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Analysis of Thresholding versus Image Fusion Techniques to Change Detection using remote sensing Images

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***Abstract:** Change detection is the one of the most important application of Image processing. In this paper presented performance analysis of various Thresholding methods versus Image fusion methods to Change Detection (CD). Thresholding is the one of the traditional and very simplest change detection methods. Image fusion is the process of integrating two or more relevant images into a single new quality image. As a result, new image will be more informative than any of the original input image. Image fusion with Change Detection (CD) analysis provides more advantages than traditional Thresholding Change Detection methods. Otsu, Kapur, Kittler, MRF, DWT, MVF, methods are used to prove the efficiency of Thresholding and Image fusion Techniques. It is observed that MRF Fusion method provide average error rate of 1.44 and Otsu method provides very high error rate of 13.24. Likewise Kittler and DWT methods are having moderate error rate.*

***Keywords:** Image Fusion, Thresholding, Unsupervised Classification, Change Detection, Remote sensing, Performance Analysis.*

I. INTRODUCTION

Change detection is the process of measuring the land cover classes of a particular area which has changed between two or more time period. The main objective of Change detection is used to assess shifting cultivation, forest degradation, urban development, impact of natural disasters like Tsunamis, earthquakes and use/land cover changes, etc. (Ashish Ghosh et al 2013). Many number of change detection techniques and methodologies, utilizing remote sensing images to analyse change detection. Change detection techniques are basically divided into seven categories such as algebra based approach, Transformation, Classification, Advanced models, GIS, Visual analysis and other change detection techniques such as measures of spatial dependence, Knowledge-based vision system, Image fusion etc. (D.Lu et al 2004). Remote sensing (RS) data is a very useful source for change detection studies. Generally remote sensing data's are occurred between two or more time period at same geographical area (Ming Hao et al 2014). We can achieve the accuracy of change detection through two main steps. First step is two or more different dated images of same geographical area images are compared. Second step is changes are identified as changed region and no-changed region. (Farid Melgani et al, 2006).

For robust change detection through satellite images can play a very important role in observing the Earth's surface which became one of the powerful research topics in remote sensing. (Turgay Celik et al, 2010). Generally two categories of change detection methodologies are supervised and unsupervised. Supervised classification need a prior knowledge about the geographical area for training the samples such as post-classification comparison (PCC), support vector machine (SVM), and artificial neural network (ANN), etc. Unsupervised classification doesn't need prior knowledge about the geographical area and it is based on the clustering algorithm such as K-nearest neighbours (k-means), Fuzzy c-means (FCM), etc. (Peijun Du et al, 2012). Many of the unsupervised Change Detection (CD) methods are based on the analysis of calculating the Difference Image (DI).There is two ways to build a Difference Image; one is calculating the difference of two images or by calculating the logarithm function of the two images (log-ratio Image). (Turgay Celik, 2010).By classifying the changed and unchanged region of difference image, it is possible to produce the change detection map of the particular area (Ashish Ghosh et al, 2013).

II. THRESHOLDING METHODS

Thresholding method is the one of the simplest and traditional methods to change detection problem. In thresholding method, threshold value can separate the change and no-change region from the difference image (Swarnajyoti Patra et al, 2011). The following three methods are used to analyse the performance of change detection methods.

2.1. Otsu Method

It is one of the most popular thresholding methods. Otsu thresholding method calculating the thresholding value on the basics of minimises the within-class variance of resultant foreground classes and background classes. Otsu method provides results as very strong and it can provide the result for variety of classes. When the number of foreground pixels is less than 5% of the total multitemporal image size, this method fails to find appropriate threshold value. (A. Drobchenko et al,2005). Otsu method obtained the results for the datasets for Po image(northern Italy; agricultural changes; April–May 1994; Landsat-5 TM),Trentino image (northern Italy; changes due to cloud contamination; May–July 2000; Landsat-7 ETM+), Elba image (Elba Island, Italy; changes caused by forest fire; August–September 1994; Landsat-5 TM),Bern image (near Bern, Switzerland; changes due to flooding; April–May 1999; ERS2-SAR), Pavia image (Pavia, Italy; changes caused by flooding; October 2000;ERS2-SAR).(FaridMelgani et al,2006) as follows. Thus, the optimal threshold T is calculated by minimizing the criterion function. (A. Drobchenko et al, 2005).

Table 1 Performance analysis of Otsu method

Otsu method	PO			Trentino			Elba			Bern			Pavia		
	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M
	3.9	5.8	1.1	**1.6**	1.0	8.4	**30.3**	30.9	0.2	**0.8**	0.4	28.3	**29.6**	30.0	2.1

Error Rate (P_E), False Alarm rate (P_F), Missed Alarm rate (P_M) in Percentage (FaridMelgani et al, 2006).From table 1 we have obtained percentage of error rates of Otsu method using different data set respectively PO, Trentino, Elba, Bern, Pavia is 3.9, 1.6, 30.9, 0.8, 29.6.The average error rate is 13.24. Like the average False alarm rate and Missed alarm rate is respectively 13.62, 8.02.

2.2. Kapur's Method

This method is proposed by Kapur's et al and it is based on entropy. (J.N.Kapur et al, 1985) .Kapur's method maximizes each classes of entropy, and it can be constructed as measures of class density and separability. (A. Drobchenko et al, 2005). Kapur's method obtained the results for the datasets for Po image(northern Italy; agricultural changes; April–May 1994; Landsat-5 TM),Trentino image (northern Italy; changes due to cloud contamination; May–July 2000; Landsat-7 ETM+), Elba image (Elba Island, Italy; changes caused by forest fire; August–September 1994; Landsat-5 TM),Bern image (near Bern, Switzerland; changes due to flooding; April–May 1999; ERS2-SAR), Pavia image (Pavia, Italy; changes caused by flooding; October 2000;ERS2-SAR).(FaridMelgani et al,2006) as follows.

Table 2 Performance analysis of Kapur's method

Kapur's Method	PO			Trentino			Elba			Bern			Pavia		
	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M
	5.1	8.0	0.8	**1.6**	0.8	21.6	**1.1**	0.4	35.7	**1.0**	0.8	14.6	**1.6**	0	97.7

Error Rate (P_E), False Alarm rate (P_F), Missed Alarm rate (P_M) in Percentage (FaridMelgani et al, 2006).From table 2 we have obtained percentage of error rates of Kapur's method using different data set respectively PO, Trentino, Elba, Bern, Pavia is 5.1, 1.6, 1.1, 1.0, 1.6.The average error rate is 4.96.Like the average False alarm rate and Missed alarm rate is respectively 2, 34.08.

2.3. Kittler method

This method is proposed by Kittler et al and it is based on Bayesian classification rule. Kittler's methods work on histogram as a bi-modal sharing and find the cut-off point, so as to fragment the image into two parts. One is foreground and another is background. This work is very suitable for one object in a background and can be extended for many classes. (A. Drobchenko et al, 2005). Kittler's method obtained the results for the datasets for Po image(northern Italy; agricultural changes; April–May 1994; Landsat-5 TM),Trentino image (northern Italy; changes due to cloud contamination; May–July 2000; Landsat-7 ETM+), Elba image (Elba Island, Italy; changes caused by forest fire; August–September 1994; Landsat-5 TM),Bern image (near Bern, Switzerland; changes due to flooding; April–May 1999; ERS2-SAR), Pavia image (Pavia, Italy; changes caused by flooding; October 2000;ERS2-SAR).(FaridMelgani et al,2006) as follows.

Table 3 Performance analysis of Kittler method

Kittler Method	PO			Trentino			Elba			Bern			Pavia		
	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M
	4.9	0.6	11.3	**3.7**	3.7	4.9	**1.6**	1.3	15.57	**0.9**	0.6	19.7	**1.2**	0.7	33.4

Error Rate (P_E), False Alarm rate (P_F), Missed Alarm rate (P_M) in Percentage (FaridMelgani et al, 2006).From table 2 we have obtained percentage of error rates of Kittler method using different data set respectively PO, Trentino, Elba, Bern, Pavia is 4.9, 3.7, 1.6, 0.9, 1.2.The average error rate is 2.46.Like the average False alarm rate and Missed alarm rate is respectively 1.38, 16.97.

III. IMAGE FUSION METHODS

Integrating two or more relevant images into new quality image is called image fusion. Change detection with image fusion provides more advantages than algebra based approach, transformation, classification etc. Generally four different types of fusion methods are available, they are 1) Signal Level Fusion 2) Pixel Level Fusion 3) Feature Level Fusion 4) Decision Level Fusion.

1) Signal Level Fusion (SLF): SLF means signals from different satellite sensors are integrated into new signal. This new signal provides better signal-to noise ratio than original signal.

2) Pixel Level Fusion (PLF): PLF is implemented based on pixel-by-pixel. It built a new fused image in which data associated with each pixel is determined from a set of pixels in original image to provide better results of image processing task such as classification, segmentation, etc.

3) Feature Level Fusion (FLF): FLF is performed based on extracting the important feature of object recognized in the different images. It depends on their pixel values, shape, edges, etc. These same features are extracted from the source images which are fused.

4) Decision Level Fusion (DLF): DLF is performed based on integrating information at higher level of perception. It merges results of different methods to yield a final fused decision. Finally combine all the decision rules to support common analysis.(Dong Jiang et al)

The main applications of image fusion are Object identification, Land Use Land Cover Classification, Change Detection, etc. (Dong Jiang et al). New Difference Image (DI) fused with the use of mean-ratio and log-ratio provides better results than the individual Difference Image. (Jingjing Ma et al, 2012). The accuracy assessment of change detection is very difficult task when compare to accuracy assessment of single image. (Xiaolong Dai et al,1998).

3.1. MRF Fusion Method

This method is based on a Markov Random Field Fusion approach. The two main advantages of MRF Fusion methods are 1) demonstrating a mathematically well-proved framework and it is very suitable for fusing many sources of data.2) analysing through a model of local imagery spatial properties at a global scale. MRF Fusion approach is the capable of taking best individualities from an ensemble of different thresholding algorithm (T.Vignesh and K.K Thyagharajan). Because it achieves spatial contextual data combined in the fusion framework naturally. And it is implemented at both pixels and image levels. MRF Fusion method obtained the results for the datasets for Po image(northern Italy; agricultural changes; April–May 1994; Landsat-5 TM),Trentino image (northern Italy; changes due to cloud contamination; May–July 2000; Landsat-7 ETM+), Elba image (Elba Island, Italy; changes caused by forest fire; August–September 1994; Landsat-5 TM),Bern image (near Bern, Switzerland; changes due to flooding; April–May 1999; ERS2-SAR), Pavia image (Pavia, Italy; changes caused by flooding; October 2000;ERS2-SAR).(FaridMelgani et al,2006) as follows.

Table 4 Performance analysis of MRF method

MRF Fusion Method	PO			Trentino			Elba			Bern			Pavia		
	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M
	2.8	2.4	3.4	**0.7**	0.5	5.4	**2.2**	2.2	0	**0.3**	0.1	15.6	**1.2**	0.8	26.6.4

Error Rate (P_E), False Alarm rate (P_F), Missed Alarm rate (P_M) in Percentage (FaridMelgani et al, 2006).From table 2 we have obtained percentage of error rates of MRF method using different data set respectively PO, Trentino, Elba, Bern, Pavia is 2.8, 0.7, 2.2, 0.3, 1.2.The average error rate is 1.44.Like the average False alarm rate and Missed alarm rate is respectively 1.20, 10.20.

3.2. DWT Fusion Method

This fusion method is based on Discrete Wavelet Transformation (DWT). DWT can be segregates both time frequency and space frequency, allowing detail information to be easily extracted from images. There are three main steps involved in the DWT method. In the first step calculate the DWT of two co-registered images and achieve the multiresolution decomposition of two co-registered images. Second, fuse the matching coefficients of approximate detail subband of the decomposed two co-registered images with the use of created fusion protocol. Third, the fused image is getting by applying the inverse DWT (Jingjing et al, 2012). For image fusion purpose we have been used wavelet transform. Wavelet transform overcomes the weakness of the poor relationship among the neighbouring scale image information and fully reflects local variation of the original image (Biao Hou et al, 2014).DWT fusion method obtained the results for the data set of Ottawa, Bern, Small Yellow and Large Yellow.

Table 5 Performance analysis of DWT method

DWT Fusion Method	Ottawa			Bern			Small Yellow			Large Yellow		
	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M
	0.86	0.29	0.87	**0.31**	0.15	12.55	**3.29**	1.03	37.61	**9.33**	4.88	33.55

Error Rate (P_E), False Alarm rate (P_F), Missed Alarm rate (P_M) in Percentage (FaridMelgani et al, 2006).From table 5 we have obtained percentage of error rates of DWT method using different data set respectively Ottawa, Bern, Small Yellow, Large Yellow is 0.86, 0.31, 3.29, 9.33.The average error rate is 3.38.Like the average False alarm rate and Missed alarm rate is respectively 1.58, 21.14.

3.3. MWF

MWF stands for Multiple Wavelet Kernels Fusion (MWF). There are three main steps to construct wavelet kernels.1) Wavelet kernels at many scales are built for every difference Image (DI).In each kernel space, wavelet kernel can apply approximates arbitrary nonlinear functions. 2) Based on the correlation coefficients, consistent scales are selected. The kernels at consistent scales give the data of the original difference image.3) The two different images of wavelet kernels at the consistence scales are fused under the supervision of result, this result is considered as an initial change detection result, which result in the MWF kernel. MWF kernel using the data's of subtraction image of changed region and the data's of the ratio image of unchanged region. Thus it is called as region based fusion approach. MWF Fusion method obtained the result of the data set for Gloucester flood, Italy agriculture, Mexico fire, Japan earthquake as follows. (Lu Jia et al).

Table 6 Performance analysis of MWF method

MWF Fusion Method	Gloucester flood			Italy agriculture			Mexico fire			Japan earthquake		
	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M	P_E	P_F	P_M
	3.94	1.4	2.34	**7.73**	4.1	1.76	**2.44**	0.44	0.89	**1.57**	0.51	0.79

Error Rate (P_E), False Alarm rate (P_F), Missed Alarm rate (P_M) in Percentage (FaridMelgani et al, 2006).From table 6 we have obtained percentage of error rates of MWF method using different data set respectively Gloucester flood, Italy Agriculture, Mexico fire, Japan earthquake is 3.14, 7.73, 2.44, 1.57.The average error rate is 3.92.Like the average False alarm rate and Missed alarm rate is respectively 1.61, 1.44.

IV. Performance Analysis Factors

Based on the following three factors, we can analyse the performance of different fusion methods. False Alarm (FA), Missed Detection (MD), and Total Errors (TE).

1) False Alarm (FA): The numbers of the unchanged pixels in the ground truth map are detected as changed and the FA rate in percentage is described as .P_F =FA/N_U×100, where FA –False Alarm, N_U-Ground truth map detected as changed.

2) Missed Detection (MD): the numbers of changed pixels in the ground truth map are detected as unchanged and the MD rate in percentage is described as P_M=MD/N_C×100, where MD-Missed detection, NC – Ground truth maps are detected as unchanged.

3) Total Error (TE): The sum of FA and MD and the TE rate in percentage is described as P_{TE} = (FA+MD)/(N_U+N_C)×100. (Biao Hou, 2014).

V. Performance Comparison

From Table 1-6, we have derived new table called average error rates (Table 7) of different method for different data sets. In this paper we have discussed six different kinds of methods such as Otsu, Kapur, Kittler, MRF, DWT and MWF. From the above all methods, MRF Fusion Method Obtained very less Average error rate specifically 1.44.Therefore MRF method obtained 98.56 percentage Change detection accuracy for above mentioned image. Table 7 and Figure 1 illustrates Image fusion methods provides better performance than thresholding methods. Thresholding methods are traditional and simplest methods for change detection. But classification accuracy is the very important factor for evaluating the performance of change detection. Same time image fusion methods are producing less false alarms and missed alarms when compare to thresholding methods. The average error rates of thresholding methods level range from 2.46-13.24 and image fusion methods level range from 1.44-3.92. Table 7 describes as follows.

S.No	Method Name	P_{AE}
1	Otsu	13.24
2	Kapur	4.96
3	Kittler	2.46
4	MRF	1.44
5	DWT	3.38
6	MWF	3.92

Table 7 Average Error Rate (P_{AE}) of Different MethodS

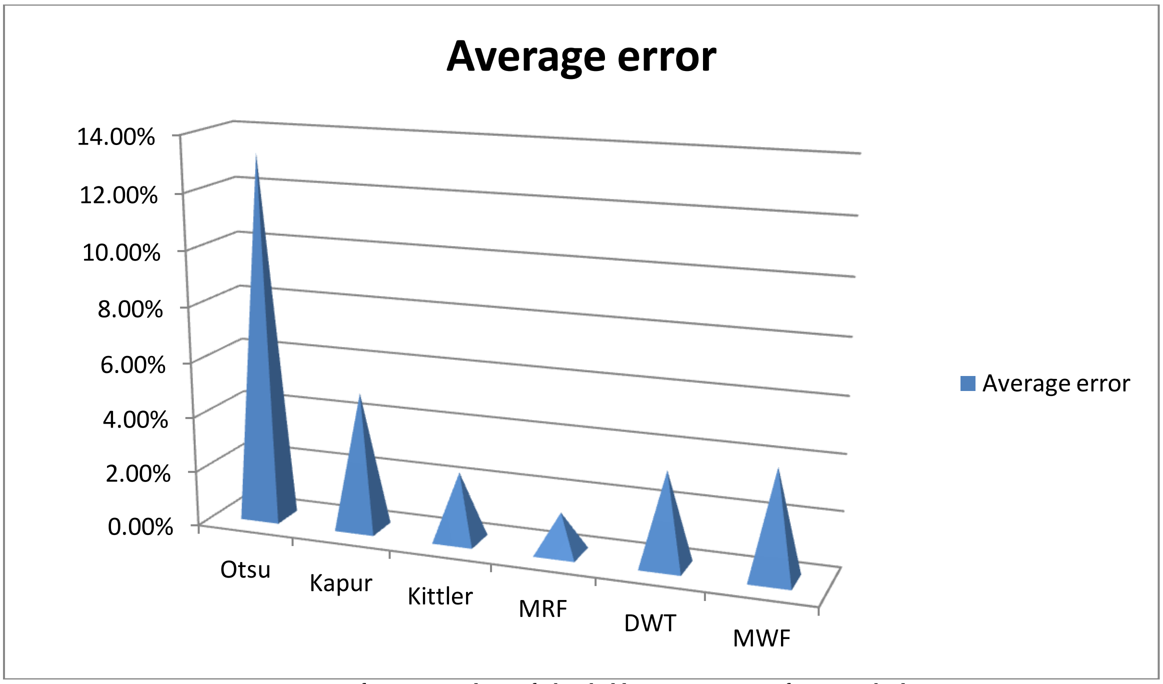

Figure 1. Performance analysis of Thresholding Versus Image fusion methods

The statistical analysis shows that mean value and standard deviation of the average error is 4.85 and 3.66 respectively. The MRF Fusion method is holding the least average error rate of 1.44 while the Otsu method is holding the highest average error rate of 13.24. The DWT and Kittler methods are having the similar performance.

VI. Conclusion

In this paper, we have compared different types of thresholding and image fusion methods for change detection. It is proved that image fusion methods provide better result when compared to using thresholding methods for change detection. Thresholding methods are very simple and traditional methods. Although Image fusion methods, provides high classification accuracy and less error rate accuracy. Among six methods, an MRF fusion method provides better result. The average error rate of MRF Fusion method is 1.44. Hence MRF Fusion Method obtained very lowest average error rate. The average error rate of Otsu method is 13.24. Hence Otsu method obtained very highest average error rate. Same while average error rate of DWT and Kittler methods are respectively 3.38 and 3.92. So both methods obtained average performance.

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