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Monitoring Change Detection By Altering MRF Energy Function In SAR Images For Disaster Analysis

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Abstract

This approach classifies images by detecting the changes in two different images taken using synthetic aperture radar (SAR) for analyzing disaster. It monitors the unchanged & changed regions using fuzzy c-means (FCM) clustering technique with an altered Markov Random field (MRF) energy function. To reduce the speckle noise, the membership of each pixel is altered by the new approach of Markov Random Field energy function with an additional term. This alteration is done by the studyof relationship between neighborhood pixels. The additional term which is used in MRF energy function is determined by the utilization of least square method. With this approach, the time consuming is very less in detecting the changes between two SAR images, of same scene taken at different time is concluded by theoretical analysis and through experimental results

Index Terms—Markov random field (MRF), Fuzzy c-means clustering algorithm,Image change detection,synthetic aperture radar (SAR).

I. INTRODUCTION

Many researches are based on remote sensing that are related with image change detection. It detects changes in images based on Markov random field (MRF) technique and a fuzzy c mean clustering algorithm. Fuzzy c-mean (FCM) algorithm, it gets more information by grouping similar elements together. It also retains more information than any other clustering technique. In order to stop background noise Markov random fields with fuzzy c mean clustering algorithm is used. It classifies changed and unchanged regions. This approach follows four steps, first step is interest point extraction, second step is context computation, third step is Markov random field which includes image preprocessing, generation of difference image from multiple images and analysis of difference image, fourth step is matching process. Image change detection used for the purpose of remote sensing, such as medical diagnosis, video surveillance, military purpose, risk management, disaster analysis updating maps, sea state, ice hazard, oil spill boundaries on water to environmentalists and monitoring vegetation.

With the help of SAR images, the changes happening on earth space can be monitored. Synthetic Aperture Radar (SAR) provides such a capability to monitor region continuously. SAR is used for long-range propagation of radar signals and gives high resolution images for analyzing change detection between images.

II. LITERATURE SURVEY

Research in image change detection is carried out from the past several years. Its objective is to detect region of changes in images. It is found that in some of the researches, various change detection methodologies were followed. In [1],A.A. Nielsen proposed an unsupervised identification in multi temporal images using Multivariate alteration detection (MAD) transformation and Canonical Correlation Analysis (CCA) which gives correlated and generalized orthogonal difference in images. In [2], Cai et al proposed an FGFCM (fast generation fuzzy c-means algorithm) for segmenting images focusing on intensity of local pixel neighborhood and gray level for the images. In [3], Diego Fernandez Prieto and Lorenzo Bruzzone, proposed an unsupervised identification of changes in multiple images using an adaptive semi-parametric which generates change detection map, this provides a methodological framework analysis of difference images. In [4], Chatzis and Krindis, proposed a Robust fuzzy local information c-means clustering(FLICM)algorithm segmentation for image detail preservation and noise insensitiveness. In [5],S. Q. Huang, proposed novel integration change detection technique and texture fusion to reduce the error of change detection, to identify the change quality, to calculate the coefficients corresponding to multiple images and to eliminate the difference of brightness and contrast between images. In[6],LinzhiSu, Maoguo Gong MengJia and Weisheng Chen, they proposed Reformulated Robust fuzzy local information c-means clustering (RFLICM) which includes data about spatial context by adding some factors into the objective function for detecting change information and to reduce the speckle noise from images. In [7], FizaziIzabatene Hadria and Riffi Mohamed Amine, proposed techniques such as Tasseled Cap Transformation (TCT) & Integration Normalized Difference Vegetation Index to reduce errors of omission and to improve changes in classes of vegetation. In [8],S. Hachicha and F. Chaabane, they proposed SAR Filter preprocessing to monitor thechange detection and to analyze the time series. In [9],F.Katlane, M.S.Naceur and M.A.Loghmari,they proposed Spatial analysis technique for tracking seasonal change detection in soil and for managing natural resources. In [10]NiladriShekhar Mishra,AshishGhosh, SusmitaGhosh, they proposed an context-sensitive and fuzzy clustering techniques for quantitative evaluation of the performance with low time complexity. In [11], YakoubBaziproposed an unsupervised change-detection approach which uses closed loop process to analyzevarious single-channel synthetic aperture radar images, to produce change detection map and to generate a log ratio image and reduce speckle noise. In[12],MujdatCentin& William Clem Karl, they proposed a quadratic regularization process, image Reconstruction and non quadratic optimization process for increased resolvability of point- scattered and enhancement of object shapes remove side lobe artifacts. In [13]F.Chatelain, Tourneret, Inglada.J, proposed Multisensory Multivariate Gamma Distributions (MuMGDs) and correlation coefficient for detecting changes in images with different number of looks, monitoring application and produce indicator for changed images.

III. CONTEXT COMPUTATION AND THE DESCRIPTION OF MARKOV RANDOM FIELD PROCESS

An interest point gives well-defined position to determine the difference between two SAR images. Context computation is calculated with local spatial configuration. The interest points between two images are found for log detection.

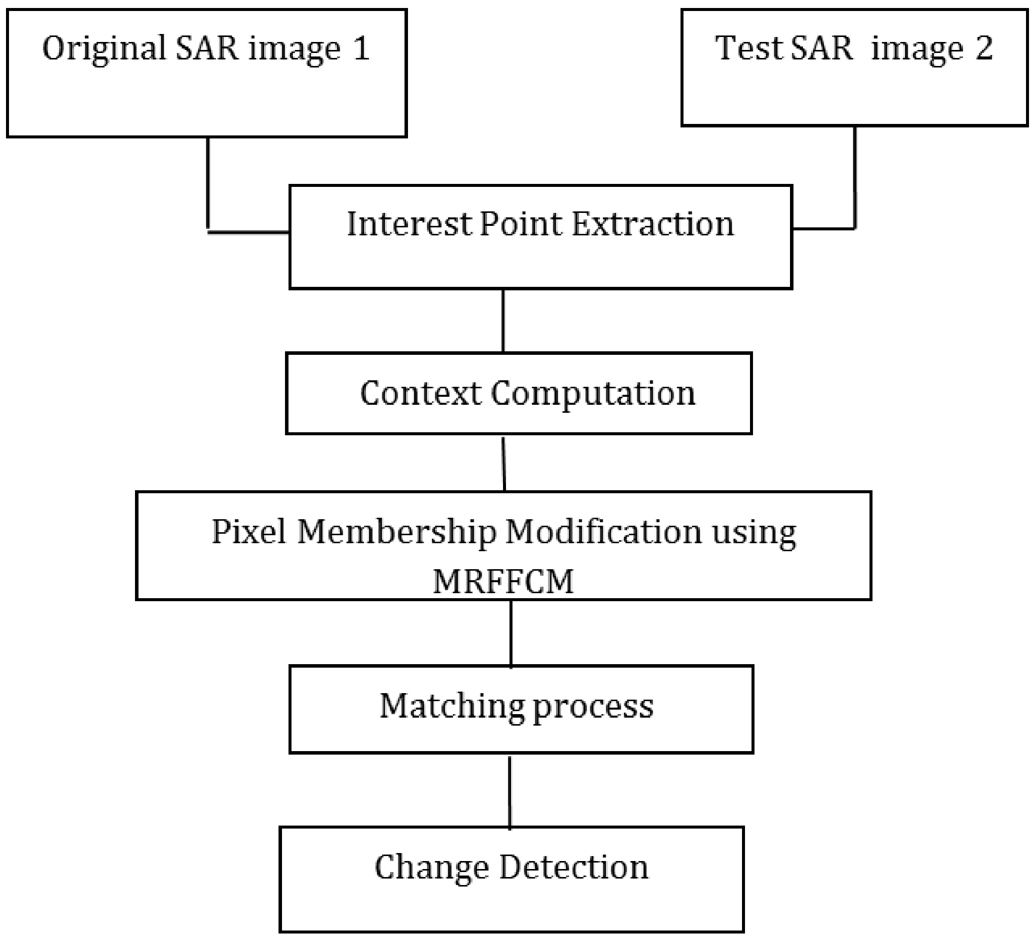


Fig 1. Change Detection Process

The membership of pixelsis modified using MRF process and the information provided by the neighborhood pixels serves as spatial context. The energy function is then established and the Gibbs expression is computed to generate point wise prior probability before updating the membership. The various steps involved include i) Thespatial context iscomputed byintegrating the MRF into FCM. It involves image preprocessing, generation of difference images from multi temporal images and analysis of the difference image.Image preprocessing is used to enhancethe data such as to eliminatelow- frequency backgroundand tonormalize the intensity andfor removing reflection.

IV. MATCHING PROCESS

During matching process, the binary map is evaluated and in this approach, ground truth image is taken as reference image, all pixels and actual numbers of pixel based on unchanged and changed class(*Nu*and *Nc*) are then calculated. The value of Kappa Coefficient ranges from 0 to 1. TheKappa Coefficient depends on the dependent values of TN(True Negative) and TP(True positive). But PCC (Percentage Correct Classification) depends on the sum of the value of TN and TP. It is found that, the values of Percentage Correct Classification or Overall Erroris very similar on some algorithms, but Kappa coefficient has large discrepancy. True positive (TP)&True negative (TN)can be referred as sensitivity and specificity.

V. STEPS INVOLVED IN FINDING IMAGE CHANGE DETECTION

(a) Let the two size of SAR images be P× Q.

$$I_1 = \{I_1 (h, l), 1 \leq h \leq P, 1 \leq l \leq Q\},$$

$$I_2 = \{I_2 (h, l), 1 \leq h \leq P, 1 \leq l \leq Q\}.$$

(b) Then mean ratio operator and log ratio operator is used

$$\text{Mean ratio operator } m = 1 - \min\left(\frac{e1}{f1}, \frac{f2}{e2}\right)$$

Log ratio operator $log = (\frac{e1}{f1})$, wheree_1 &$e_2$arelocal mean value and f_1 &f_2 are absolute logarithmic values. Mean ratio operator generates difference image. Log ratio operator is used to enhance the low intensity pixel values. Log ratio operator covers large area for detecting the change in regions.

(c) On applying MRFFCM algorithm

During the kth iteration, let k be 1, meanμ_i^1 and standard deviation σ_i^1, energy function E_{ij}^k. On applying Gibbs expression, the point wise prior probability matrix (π_{ij}^k) is computed

$$\pi_{ij}^k = \frac{\exp(-\mathrm{E}_{ij}^k)}{\exp\left(-\mathrm{E}_{ij}^k\right) + \exp(-\mathrm{E}_{ij}^k)}$$

Then the conditional probability (p_I^K)is found and then the distance matrix(d_{ij}^k)is generated

$$p_i^k\left(\frac{y_j}{\mu_i^k,\sigma_i^k}\right) = \frac{1}{\sigma_i^k\sqrt{2\pi}} exp\left|-\frac{y_{j-}\pi_i^{k^2}}{2(\sigma_i^k)^2}\right|$$

$$d_{ij}^k = -ln\left[p_i^k\left(\frac{y_j}{\mu_i^k,\sigma_i^k}\right)\right]$$

Theobjective function d_{ij}^k is then found by

$$d_{ij}^k = -ln\left[p_i^k\left(\frac{y_j}{\mu_i^k,\sigma_i^k}\right)\right]$$

$$\left|J_{ij}^k - J_{ij}^{k-1}\right| \leq \delta$$

The new membership matrix$\{\mu_{ij}^{k+1}\}$ is then generated as

$$\mu_{ij}^{k+1} = \frac{\pi_{ij}^k \exp(-d_{ij}^k)}{\pi_{ij}^k \exp\left(-d_{uj}^k\right) + \pi_{cj}^k \exp(-d_{cj}^k)}$$

Themean$\mu_i^{k+1}$and standard deviationσ_i^{k+1} are updated respectively,

$$\mu_i^{k+1} = \frac{\sum_{j\epsilon I_x}(\mu_{ij}^k\, y_j)}{\sum_{j\epsilon I_x}(\mu_{ij}^k)}$$

$$\sigma_i^{k+1} = \sqrt{\frac{\sum_{j\epsilon I_x}\left[u_{ij}^k\ (y_j - \mu_i^{k+1})^2\right]}{\sum_{j\epsilon I_x}(u_{ij}^k)}}$$

VI. EXPERIMENTAL RESULTS

i) Bern, Switzerland Dataset

fig 2(a)

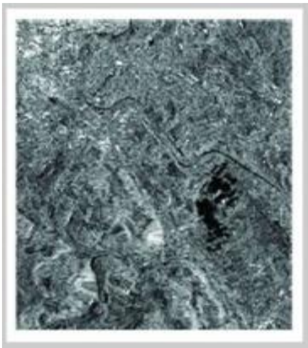


fig 2(b)

fig 2(c)

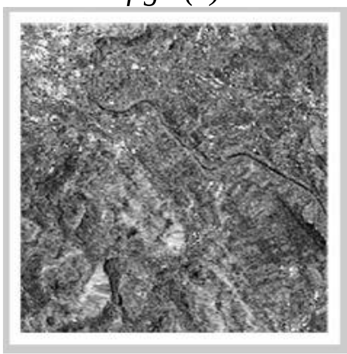


fig 2(d)

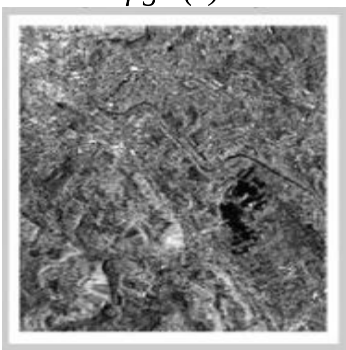


fig 2(e)

fig 2(f)

fig 2(g)

fig 2(h)

fig 2(i)

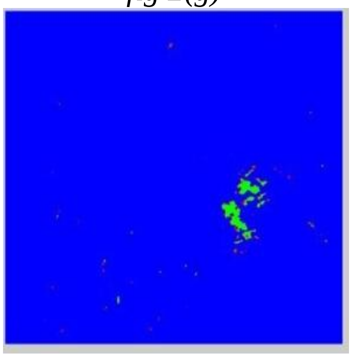


fig 2(j)

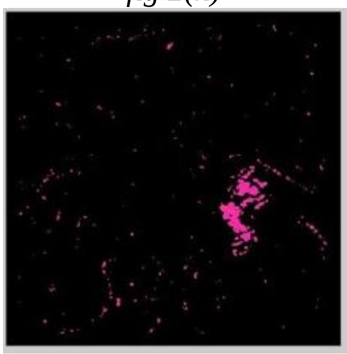


fig 2(k)

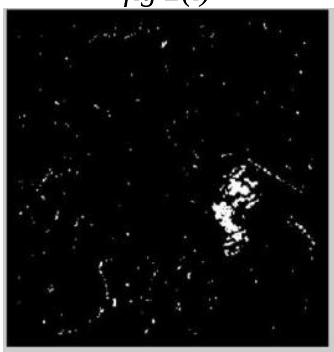


fig 2(l)

fig 2(m)

fig 2(a)& 2(b) - Image captured in April and May1999 respectively,fig 2(c)Ground Truth Image based on MRFN, fig 2(d) &fig 2(e) black and white of input images, fig 2(f) Mean Ratio Operator,fig 2(g) Log Ratio Operator, fig 2(h) Discrete Wavelet Transform Fused Image,fig 2(i) Ground Truth Image,fig 2(j) First HSV (hue saturation value) image,fig 2(k) Second HSV Image, fig 2(l) Third HSV Image, fig2(m) MRFFCM Output.

ii) Ottawa Dataset

fig 3(a)

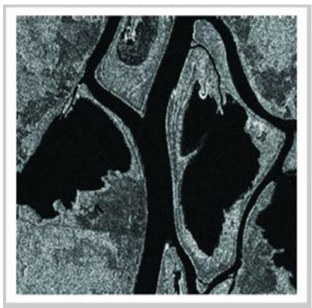


fig 3 (b)

fig 3 (c)

fig 3(d)

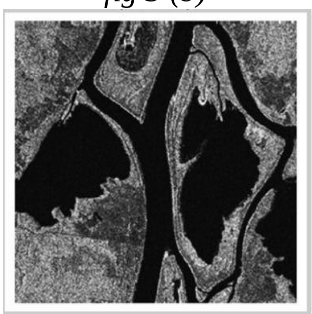
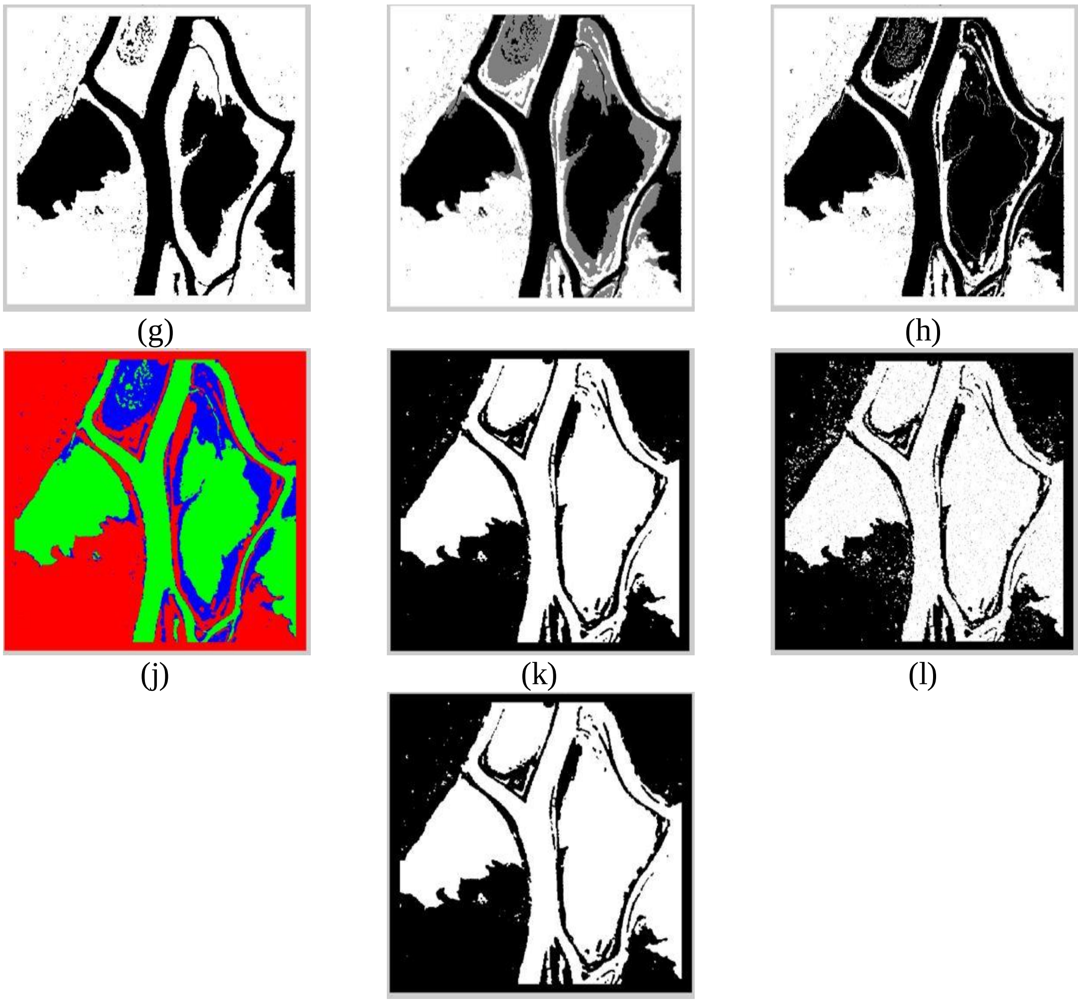


fig 3(e)

fig 3(f)



(g) (h)

(j) (k) (l)

(m)

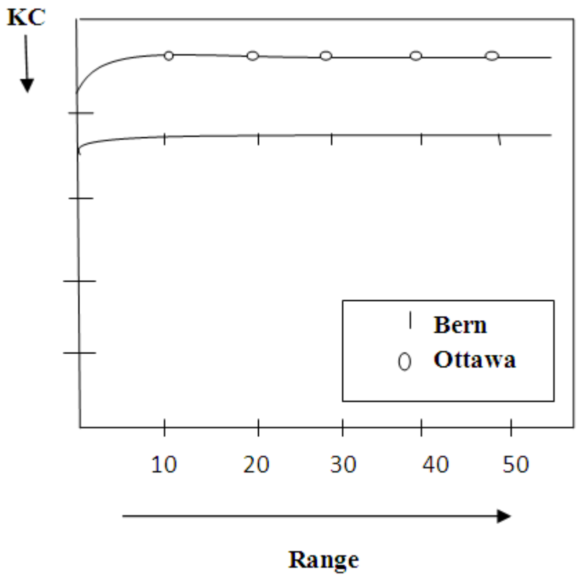
Fig 3(a) & 3(b) Image captured in May& Aug 1997, fig 3(c) Ground Truth Image based on MRFN, fig 3(d) & 3(e) black and white of input images, fig 3(f) Mean Ratio Operator, fig 3(g) Log Ratio Operator, fig 3(h) Discrete Wavelet Transform Fused Image, fig 3(i) Ground Truth Image based on MRFFCM Algorithm, fig 3(j) First HSV (hue saturation value) image, fig 3(k) Second HSV Image, fig 3(l) Third HSV Image, fig 3(m) MRFFCM Output.

TABLE 1 shows values for the evaluation criteria of Bern dataset.

	FP	FN	OE	PCC	KC	T/s
RFLICM	2381	469	2850	0.971	0.907	161.3
MRFN	2642	414	3056	0.96	0.892	63.5
MRFFCM	359	726	103.9	0.912	0.91	65.18

where FP (False Positive) and FN (False Negative) number of the pixels belonging to changed and unchanged classes, OE (overall error), PCC (percentage correct classification), KC (kappa coefficient), T/s (Time per second).

The following graph represents the Kappa coefficient values of two datasets. *Testing curve of two dataset*



VII. CONCLUSION

This approach detects the real Changes between two synthetic aperture radar (SAR) images based on Markov random field fuzzy c Means (MRFFCM) clustering algorithm with altered energy function. The experimental result shows less time consuming and it also effectively reduces the speckle noise by the least square method on the additional term in MRF energy function. Based on this algorithm , it is easy to predict the real changes between two SAR images in low time complexity. These techniques basically rely on the mathematical results such as elementary function data and least square method. These approaches are based on the gray level intensity and serves as an unsupervised approach. This paper is focused on reducing the speckle noise and the simplicity in computation with low time complexity. This can be further extended by computing the energy function with prior information about the scene.

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