Change Detection in Multispectral Satellite Images using Histogram based Thresholding Technique

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Abstract—In this paper, an unsupervised global threshold technique, which is based on histogram analysis, is proposed. This technique analyzes the histogram. The histogram is partitioned in intensities at equal interval, and each interval assigned as single intensity. Then, differentiation is applied to get location of maxima in histogram. Depending on the locations of maxima, threshold is calculated to separate the two regions as change and no-change. The utilization of the differentiation improves the visualization of the maxima of different regions. To demonstrate the effectiveness of technique, experiments are conducted on two multispectral satellite images.

Index Terms—Binary change map, change detection, histogram analysis, multispectral satellite image, thresholding.

I. INTRODUCTION

Change detection is the way of distinguishing changes in images of earth surface by monitoring it at various instants [1]. The changes on land surface can be detected by using the satellite images. Nowadays, different kinds of satellite images are available like optical images or SAR images. For collecting such data or images, the land surfaces are monitored by airborne sensor or spaceborne sensor at different frequencies [2]. The data, which is captured in number of bands or frequencies, is called multispectral data. In multispectral data, some subtle parts can be observed at different bands, and each individual band has different use. Here, the changes on land surfaces are detected by using the multispectral data, and these images are taken at multiple times for change detection analysis. Hence, it can be called multitemporal multispectral data.

A lot of change detection techniques have been proposed based on the difference image to get the change map from multitemporal images. These change detection methods generally consists of two steps: 1) Generation of a difference image using different kinds of operators and 2) Unsupervised or supervised techniques having classification on the image into two classes i.e. change and no-change. In first step, different kinds of operators are applied to the multitemporal images to get the single difference image. In second step, the classification is carried out by either clustering or thresholding techniques. In literature, the classification is done either directly on difference image or in extracted features of difference

image. Former approach in classification are thresholding techniques that are directly applied on difference image. In [3], expectation-maximization (EM) algorithm is introduced, which uses the parametric approach to calculate the threshold based on the Bayes theory. Further, in [4], logarithmic mean based threshold is calculated to generate the change map based on the difference image. In latter case, recently, k-means and fuzzy c means clustering algorithms are utilized to classify the extracted feature from the difference image [5]–[7]. In [6], Gabor wavelet is used to extract the feature of the log ratio based difference image, and features are clustered by fuzzy c means clustering. Moreover, discrete wavelet transform (DWT) is used to create fused image by taking two difference images in [8], where features are extracted by applying the compressed projection technique on local patch around each pixel. Then, k-means clustering techniques classifies the extracted feature into binary classes. In addition with these techniques, thresholding algorithms are also considered to classify the extracted feature from the difference image. In [9], features are extracted in two stages using (SIFT) key points and region information. In this method, bloblike structure information is offered by SIFT keypoints. After getting the region information around interested keypoints, Otsu's thresholding is applied to generate the binary map. Along with these technique, some local thresholding based techniques are also introduced to detect changes [10]–[12]. In [10], binary descriptors are created by using local thresholding approach. In recent past, the combination of local and global thresholding based algorithms are suggested to detected changes in multitemporal images [13], [14]. In [13], local binary similarity pattern descriptor is applied on multitemporal images to create binary feature vectors by using the combine threshold. A combined threshold is again used in [14] to create binary change map. Here, local Otsu's threshold is combined with global threshold.

Although different thresholding methods are presented, some of them are using local information based thresholding. However, local thresholding may provide misclassification, because small areas are not guaranteed to have two different regions. To avoid this problem, global thresh-

old is adapted in this paper, which separates the image into two regions. The proposed thresholding technique is based on the difference image. To utilize the whole multispectral band information, the difference image is obtained by change vector analysis (CVA) method [15]. Now, histogram analysis is carried out on the difference image [16]. Presence of less probability intensity values in difference image makes it difficult to visualize different regions. To get rid of this, the intensities are partitioned into different parts, and each part is represented with maximum intensity among its available intensities. Then, differentiation is applied on obtained samples. Finally, the maxima of different regions are used to evaluate the threshold value.
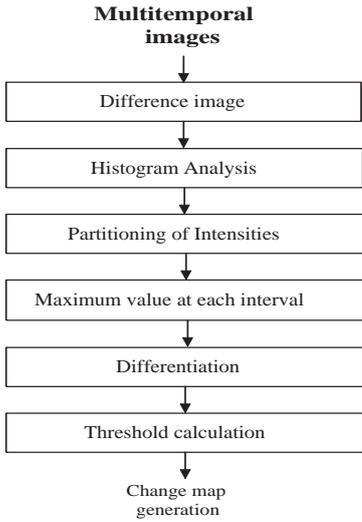
Fig. 1. Block diagram of the proposed method.

II. PROPOSED METHOD

Let us consider, two multitemporal multispectral images I_1 and I_2 of the same geographical region. The size of these images is $M \times N$ pixels, they have been acquired at different times t_1 and t_2. The main objective of this work is to separate the regions of images into binary classes i.e. change and no-change. The block diagram of the proposed thresholding technique is shown in Fig. 1. The proposed method consists of the following steps: obtaining the difference image, calculating the repetition of pixels and location of the pixels, dividing the length of the count into different parts, locating the maxima in histogram, differentiation, calculating the threshold value. The comprehensive description of the proposed method is described as follows.

A. Difference image generation

To effectively utilize of all spectral bands of the data, difference image is generated by using CVA technique. CVA is a mathematical operation that is applied to corresponding bands of the multitemporal images to get the spectral change vector. The magnitude of the spectral change vector, which is the difference image, is taken for further analysis. The difference image can be represented as

$$C = \sqrt{(P_1 - Q_1)^2 + (P_2 - Q_2)^2 + \cdots + (P_B - Q_B)^2} \tag{1}$$

$$I_1 = \{P_1, P_2 .... \ P_B\} \tag{2}$$

$$I_2 = \{Q_1, Q_2 .... \ Q_{2B}\} \tag{3}$$

where, I_1 is observed image at time t_1 and I_2 is observed image at time t_2. P_i and Q_i represents bands in I_1 and I_2

B. Histogram analysis

In this step, the histogram of the difference image is analyzed to get the number of pixels and intensities information. The histogram is used to represent the number of repetitions of the data that are present in image. It is represented as

$$k = \sum_{i=1}^{m} r_i \tag{4}$$

where k indicates the number of observation, and m represents the total no of bins and r_i represents the intensity value.

Histogram mainly focuses on the density functions or Probability density function. As it is known, difference image contains two regions. Hence, there could be two density functions in histogram, which can be well separated with a value, and this value is taken as threshold. However, variation in no-changed pixels among that regions can reduce the separability of two density functions. It may happen that the two density function of different regions may overlap, and it is difficult to determine the exact threshold. Usually, histogram tells the probability of occurrence of intensities. The variation among values of pixels may be high, and this can generate the uniform probability values for certain intensities. This will increase the probability of error, and hence, the calculated threshold may not be optimal.

To reduce the probability of error, some intensity values will be assigned to a certain bin. For that either certain range of intensities will be assigned as one bin or a number of intensities will be assigned as one bin. Here, the latter case is considered. In this approach, bin width can be assigned by rounding the pixels to certain intensities.

C. Partition of intensities at uniform interval

In this step, the bin widths are updated again by dividing the length into uniform interval such that it is easy to find the changes where change in density will occur. Here, the division of length plays a vital role, because the single part may contain the information of change in density function, which can provide a threshold. Therefore, assigning of the width of the bins depends on the intensities that present in the data. This partition technique can be more efficient for calculating the threshold value for identifying the change regions.

D. Locating maxima at each interval

After obtaining the values from each bin, the bin value should be represented with a single value such that the analysis is better for detecting variation on the histogram. This can be done by representing the bin with single value that is taken as the maximum in each interval. The maximum value is given by

$$O = \max(k_i) \qquad (5)$$

where i represents sub parts or interval of the histogram.

E. Differentiation

As it is known, differentiation can find the maximum changes among the samples. The numerical differentiation of discrete signals has many uses in analytical signal processing for calculating higher difference values. Here, this differentiation is applied on samples that are obtained in previous step. This procedure will provide the information of change in adjacent maximum probability values. This helps to find the presence of change from one region to another. The differentiation is presented as

$$f = \frac{O(x) - O(x-1)}{h} \qquad (6)$$

where f stores the values of differentiation of O, x represents the sample location, and h represent the unit change in the intensity from one maximum to another . Here, we are interested only in peak values not in the sign of change, therefore, absolute values are taken by using $|\ |$ operator.

F. Threshold calculation

For calculating the threshold, the location of maximum change between the intensities has to be found. This location can be decided by the maximum value of the differentiation values. The location of intensity, where maximum change has occurred, is defined as

$$j = \max(\Delta) \qquad (7)$$

This location can tell us the existence of threshold for separation of two regions. Corresponding to j, adjacent maximum change value is considered for threshold calculation. Here, left adjacent intensity value is taken, because this part of the histogram contains separation of two regions. Using two values threshold is derived as follows:

$$t_h = \frac{\text{intensity}\left(j^{th}\right) + \text{intensity}\left((j-1)^{th}\right)}{2} \qquad (8)$$

where t_h is threshold. It is used to classify the regions.

G. Binary change map

After getting the threshold, the histogram is divided into two regions such that the regions having less intensities are considered as no-change region and the regions which have higher intensities are considered to be the change region.

$$B(i,j) = \begin{cases} 1, & \text{if } C(i,j) < t_h \\ 0, & \text{else} \end{cases} \qquad (9)$$

where B is the final binary change map. The no-change region are assigned with the values 1, and the change region are assigned with 0 binary values.

III. EXPERIMENTAL RESULTS

To show the effectiveness of the proposed technique, two satellite datasets are taken for the experiments. These satellite images are acquired by Landsat satellite.

A. Database Description

Dataset I: This dataset contains two images obtained from the study of Natural lake in Jaisalmer district, Rajasthan India. The images are captured at different times on Febuary 09 and september 21, 2001 [17]. The images acquired from Landsat 7 Enhanced Thematic Mapper Plus(ETM+) sensor. The size of the image considered is 220×550 pixels, and they are shown in Fig. 2 (a) and (b). The ground truth image or reference map image is shown in Fig. 2 (c), this image has two regions i.e. change and no-change. These regions are represented by 0 and 1, respectively. The changes are observed in the image where the lake was dried.

Dataset II: The dataset is acquired by Landsat 5 Thematic Mapper (TM) sensor on the study area of upper lake in Bhopal city situated in Madhya Pradesh, India on May 29, 2009, and November 09, 2011 [17]. The size for this image is of 206×424 pixels, and they are shown in Fig. 3 (a) and (b). The reference map image or ground truth image is shown in Fig. 3 (c), this image has two regions i.e. change and no-change. These regions are represented by 0 and 1, respectively.

B. Experimental setup

For partitioning of the intensity in uniform intervals, empirical values are chosen in this experiment. The minimum number of intensity values between each interval is taken as 15 for both datasets. Accordingly, the number of intervals are 10 and 6 for dataset I and dataset II, respectively.

C. Qualitative Results

This part of the experimental results provides the rough idea of the binary change map in terms of the visual results. Here, ground truth information is utilized to compare the binary change map visually. In binary change map, changed regions are represented with black pixels whereas no-change regions are with white pixels. To compare the visual results, some earlier techniques are taken like EM [3], BDLM [10], GaborTLC [6], NTIRC [13], and OTLNI [14] method. The binary change maps of EM [3], BDLM [10], GaborTLC [6], NTIRC [13], OTLNI [14] and the proposed methods are shown in Fig. 2 and Fig. 3 for dataset I and dataset II, respectively. It is observed that EM and BDLM have high false alarms. GaborTLC method has less false alarms but it fails to detect changes at many places. NTIRC method also produces high false alarms rate. The change map of OTLNI method is good but not with respect to the proposed technique. The visual change
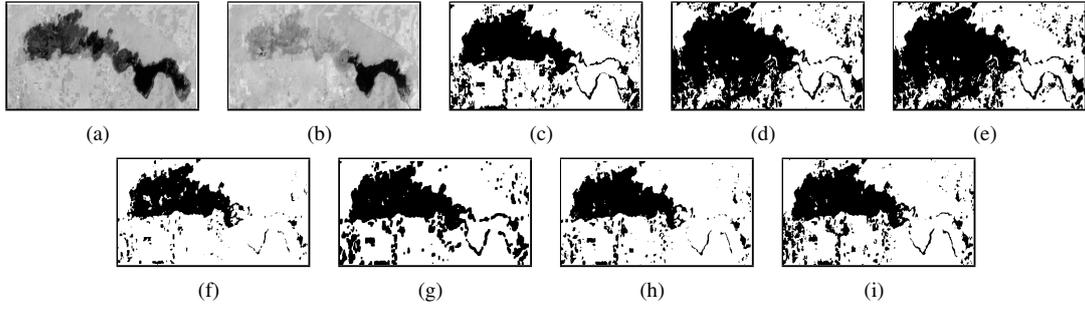
Fig. 2. Landsat satellite images change detection results for dataset I. (a) and (b) Landsat 7 ETM+ sensor Near Infrared (NIR) band multitemporal images. (c) ground truth. (d), (e), (f), (g), (h) and (i) are binary map of EM, BDLM, GaborTLC, NTIRC, OTLNI and Proposed method, respectively.
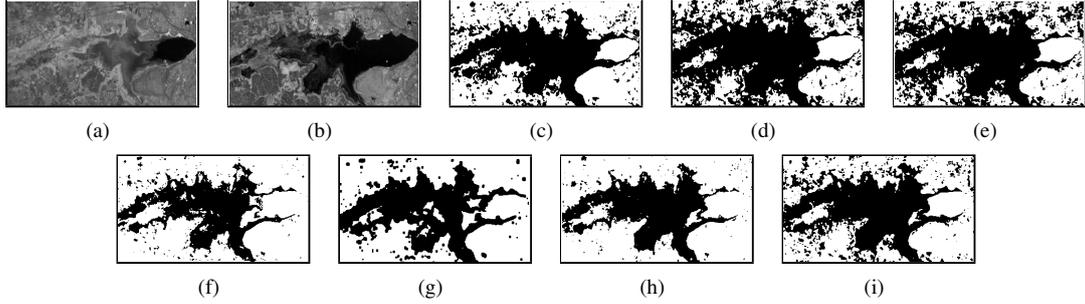
Fig. 3. Landsat satellite images change detection results for dataset II. (a) and (b) are Landsat 5 TM sensor Near Infrared (NIR) band multitemporal images. (c) ground truth. (d), (e), (f), (g), (h) and (i) are binary map of EM, BDLM, GaborTLC, NTIRC, OTLNI and proposed methods, respectively.
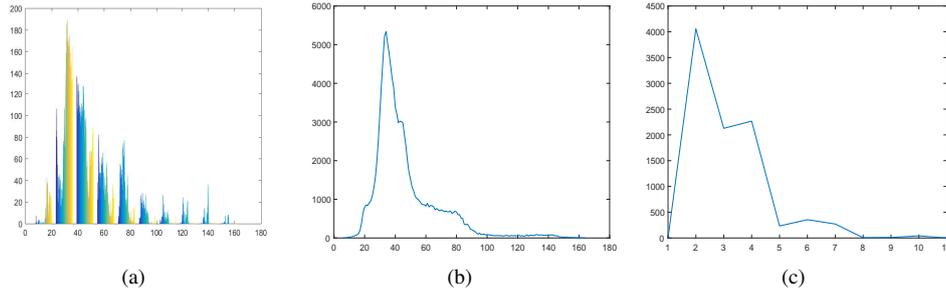
Fig. 4. Intermediate results of the proposed algorithm of Dataset I. (a) Histogram of the difference image. (b) Histogram obtained after combining the pixels to a single bin. (c) Histogram after the differentiation.

map of the proposed technique is better with comparatively less false alarms.

The intermediate results are also analyzed herein. Fig. 4 (a) and Fig. 5 (a) show the histogram of the difference image of dataset I and dataset II, respectively. Fig. 4 (b) and Fig. 5 (b) show the histogram after rounding the intensities to the nearest intensity value of dataset I and dataset II, respectively. Fig. 4 (c) and Fig. 5 (c) show the histogram after applying the differentiation of dataset I and dataset II, respectively. From Fig. 4 (c) and Fig. 5 (c), it can be observed that two regions are clearly visible than compared to original histogram.

D. Quantitative Results

To compare the proposed method with ground truth and various techniques such as EM [3], GaborTLC [6], BDLM [10], NTIRC [13], and OTLNI [14] have been taken. To accomplish this, some predefined parameters are used [6], [18]. That are overall accuracy OA, 2) False alarms (FA), 3) Kappa coefficient (κ) [19], and 4) Total error TE. Parameters are calculated in percentage (%).

In qualitative results, generated change map using proposed method is compared with EM [3], GaborTLC [6], BDLM [10], NTIRC [13], and OTLNI [14] methods with respect to some predefined parameters [6], [18]: Overall accuracy OA, 2) False alarms (FA), 3) Kappa coefficient (κ) [19], 4) Total error TE.

The results with respect to quantitative measures is shown in Table I and II. The proposed method achieves 92.33% and 88.73% of total accuracy, and 7.67% and 11.27% of total error for dataset I and dataset II respectively, which are better than the compared methods as shown in table. The proposed technique uses maxima at each interval, this process enhances the histogram smoothness that improves the separability between two regions. The false alarm rate is high in dataset II compared to dataset I, because the calculated threshold value is just approaching to optimal threshold. The reason is that the intensity at maximum bin count in unchanged region may be very less compared to intensity at maximum bin count in changed region.
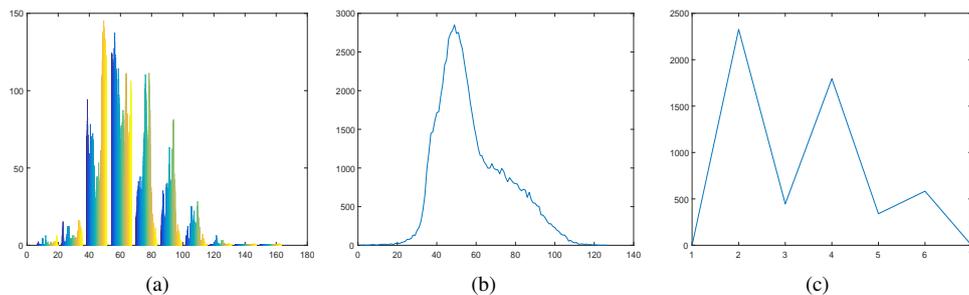
Fig. 5. Intermediate results of the proposed algorithm of Dataset II. (a) Histogram of the difference image. (b) Histogram obtained after combining the pixels to a single bin. (c) Histogram after the differentiation.

Table I
Performance Measures for Dataset I (Natural Lake)

Change detection methods	OA	FA	TE	Kappa
EM [3]	80.69	25.17	19.31	60.55
BDLM [10]	80.80	25.00	19.20	60.74
GaborTLC [6]	87.99	0.24	12.01	69.63
NTIRC [13]	91.08	7.72	8.92	79.85
OTLNI [14]	91.24	1.07	8.76	78.69
Proposed	92.33	3.52	7.67	82.02

Table II
Performance Measures for Dataset II (Bhopal City)

Change detection methods	OA	FA	TE	Kappa
EM [3]	81.67	28.33	18.33	64.00
BDLM [10]	82.92	25.63	17.08	66.31
GaborTLC [6]	85.46	1.32	14.54	69.42
NTIRC [13]	85.81	8.73	14.19	70.83
OTLNI [14]	87.75	1.23	12.25	74.40
Proposed	88.73	9.74	11.27	71.09

IV. Conclusion

In this paper, an unsupervised histogram based change detection technique is proposed. The proposed method analyzes the histogram of the difference image that is generated using CVA technique. To get a smooth histogram, partitioning of the intensities is performed, and each interval is represented with single intensity, which is maximum among it. Then, differentiation is applied on the obtained samples. Further, based on the location of maximum value of two parts, threshold is calculated. The calculated threshold is the global threshold and it is able to detect large changes as well as the small changes. The proposed method is experimented on two multispectral datasets of the Landsat satellite. It shows better accuracy than other compared techniques.

Acknowledgment

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