An unsupervised change detection system for satellite images with various dimensions

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ABSTRACT

This paper proposes a system for finding changes in satellite images taken at two different intervals of time and it may be some years or occurrences of images before and after flooding etc.,. The changes are obtained as binary labels (changed / unchanged) for each pixel. The input images may be of monochromatic or color images and also these images may be of various graphic file formats like PNG, BMP, JPG etc.,. The RGB images are converted to gray images. The mean ratio and log ratio are obtained from both input images. These are fused together to form a difference image using Discrete Wavelet Transform (DWT). A fuzzy clustering approach is applied to classify both changed and unchanged regions in the difference image. Previously this system is done using Fuzzy Local Information C means clustering. To enhance the changed information and to reduce the effect of noise, the spatial contextual information is added along with the self data information using Reformulated Fuzzy Local Information C-means Clustering (RFLICM). The resultant change detected images are showing good performance than the existing techniques. The performance measures are compared using Percentage of Correct Classification (PCC) and Kappa statistic parameter which gives the measure of accuracy for FLICM and RFLICM. Experimental results are compared for different dimensions of satellite images with different file formats taken at different intervals of time and the computation time is also found out.

Keywords: Image Fusion, Reformulated Fuzzy Local Information C-means Clustering, Percentage of Correct Classification, Spatial Contextual Information, Dimensions

I. INTRODUCTION

The community of computer vision has been directed towards the research of automatically detecting changes in images (R. J. Radke, 2005) because of its importance in wide areas. The most important application areas include video surveillance (L. Bruzzone and D. F. Prieto, 2002; A. A. Nielsen, 2007; Y. Bazi, 2005; F. Bovolo, 2005), medical diagnosis, multitemporal remote sensing images, tracking moving objects in traffic monitoring systems, or driver assistance systems.

Image Change Detection is the process of distinguishing differences in the state or the feature of the phenomenon by observing images at two different intervals of time. It is also defined as the process that analyzes the same image taken at two different times in order to identify the changes occurred between acquisition dates.

The Change detection system is more difficult in satellite images because satellite sensors are independent of atmosphere and sunlight (F. Bujor, 2004; F. Chatelain, 2008; J. Inglada and G. Mercier, 2007). There are two types of change detection methods available. They are unsupervised and supervised change detection methods. The unsupervised method consists of mainly three steps: preprocessing, creation of difference image, analyzing difference image. The preprocessing can be done using co-registration or by geometric correction. Then the two co-registered images are compared pixel by pixel to generate the difference image or the ground truth image which can be produced using rationing or differencing technique. The histogram for the difference image is drawn. The changes in the difference image can be detected by applying suitable threshold on the histogram. There are some thresholding methods available like Otsu and Expectation Maximization algorithms (M. Sezgin and B. Sankur, 2004). This is called as unsupervised change detection because the generation of ground truth image has no prior knowledge about the environment.

The changes can be detected accurately by the quality of the difference image and the correct classification of the image into changed and unchanged regions. A new methodology is proposed on the satellite images for detecting the changes in those images acquired at two different times with same size. Here a difference image is produced by fusing the mean-ratio and log-ratio images. Then the RFLICM is applied which is not sensitive to noise and to identify the changed areas accurately.

II. CONTIBUTION OF THIS PAPER

The two satellite images X_1 and X_2 may be of monochromatic or colour images acquired over same geographical area at two different times like T_1 and T_2 respectively. These images are converted to gray images using gray scale conversion.

The objective of our research is to classify both changed and unchanged classes. So generate the difference image using mean-ratio and log-ratio and fuse those images using wavelet fusion. Both ratio images yield effective results for various images as it is explained in the literature. The log ratio has a disadvantage of enhancing the low intensity pixels while weakening the high intensity pixels. So it can't able to classify the correct differences in the resultant image.

The optimal difference image should contain the unchanged area information and should also enhance the changed area information. Therefore these two ratio images are fused to get the effectiveness of both images by using complementary information. So instead of getting simply the difference image, if we use the fused difference image it will provide better results than methods available in the literature (A. Singh, 1989).

Normally the analysis is done in the difference image by seeing the histogram of the image. But for that the decision threshold must be an important factor. So automatically the analysis is done in the fused image by applying the spatial contextual information in the Fuzzy C-means (FCM) clustering algorithm (E. J. M. Rignot and J. J. Van Zyl, 1993). The experiment is tested for various graphic file formats. Also the dimensions can be varied for the input satellite images and the experiment is conducted to analyze the correctly detected area and to analyze the computation time for these images.

III. IMAGE CHANGE DETECTION SYSTEM

The image change detection system for satellite images is a great challenge. The Image change detection steps are depicted in Figure 1. The aim of this approach is to label each pixel of the incoming various file format images as changed or unchanged.

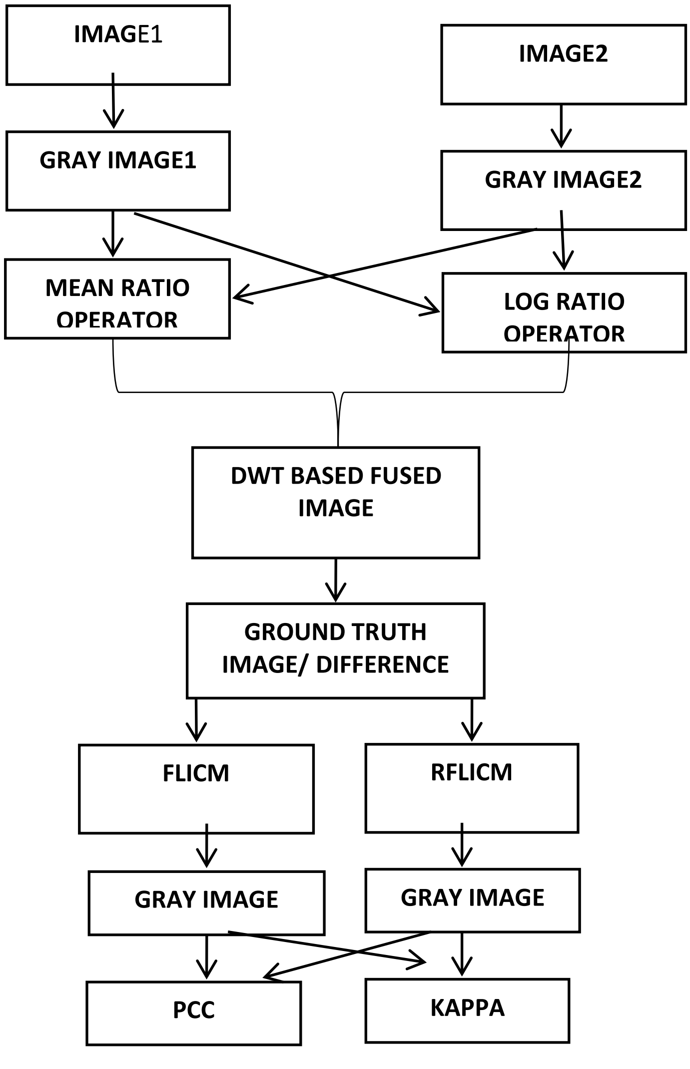

Fig.1.Image Change Detection System

The satellite images must be co-registered and must be taken at different intervals of time. The dimensions of the images should also be same. The satellite images are very sensitive to noise as these images carry a lot of effective information on these pixels.

The proposed system consists of mainly two steps: Generating the difference or Ground Truth image using image Fusion, Detecting the changed areas in the difference image using FLICM. The flowchart is explained as follows:

1) Gray Scale Conversion: The change detection approach is suitable for finding changes in color images and also for Gray images. The inputs images may be of various file formats. The color images have to be converted to gray scale images. All processing can be done on Gray images.

2) Mean-Ratio Operation: The local mean values of the gray images are calculated as μ_1 and μ_2. Now the mean-ratio operator can be applied as $X_m = 1 - \min\left(\frac{\mu_1}{\mu_2}, \frac{\mu_2}{\mu_1}\right)$

3) Log-Ratio Operation: The log values of the gray images can be calculated by obtaining the logarithm of these images. Now the log-ratio operator can be applied as follows:

$$X_l = \left|\log X_2 - \log X_1\right|$$

4) DWT based Image Fusion: The Image fusion is the technique to obtain the greater quality information by using the complementary information supplied by both mean-ratio and log-ratio images. In (G. Piella, 2003), the image fusion takes place at the pixel level of source images where DWT is mainly used. The DWT is used because of its preserving image details. The proposed system has to generate the difference image which should contain the unchanged area information and should augment the transformed region data.

5) Change Detected areas in fused image using FLICM: The clustering is the process for classifying objects in the samples of the same cluster are similar to one another. So the difference image must be divided into two categories into changed and unchanged regions. FCM is the most popular method because it retains more information from the original image and it is more robust. It is sensitive to noise but not considering the spatial contextual information. This disadvantage can be overcome by combining the self-information and local gray information (S. Krinidis and V. Chatzis, 2010).

In (D. Beulah David and B. V. Krishna, 2010), the pixel in the image has influence on its neighbourhood so by including the spatial contextual information along with the self-data information will increase the overall performance. Also in (L. Bruzzone and D. Fernández Prieto, 2000), another method is proposed which significantly reduces the computation time by clustering on the histogram of gray level. It is also less sensitive to noise. But the method must be generated which should provide the robustness and effectiveness of preserving the image details as there is no prior knowledge about the image.

The FLICM is a method which provides these two parameters and enhances the clustering performance. It includes the spatial contextual information i.e. the information supplied by the neighbors is also included for the corresponding pixel. The characteristics of FLICM method includes noise immunity, preserving the details of the image. The objective function of this method must be carefully defined which represents the cluster and the membership of the pixel in that cluster.

The RFLICM method is generated because of the measure of damping extent of neighbors with spatial distances from central pixel. If the spatial distance is greater, then the damping extent is smaller and it is vice versa. So instead of spatial distance the local variance and the mean of the local window say 3 X 3 in the image is calculated. So it has more effect on the edges and in the noise corrupted areas. So it produces good changes in the resultant image than the previously developed methods.

The same methodology is repeated for the images with various dimensions like 512 X 512, 400X400 and 100 X 100 and the computation time for all these images can be got. The outdoor environment images are tested for this experiment. Also various graphic file formats are tested.

IV. DESCRIPTIONS OF DATA SETS AND EXPERIMENTS

A. **Description of the Data Sets:** Different experiments have been carried out in various environments with various graphic file formats images like PNG, JPEG, GIF and GIF to assess the validity and robustness of the proposed approach. The window size is the neighborhood required for mapping the contextual information. The experiments are done in outdoor, indoor and Bio medical environments where different formats like JPEG, GIF, BMP and PNG performance are compared. The images are taken in their normal size and also tested with various dimensions (Pajares G, 2006). Finally the execution time of finding the changes in the images is also calculated for various dimensions. The execution time is expressed in seconds and it will vary for different environments.

B. **Experimental Results:** The quantitative analysis or the performance parameter for finding the changes in the images can be calculated from (PCC) percentage of Correct Classification and Kappa parameter.

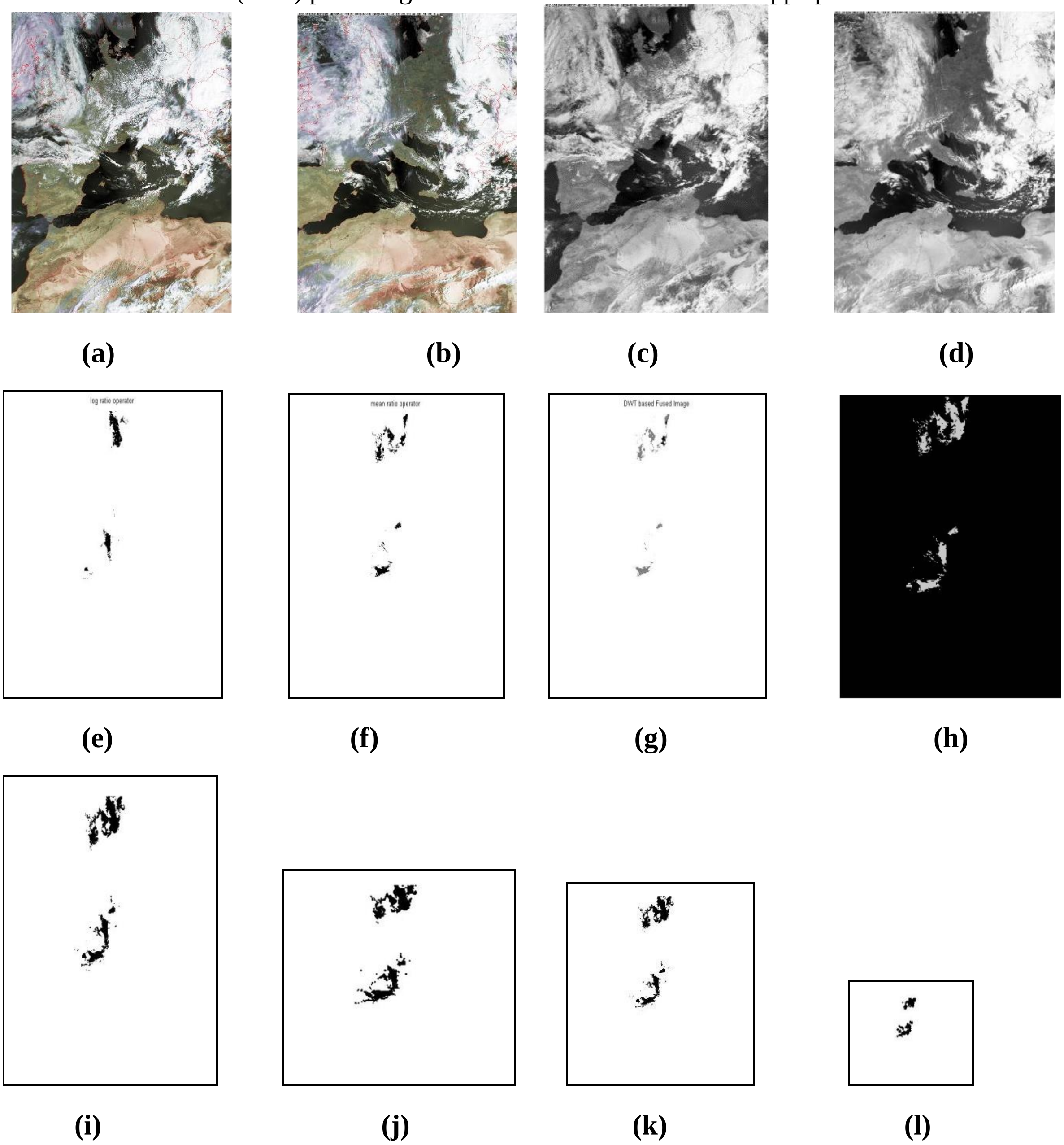

Fig.2.Outdoor Environment taken at two different time instances [24] : (a) and (b) Two images of the same sequence at different times (c) Gray image of (a) (d) Gray image of (b) (e) Difference image by Log-Ratio (f) Difference Image by Mean-Ratio Operator (g) Complementary Fused Image based on DWT (h) Ground Truth Image (i) Change Detected Image By RFLICM for 485 X 526 (j) Change Detected Image By RFLICM for 400 X 400 (k) Change Detected Image By RFLICM for 256 X 256 (l) Change Detected Image By RFLICM for 100 X 100

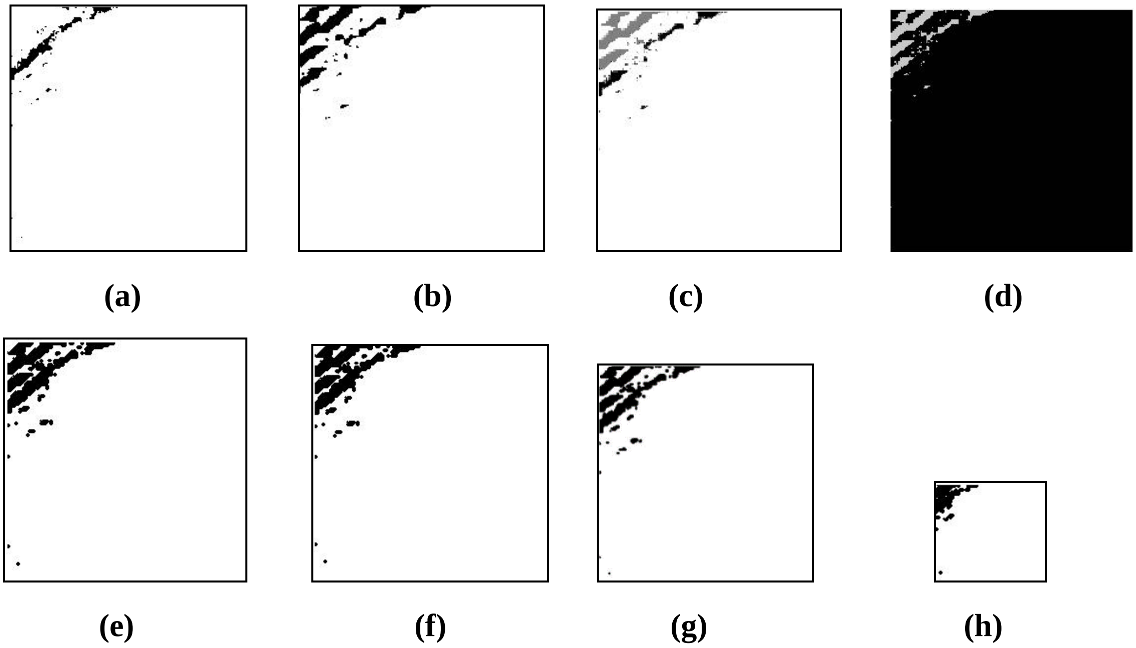

Fig.3.Images taken by IKONOS Satellite [25] at different times: (a) Difference image by Log-Ratio (b) Difference Image by Mean-Ratio Operator (c) Complementary Fused Image based on DWT (d) Ground Truth Image (e) Change Detected Image By RFLICM for 421 X 342 (f) Change Detected Image By RFLICM for 512 X 512 (g) Change Detected Image By RFLICM for 400 X 400 (h) Change Detected Image By RFLICM for 100 X 100

The PCC can be calculated using False Negative (FN), False Positive(FP), True Negative(TN), True Positive (TP). It is given by PCC= (TP+TN)/(TP+FP+TN+FN). TP is the number of pixels correctly labeled as changed and TN is the number of pixels correctly labeled as unchanged and FN is the number of pixels are incorrectly labeled as unchanged and FP is the number of pixels incorrectly labeled as changed. *Kappa* is the parameter for finding the accuracy in the reference map and in the difference image. It is also calculated for all set of images.

Table.1.TP, FP, FN, TN OF RFLICM, FLICM, Mean-Ratio and Log-Ratio

Parameters	Rflicm	Flicm	Mean- Ratio	Log- Ratio
TP	64131	61560	64156	64053
FP	0	798	568	745
FN	278	2598	2	105
TN	1378	580	810	633

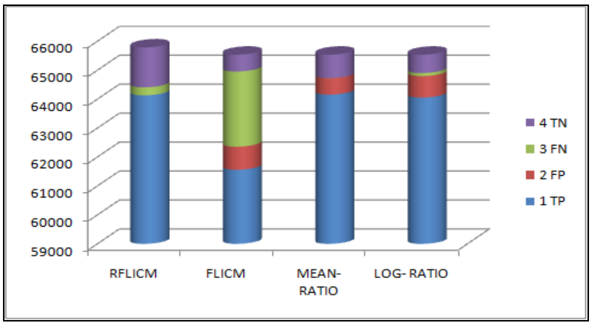

Fig.4.TP, FP, FN, TN OF RFLICM, FLICM, Mean-Ratio and Log-Ratio

Table.2.Accuracy of RFLICM, FLICM & Computation Time for Various Environments with Diverse Graphic File Formats

Environment	Image type	Accuracy		Time duration [SEC]
		RFLICM	FLICM	
Ikonos image	JPG	98%	I%	64
	BMP	7%	1%	84
	PNG	98%	1%	77
Out Door	JPG	98%	99%	613
	BMP	98%	99%	550
	PNG	99%	98%	600
Indoor	JPG	91%	4%	66
	BMP	91%	3%	59
	PNG	9%	3%	58

Table.3.Pcc and Kappa error values for various dimensions for various environments

Environment	Size	PCC		KAPPA ERROR	
		RFLICM	FLICM	RFLICM	FLICM
Out door	640 x 880	99%	75%	0.003	0.004
	400 x 400	98%	73%	0.02	0.03
	256 x 256	97%	71%	0.006	0.008
	100 x 100	97%	65%	0.009	0.014
Ikonos	512 x 512	99%	96%	0.004	0.001
	162 x 139	98%	17%	0.009	0.014
	400 x 400	99%	95%	0.002	0.005
	100 x 100	97%	85%	0.022	0.02
INDOOR	256 x 256	95%	32%	0.006	0.008
	512 x 512	96%	95%	0.003	0.95
	400 x 400	96%	34%	0.003	0.005
	100 x 100	88%	74%	0.012	0.018
	191 x 142	49%	23%	0.006	0.008

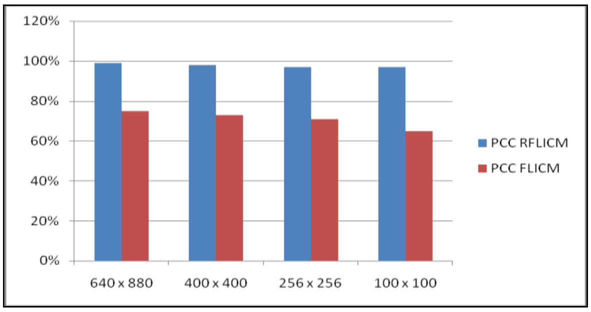

Fig.5.PCC value comparison for RFLICM and FLICM

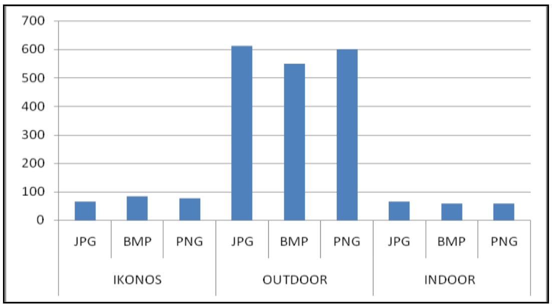

Fig.6.Computation Time comparison of various environments with diverse file formats

V. CONCLUSION

In this paper, a new approach for image change detection has been developed based on the well-found RFLICM paradigm by Image fusion and Clustering Algorithms. The Log-Ratio and Mean-Ratio images are fused in order to restrain the unchanged area information and to enhance the changed area information. The changed region information reflected by Mean-Ratio images is relative with real changes in satellite images. The background information is obtained by Log-Ratio operation. The complementary information is utilized to fuse the new difference image. The proposed approach can reflect the real changes and background information.

The RFLICM algorithm incorporates the local information and spatial contextual information to incorporate the local information more exactly. The computation time and the accuracy are compared for both RFLICM and FLICM algorithms. This is tested for various environments with diverse dimensions and graphic file formats. The experimental results show that RFLICM performs best and yields good results than FLICM in computation time and accuracy.

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