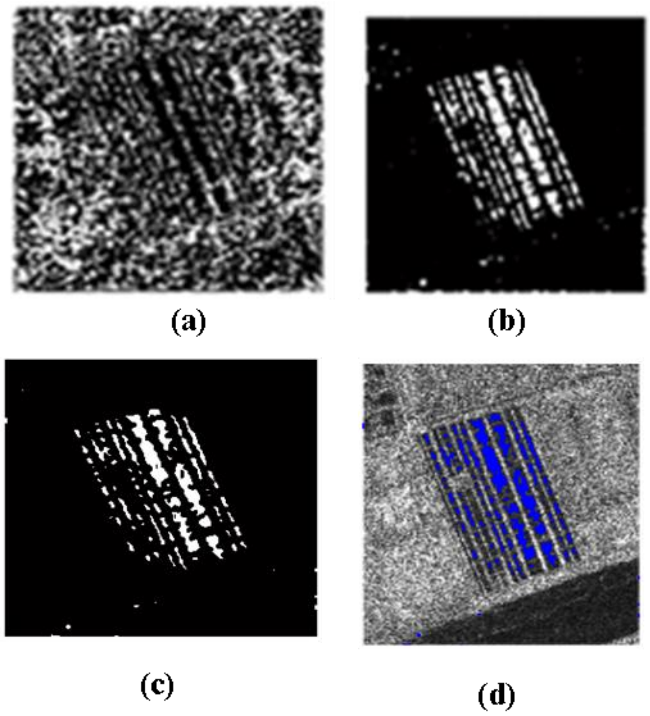


Fig.4. Image change detection (a) results of fused image, (b) results of spatial fuzzy clustering (c) results of morphological operation, (d) results of labeling

III. EXPERIMENTAL RESULTS AND DISCUSSION

In order to validate the effectiveness of the proposed image change detection method, we used performance evaluation metrics. Peak signal-to-noise ratio (PSNR) is used to estimate the quality of the image. In order to calculate PSNR value, the dB value is adopted in this study. The larger value of PSNR indicates, the higher the image quality, which means the differences between the input and fused images are very less. Furthermore, a smaller PSNR value indicates that there is a high difference exists between the images. In addition we used sensitivity measurements for computing the proportion of correctly identified changes on images and accuracy for computing the degree of closeness of observed value to the true value. In addition the performance of the proposed SFC approach is compared with that of the conventional *k*-means method [15]. The objective criterion of *k*-means was to minimize the sum of the within-cluster variations. The number of clusters *k*=3 was used to allocate every pixel according to the group with nearest centroid based on the measured minimum squared Euclidean distance. The proposed SFC based change detection showed high dB (59.44) value than *k*-means, indicated that the visual evaluation in terms of image quality is higher compared to k-means method is presented in Table I. Furthermore, the sensitivity (99.6%) and accuracy (85.79%) of the proposed method is much higher than those (92.5%, and 69.2%, respectively) with the *k*-means method. The vast performance difference between these two methods is reasonable because the proposed SFC based method is less sensitive to noise than the *k*-means method. However this study evaluated just two sets of satellite radar images is the limitation of this study. Hence the proposed method should evaluate large number of other multi temporal images for generalization performance. In this study we proposed a change detection technique by integrating NSCT image fusion and spatial fuzzy clustering method. The NSCT decomposition adopted in this study was effectively extracted the smoothing and contour wedges from images. The fuzzy clustering that incorporates spatial information into the membership function improved the segmentation of the fused image. Preliminary results suggested that the effect of noise and artifacts on satellite radar images was considerably reducing and produced better segmentation results than with the conventional k-means method.

TABLE I. Performance comparison of the proposed method with k-means

Methods	PSNR(db)	Sensitivity (%)	Accuracy (%)
Proposed method	59.44	99.61	85.79
K- means	47.85	92.52	69.15

IV. REFERENCES

[1]. M. K. Rid and J. Liu, “A comparison of four algorithms for change detection in an urban environment,” Remote Sens. Environ. vol. 63, no. 2, pp. 95–100, Feb. 1998.

[2]. S. Huang, L. Danish, and H. Mingling, "Multi-temporal SAR Image Change Detection Technique Based on Wavelet Transform," Act Geodetic etc Cartog. Son., Vo1.32, NO.2, pp.180-185, 2010.

[3]. E. Rig not and J. van Zyl, “Change detection techniques for ERS-1 SAR data,” IEEE Trans. Geo science Remote Sens., vol. 31, no. 4, pp. 896–906, Jul. 1993.

[4]. A. Robin, L. Moissan, and S. Le Hegarat-Mascle, “An a-contraries approach for sub pixel change detection in satellite imagery,” IEEE Trans. Pattern Anal. Mach. Intel., vol. 32, no. 11, pp. 1977–1993, Nov. 2010.

[5]. A. P. Dempster, N. M. Laird, and D. B. Rubin, “Maximum likelihood from incomplete data via the EM algorithm,” J.R. Stat. Soc., vol. 39, no. 1,pp. 1–38, 1977.

[6]. F. Chatelaine, J.-Y. Tournament, and J. Include, “Change detection in multi sensor SAR images using vicariate Gamma distributions,” IEEE Trans. Image Process. vol. 17, no. 3, pp. 249–258, Mar. 2008.

[7]. M. Marinaki, Y. Marinakis and C. Zopounidis, “Honey Bees Mating Optimization algorithm for financial classification problems,” App. Soft Comp., 10 (3) (2010), pp. 806-812

[8]. D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," J. Glob. Optim., 39 (3) (2007), pp. 459-471
[9]. X. Cai and G. Han, "Improved Statistical Image Fusion Method Using a Continuous-Valued Blur Factor," Opt. Eng., vol. 51, pp. 047004-1–047004-10, 2012.
[10]. L. Yang, B. L. Guo, and W. Ni, "Multifocus Image Fusion Algorithm Based on Region Statistics in Contourlet Domain," J. Xi'an Jiaotong Univ., vol. 41, pp. 448–452, April 2007.
[11]. M.N. Do and M. Vetterli, "The contourlet transform: an efficient directional multiresolution image representation," IEEE Trans. Image Process., 14 (2005), pp. 2091-2106
[12]. K.S. Chuang, H.L. Hzeng, S. Chen, J. Wu and T.J. Chen. "Fuzzy *c*-means clustering with spatial information for image segmentation," Comp. Med. Imag. Gra., 30 (2006), pp. 9-15
[13]. W. Cai, S. Chen and D. Zhang. "Fast and robust fuzzy *c*-means clustering algorithms incorporating local information for image segmentation," Pattern Recognition, 40 (2007), pp. 825-838
[14]. .J. R. G. Townshend and C. O. Justice, "Spatial variability of images and the monitoring of changes in the normalized difference vegetation index," Int. J. Remote Sens., vol. 16, no. 12, pp. 2187–2195, 1995
[15]. .J.A. Hartigan, Clustering Algorithms, Wiley, New York, 1975.

.