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Performance Analysis of Unsupervised Change Detection Methods for Remotely Sensed Images

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Abstract

The accuracy of a change detection method has been an issue of major concern in remote sensing applications. This paper gives performance analysis of different change detection algorithms like Image differencing, image ratioing based on log ratio and mean ratio operator and Image regression. The algorithms have been applied on the image dataset and difference image has been generated. The change and unchanged areas has been classified through Fuzzy c means clustering to generate the change map. The results are compared based upon various parameters like false positives (F_p), false negative (F_n), Percentage correct classification or Accuracy (PCC) and Kappa coefficient (K_c). The qualitative and quantitative comparison of the studied techniques shows that log ratio offers highest accuracy and Kappa value.

Keywords: Change Detection; Image Differencing; Image Ratioing; Image Regression; Fuzzy Clustering

INTRODUCTION

Change detection in images involves comparing a set of multi-temporal images of the same scene captured at different times to generate a difference image [1-2]. The change detection has been applicable in many application likes remote sensing, medical diagnosis [3] and video surveillance [4]. The main issue of concern in change detection process is the accuracy of the change detection method to detect change and unchanged pixels. The first step involved in image changed detection process is to apply the set of co-registered images to an algorithm which compare both the images to generate a difference image. In the next step, a clustering algorithm is applied which classifies the changed and unchanged pixels into different clusters to generate a change map. Many change detection algorithms has been mentioned in the literature

[5-7]. Depending upon the methodology used, these methods can be categorized as pixel based, classification based, object based and special data mining based change detection [8]. The direct comparison based change detection methods are easy to implement and less time consuming. Some of the direct comparison based change detection methods include Image differencing, Image Ratioing and Image regression [9-10]. There are many clustering techniques in the literature like Fuzzy C means clustering [11-12], k means clustering [13] and Nonsubsampled contourlet transform (NSCT) based clustering [14].

This paper implements various direct comparison based change detection methods to generate the change map. The quantitative results have been compared based upon parameters like false positive, false negative, percentage correct classification and Kappa coefficient.

RESEARCH METHOD

As shown in Fig. 1, two co-registered multi-temporal images are compared in a change detection method to generate a difference image. The fuzzy c means clustering is applied on the difference image so as to classify the changed and unchanged areas into different clusters to generate a change map. The threshold selection is based upon the cluster center for changed and unchanged pixels.

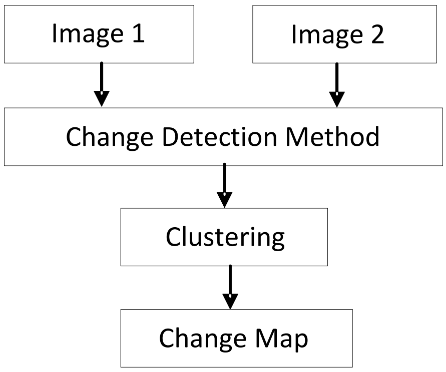


Figure 1. Methodology for change detection

The change detection techniques can be broadly classified as pixels based, object based, classification based, transformation based, machine learning based and hybrid techniques. In this paper, direct comparison based change detection techniques has been analyzed.

Image differencing

In Image differencing, two precisely co-registered images of different times are compared where residual image is produced by subtracting a first date image from second date image pixels by pixels to represent the change [9].

Mathematically, the difference image is:

$$I_d(x, y) = I_1(x, y) - I_2(x, y) \tag{1}$$

Where $I_1(x, y)$ and $I_2(x, y)$ are images from date 1 and date 2 and Id(x, y) is the difference image in the same coordinates. x and y denotes the coordinates of the pixels in both the images.

Log Ratio

In Log Ratio operator, natural logarithms of the ratio of pixels in the images are calculated as given in Eq. 2 and finally a change map is generated by converting the logarithmic image into binary.

$$I_d(x, y) = \log\frac{I1(x, y)}{I2(x, y)} \tag{2}$$

Mean Ratio

In case of Mean Ratio operator, the local mean of the pixel in one image is divided with the local mean of the corresponding pixel in the second image as given in Eq. 3.

$$I_d(x, y) = 1 - \min\left(\frac{\mu_1}{\mu_2}, \frac{\mu_2}{\mu_1}\right) \tag{3}$$

Where μ_1 *and* μ_2 in Eq. 3 represents the local mean of the pixel in the 3x3 neighborhood of first and second image respectively [15].

Image Regression

In image regression methods, the pixels of first time images are assumed to be related linearly to second time image. So least square regression function can be applied normalize the subject image radio- metrically so as to match it with the reference image. So, the difference image can be generated by subtracting the regressed image from first date image as given in Eq. 4.

$$I_d(x, y) = I_1(x, y) - I_2(x, y) \tag{4}$$

Where $I_2(x, y)$ in Eq. 4 is the regressed image and I_1 (x, y) is the first date image [8-9].

RESULTS AND DISCUSSION

To compare the effectiveness of the studied algorithms, multi-temporal image dataset of Reno Lake Tahoe areas with pixel size 200x200 acquired on August 5, 1986 and August 5, 1992 has been used [16]. The images show the effect of draught on Reno Lake. The ground has been generated by manual analysis.

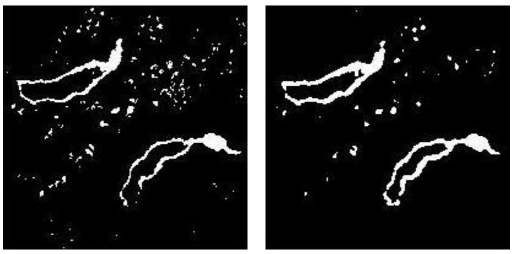
(a) (b) (c)

Figure 2. Multi-temporal images of Reno Lake Tahoe area. (a) Image acquired on August 5, 1986 (b) Image acquired on August 5, 1992 (c) Ground truth

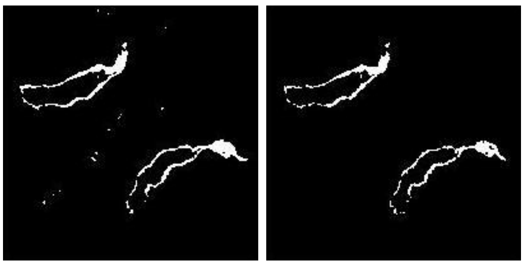
The effectiveness of the algorithms is compared based upon parameters like overall error, percentage correct classification (PCC) and Kappa Coefficient (K_c) [17]. The value of Kappa coefficient lies between 0 and 1.

Table I. Change detection results obtained by change detection methods

Method	**F_p**	**F_n**	**Overall Error**	**PCC (%)**	**(K_c)**
Image Regression	1343	138	1481	96.3	0.95
Mean Ratio	852	1	853	97.8	0.97
Direct Differencing	133	183	316	99.2	0.98
Log Ratio	0	211	**211**	**99.5**	**0.99**



(a) (b)



(c) (d)

Figure 3: Change map obtained by (a) Image Regression (b) Mean Ratio. (c) Direct Differencing (d) Log Ratio.

As shown in Table 1, Image regression method has yielded Log ratio method has yielded PCC equal to 96.3% and the value of Kappa coefficient is 0.95, Mean ratio operator has yielded PCC equal to 97.9% and the value of Kappa coefficient is 0.97, Direct differencing method has yielded PCC equal to 99.2% and value of Kappa coefficient is 0.98 and Log ratio operator has yielded the highest value of PCC equal to 99.4% along with the highest value of Kappa coefficient equal to 0.99 among all the other techniques simulated in this paper. It means that image regression has resulted in large number of false alarms because large number of changed pixels and unchanged pixels could not be recovered. Mean ratio operator has recovered most of the unchanged pixels but large number of changed pixels could not be recovered accurately. Log ratio has been most effective in recovering the pixels with least overall error. The change maps generated by direct comparison based four different methods have been shown in Fig. 3. The behavior of the four different methods can easily be analyzed through visual analysis. It is clear from the change map that log ratio method contains less speckle noise because of logarithmic transformation. Kappa coefficient of 0.99 means that the method has 99 % better agreement than by chance alone.

So, quantitative and qualitative results verifies log ratio to be the most effective method in terms of accuracy and Kappa coefficient among image ratioing, image regression and image differencing.

CONCLUSION

The paper presented performance analysis of direct comparison based changed detection techniques. The output of log ratio method has been affected less with speckle noise. This is because of its ability to convert multiplicative speckle noise into additive. The quantitative results show that log ratio methods offers the highest accuracy and kappa coefficient. As far as qualitative comparison is concerned, log ratio method has the least spots. However, other Direct differencing based change detection method is simple to implement but do not provide the changed information more accurately. So, based upon the analysis of results, it is concluded that log ratio method produce the best results for change detection.

REFERENCES

[1] R. J. Radke, S. Andra, O. Al-Kofahi, and B. Roysam, “Image change detection algorithms: A systematic survey,” *IEEE Trans. Image Process.*, vol. 14, no. 3, pp. 294–307, Mar. 2005.

[2] Abhishek Sharma and Tarun Gulati,“ Review of Change Detection Techniques for Remotely Sensed Images”, vol. 5, no. 1, pp. 22-25, 2017.

[3] M. Bosc, F. Heitz, J. P. Armspach, I. Namer, D. Gounot, and L. Rumbach, “Automatic change detection in multimodal serial MRI: Application to multiple sclerosis lesion evolution,” *Neuroimage*, vol. 20, no. 2, pp. 643–656, 2003.

[4] D. M. Tsai and S. C. Lai, “Independent component analysis-based background subtraction for indoor surveillance,” *IEEE Trans. Image Process.*, vol. 18, no. 1, pp. 158–167, 2009.

[5] Turgay Celik, “Unsupervised multiscale change detection in multitemporal synthetic aperture radar images”, *Signal processing conference*, 17th European, pp 1547-1551, 2009.

[6] Francesca Bovolo, et. al,“A Framework for Automatic and Unsupervised Detection of Multiple Changes in Multitemporal Images”, *IEEE Transactions on Geoscience and Remote Sensing*, vol. 50, no. 6, pp. 2196 – 2212, 2012.

[7] Wiemker, Rafael et al., “Unsupervised robust change detection on multispectral imagery using spectral and spatial features”, *Proceedings of the Third International Airborne Remote Sensing conference and exhibition*, 1997.

[8] Masroor Hussain a et.al, “Change detection from remotely sensed images: From pixel-based to object-based approaches”, *ISPRS Journal of Photo-grammetry and Remote Sensing*, pp. 91–106, 2013.

[9] A. Singh, “Digital change detection techniques using remotely-sensed data”, *International Journal of Remote Sensing*, vol. 10, no. 06, pp. 989–1003, 1989.

[10] M. L. Nordberg, Evertson J, “Vegetation index differencing and linear regression for change detection in a Swedish mountain range using Landsat TM _ and ETM+ _ imagery”, *Land Degradation & Development*, vol. 16, pp. 139– 149, 2005.

[11] J. C. Bezdek, *Pattern Recognition with Fuzzy Objective Function*. New York: Plenum, 1981.

[12] Abhishek Sharma and Tarun Gulati “Change Detection in Remotely Sensed Images Based on Image Fusion and Fuzzy Clustering”, International Journal of Electronics Engineering Research, vol. 9, no. 1, pp. 141-150, 2017.

[13] Turgay Celik, “Unsupervised change detection in satellite images using principal component analysis and k means clustering”, *IEEE Geoscience and remote sensing letters*, vol. 6, no. 4, pp. 772-776, 2009.

[14] A. L. da Cunha et al., “The nonsubsampled contourlet transform: Theory, design, and application,” *IEEE Transactions on Image Processing*, vol. 15, no. 10, pp. 3089–3101, 2006.

[15] Maoguo Gong et al., “Change detection in synthetic aperture radar images based on Image fusion and fuzzy clustering”, *IEEE transaction on image processing*, vol. 21, no. 4, pp. 2141-2151, 2012.

[16] http://geochange.er.usgs.gov/sw/changes/natural/reno-tahoe/index.html.

[17] Rosin P.L., Ioannidis E, “Evaluation of global image thresholding for change detection”, *Pattern Recognition Letters*, vol. 24, no. 14, pp. 2345–2356, 2003.