A NOVEL APPROACH TO LAND-COVER CHANGE DETECTION BASED ON A NEURAL NETWORK CLASSIFIER FOR MULTISPECTRAL REMOTE SENSING IMAGES USING MODIFIED DYNAMIC HISTOGRAM EQUALIZATION

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Abstract: With the expeditious technological evolution of diverse satellite sensors, multispectral remote sensing could be very important for many land cover change detection remote sensing applications. Generally, supervised change-detection techniques represent the most accurate methodological solution for mapping land-cover changes while identifying the associated land-cover transitions between two different dates. In this paper, the proposed approach focused on Object-based Change detection methods, which integrates change feature extraction and ground truth assessment. First, Modified Dynamic Histogram Equalization method is used to enhance the quality of digital images captured in low light surroundings as compared to the earlier techniques applied. Second, Modified Marker-Controlled Watershed (MMCW) segmentation algorithm is able to segment the images with least drawbacks of below segmentation and over-segmentation. Then, the Change feature extraction represents the spectral and textural feature between the corresponding images. Third, stimulated by the circumstances that deep neural network has the capability to acquire from data sets that have few labeled data, it has been used to learn the difference between changed and unchanged pixels. A further improved optimized neural network approach was employed in this study to obtain sorts of land cover types from the remotely sensed imageries. And then, a ground truth is used to rather alter the local region of the mapping associated with the pair of training data without disturbing the whole mapping. The neural network is very appropriate for comparing satellite imagery and ground truth data and achieves better than the theoretical approach in several areas. Finally, a vigorous and high-comparison change detection result can be achieved from the network using image contrast enhancement technique.

Keywords: Multispectral Remote Sensing, Object-Based Change Detection (OBCD), MDHE, Marker Controlled Watershed Segmentation and Deep Neural Network.

Introduction: Change detection is one of the most frequently used applications in remote sensing. In general, Land-cover change identification involves the evaluation of two registered remote sensed multispectral images acquired in the identical geographical location at two different times to recognize altered regions on the earth's surface. However, the application of supervised change-detection techniques depends on the availability of exhaustive ground-truth information for all the land-cover classes present in the area of interest at the times under investigation When studying human-induced or natural disasters such as floods, earthquakes, landslides, oil spills, and commercial accidents, change-detection technologies based on remotely sensed data can be effectively used to detect and estimate the extent of the damaged area. Multispectral remote sensing is typically based on acquisition of image data of Earth's surface simultaneously in multiple wavelengths. Multispectral remote sensing may be used to detect the elucidation of natural color and color infrared (CIR) aerial photography. It also proved to be of consequential value in locating and tracing the condition of vegetation. A massive number of change detection approaches and strategies, making use of multispectral remotely sensed data, have been advanced, and more recent techniques are still developing [1]. The data from remote sensing satellites produce chances to achieve information about land at numerous resolutions and has been commonly used for change detection review. Various techniques have been advanced for land cover Change Detection using pixel-based as well as object-based methods.

In Pixel-based classification methods, although the techniques are nicely developed and plenty of successful applications have been testified, it suffers from ignoring the spatial pattern in classification. Several researchers have surveyed the existing change detection methods for applications in the remote sensing data, including image differencing, image rationing, vegetation index, regression, data transformation, change vector, post classification comparison, and GIS-based methods [2–5].While evaluating those techniques on the basis of literature reviewed, it was concluded that distinct change detection techniques produced different change maps. Gustafson-Kessel clustering (GKC) algorithm is also a fuzzy clustering technique. It is a modification of Fuzzy C-Means, where FCM uses Euclidean distance to measure the distance between the cluster center and the patterns [6]. The accelerated variability present in high-resolution images and the problem of modeling the contextual information further weaken the overall performance of traditional pixel-based change detection approaches.

Unlike traditional pixel-based methods, an object-oriented method treats the image as a set of meaningful objects rather than single pixels [7].Object-based image evaluation is quickly gaining acceptance among remote sensors and has established the notable potential for classification and change detection of high spatial resolution multispectral imagery in heterogeneous urban environments [8]. In general, several researchers have confirmed that an object-based change detection framework commonly accommodates image segmentation, image objects feature extraction and comparison and classification which improve the accuracy and efficiency of change detection [9]. Although there may be a growing interest in the application of object-based approaches for change detection, relatively few studies have explored the effectiveness and coherence of an object-based approach for post-classification comparison change detection, especially, using very high-spatial resolution [10]. Actually, change detection belongs to an imbalance problem in remote sensing field, which can be further formulated as an incremental learning problem and the neural network is good at solving this form of problem.

A neural network is a nonlinear dynamic system consisting of a large number of highly interconnected processing units .Each processing unit in the network maintains only one piece of dynamic information (its current level of activation) and is capable of only a few simple computations. Numerous types of supervised classification models have been discussed in the literature, including decision trees [11], random forests [12], [13], and support vector machines (SVMs) [14]. Recently, with regard to neural network applications, deep learning has become a research hotspot, which has attracted great interest due to its effective and excellent feature learning ability. Layers which have been used in deep learning encompass hidden layers of an artificial neural network (ANN). Restricted Boltzmann Machines (RBMs) are usually used as building blocks for layer wise unsupervised learning. [15] Proposed a novel change detection method based on deep neural networks, which was applied to the SAR image change detection and performed better than traditional change detection approaches.

In this paper, we present an innovative framework for multispectral images, which integrates Histogram based image contrast enhancement and ground truth assessment by neural network. Contrast limited adaptive histogram equalization (CLAHE) operates on small data regions rather than the entire image and it is computationally expensive. As it is time-consuming, recursions are performed sequentially [16]. To overcome this issue, MDHE was proposed. The proposed method is a Dynamic Partitioned Histogram Equalization (DPHE) based method, named Modified Dynamic Histogram Equalization (MDHE), which gives a better quality image with good resolution. For image denoising evaluation, noisy input images were used for the training. By doing so, the changes will be highlighted further. Network models were trained to keep the quality of the output image close to that of the ground-truth image from the input image without image processing.

The rest of this paper is structured as follows. Section II introduces the problems and some background knowledge of neural network models. Section III describes the proposed framework in detail. The experimental setting is presented in Section IV. Section V describes the results and discussions. The conclusion of this paper is drawn in Section VI.

Problems and Motivation: High-resolution multispectral change detection was one of the earliest and is also one of the most important applications of remote sensing technology. However, it is still difficult to accurately discover the changed regions that are of interest for particular applications, due to the increased information density of high-resolution imagery. Neural network has the ability to learn from few labeled data and process many unlabeled data in turn, which is suited to solve the change detection problem.

For instance, let us consider two images acquired at different times t1 and t2 over a study area characterized by several types of land-cover changes, where some of them might be even unknown to an operator (as it happens in most practical situations). In this framework, the objective is to identify the only pixels experiencing a specific targeted land-cover transition of interest from class “A” at t1 to class “B” at t2. It is worth noting that the collection of a reliable and exhaustive ground truth for the two dates under analysis (which may allow the application of traditional fully supervised change-detection techniques) is always difficult and costly, if not completely unfeasible. However, it would be significantly easier and cheaper for an operator to collect a suitable number of reliable ground-truth samples only for classes “A” at t1 and “B” at t2, respectively. In this context, solving the above targeted change-detection problem, under the hypothesis that ground truth is only available for the targeted classes at each date, represents a complex methodological and practical challenge: on the one hand, supervised techniques cannot be used due to the lack of suitable ground truth; on the other hand, unsupervised techniques may also allow identifying all of the areas experiencing any sort of transition, however not discriminating only where the targeted land-cover transitions of interest occurred. Thus, a novel partially supervised targeted change-detection technique capable of identifying the land-cover transitions of interest by exploiting only ground-truth samples exclusively associated with the targeted classes of interest at the two considered times (thus avoiding the need to rely on an exhaustive and complete ground-truth information for all the other classes present in the area), while providing accuracies comparable to those of fully supervised methods. Recently, neural networks has become popular in many fields.

Neural network-based approaches—also named reconstruction-based [17]—have gained interest in recent years along with the evident success of neural networks in several other fields. For the change detection tasks, neural networks can be utilized to transform an image into a high-dimensional feature space, which is helpful to extract the key information for discrimination and suppress irrelevant variations caused by environment. Several general advantages of applying neural networks for classification of satellite imagery are the following [18]: (i) ANN are data driven and self-adaptive since they can adjust themselves to the data without any explicit functional specification of the underlying physical model; (ii) ANN can provide universal functional approximations; (iii) the neural classifiers do not require initial hypotheses on the data distribution and they are able to learn nonlinear and discontinuous input data. This paper presents and evaluates an approach to classify the trained for change detection in multispectral satellite imagery.

Methodology: In this section, the overall architecture of the proposed framework is shown in Fig. 1. Given two multispectral images, the transformation is done by using Improved F-Transform and the images are generated first by using Modified dynamic histogram equalization method. After fusing the equalized histogram, MMCW segmentation should be done to improve the quality of digital images. To illustrate the difference between these approaches and to further verify the validity of the neural network-based correlator, a traditional approach should be performed based on more standard image processing tools on the same data set that had been used for constructing the neural network-based model. Finally, the testing samples are fed into the network to generate the corresponding labels to obtain change detection results.

Preprocessing: The first step in the image processing includes preprocessing which is defined as any operation of which the input consists of sensor data, and of which the output is a full image. Resizing an image from one pixel grid to some another is done by means of Image interpolation algorithm. Image resizing is used to increase or decrease the total number of pixels, after converting color image into gray image, the intensity of the pixel in gray image changes.

Bilateral Filtering: This paper uses a implementation of the bilateral filtering for noise removal [19].It was the first bilateral filtering method used whose computational and memory complexity is linear in both input size and dimensionality. The proposed implementation demonstrates that the bilateral filter can be as efficient as the recent edge-preserving filtering methods, especially for high-dimensional images. The bilateral filtering is the combination of the spatial and range filtering by enforcing both geometric and photometric locality. In Eq (1), let x denote a scan line of a 2D grayscale image, then the bilateral filtered value of x at pixel i is

$$\left(y_i = \sum_{k=0}^{i}\left(R_{k,i}\ S_{k,i}\ .x_k\right)\right) \qquad (1)$$

Where $R_{k,i} = R\ (x_k,x_i)$ is the range filter kernel for measuring the range similarity of pixel k and i and $S_{k,i}= S\ (k,\ i)$ is the spatial filter kernel for measuring their spatial similarity.

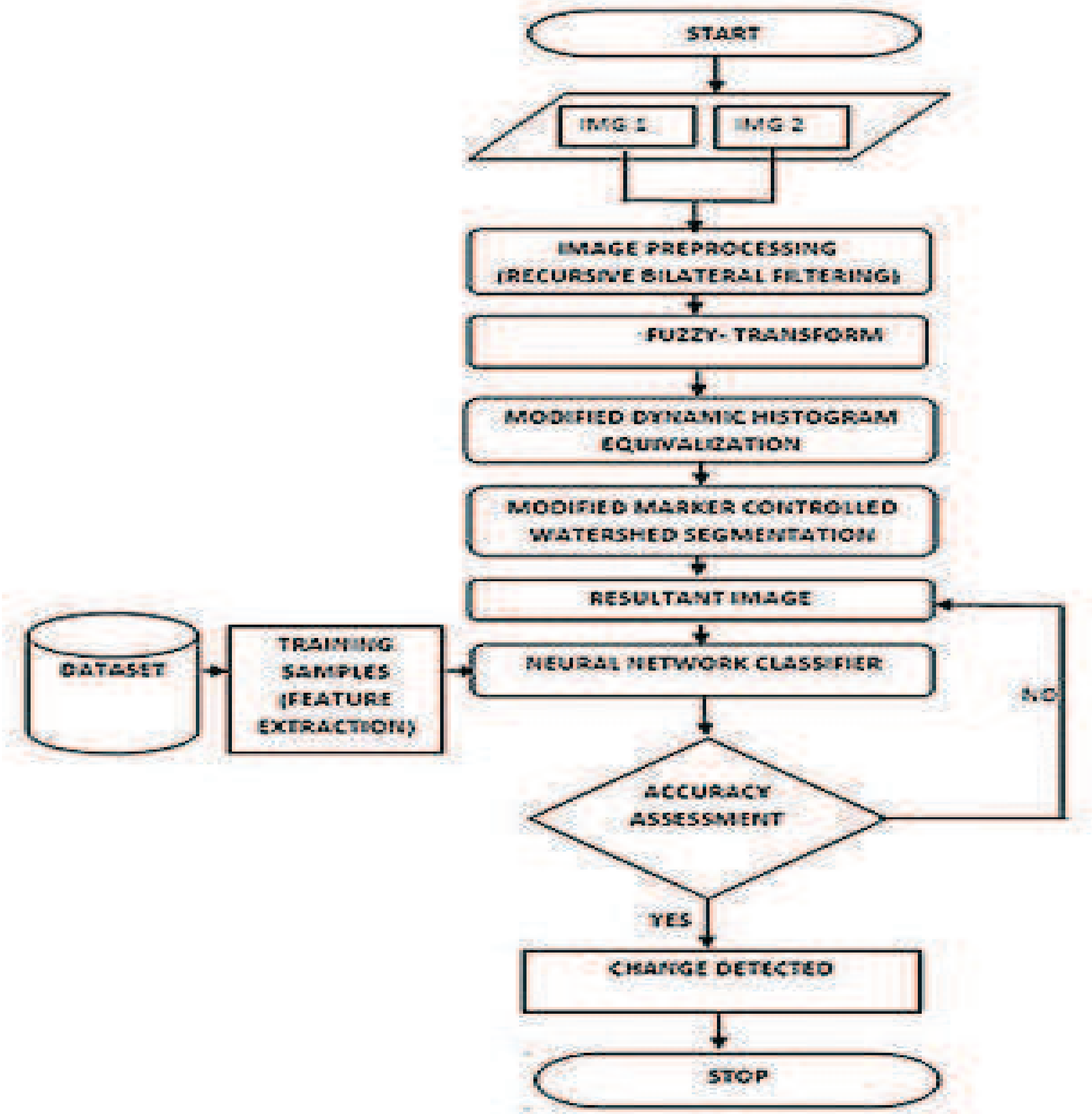


Fig.1: Flowchart of Proposed Model for Multispectral Change Detection

Generalized Fuzzy Hough Transform: Fuzzy transform is used as a linear mapping from a set of ordinary continuous/discrete functions over domain P onto a set of discrete functions (vectors) defined on a fuzzy partition of P. The main idea of the improved Fuzzy- transform fusion [20] is to enhance the Simple Fuzzy-transform by adding another run of the Fuzzy-transform over the first difference. The conventional generalized Hough transform is not suitable for a noisy and blurred image. It is an effective method for an arbitrary shape detection in a contour image.

Image Contrast Enhancement: One of the most significant quality factors in satellite images comes from its contrast. Contrast enhancement can be attained by stretching the dynamic range of important objects in an image [21].Among the applications in which ANNs have been advanced for image enhancement [22-26], one could expect most applications to be based totally on regression ANNs. The main motive of contrast enhancement technique is to show out the detail that is hidden in an image or to increase contrast in a low contrast image. There are many algorithms for histogram equalization and among those MDHE is the most common approach used due to its simplicity and efficiency. This section discusses the algorithmic construction of the proposed MDHE method in great details.

Existing Methodology: Quadrants Dynamic Histogram Equalization (QDHE) is used to enhance the contrast of the image and also reduces the possibility of low histogram components to be compressed. Due to partition in lower levels, the enhancement is restricted to the corresponding dynamic range. The finest details of the image are not well-preserved, while the picture is taken in a low light environment. In the QDHE method, the pixels nearer to white is enhanced very smoothly because it uses clipping process to control the enhancement rate.

Drawbacks:

- It does not contemplate the mean brightness preservation.
- It may cause saturation and it is far insufficient to smooth a noisy histogram.

Proposed Method: It should be mentioned that this paper focuses on the enhancement of images obtained in low illumination environment. The proposed model of histogram equalization is shown in Fig. 2 .The MDHE consists of five processes, namely the histogram partitioning, clipping, gray level range allocation, dynamic range allocation and histogram equalization.

Histogram Partitioning: MDHE develops the median intensity value of the input image histogram in partitioning the histogram. Initially, the histogram of the original image is divided into two sub-histograms. Similarly, the median of the 2nd sub-histogram is used as separating point to further divide the sub-histogram into two smaller sub-histograms each. Thus, there is total of three sub-histograms obtained. Then, the minimum and maximum intensity values of the input histogram are set as the separating points as shown in Eq (2) and Eq (3). The median-based partition method has a tendency to segment the number of pixels similarly in each sub-histogram. Hence, each separating point can be calculated using the following equations:

$$min_1 = 0.5 * \{I_{width} * I_{height}\} \quad (2)$$
$$max_2 = 0.75 * \{I_{width} * I_{height}\} \quad (3)$$

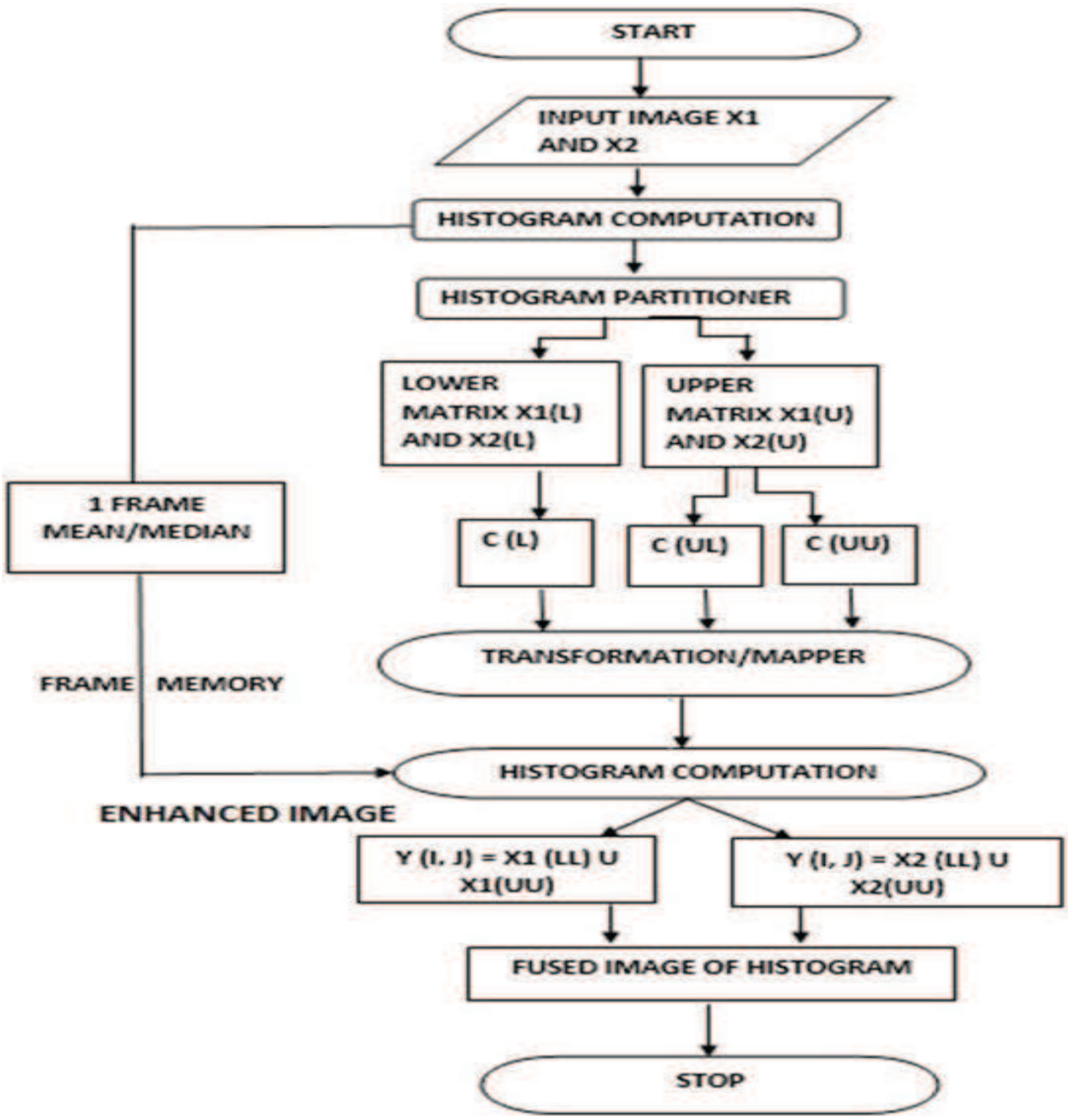


Fig. 2. The Process Flow of MDHE

Clipping Process: It is used to control the enhancement rate of histogram equalization in order to overcome unnatural and over enhancement of the processed image to occur.

New Gray-Level Allocation: In order to balance the enhancement space for each sub-histogram, the proposed

$Span_i = m_{i+1} - m_i \quad for\ i = 1{:}3$ (4)

$Range_i = (L-1) * \frac{Span}{\sum span_k} \quad for\ K = 1{:}3$ (5)

Where, $span_i$is the dynamic gray level utilized by i-th sub histogram in the input image in Eq (4) ,$m_i$denotes i-th separating point and total number of pixels in i-th sub-histogram and in Eq (5), $Range_i$is the dynamic level range for i-th sub-histogram in the output image.

4) New dynamic range allocation*:* In the i-th sub-histogram, the new dynamic range is allocated from $[i_{start}\ i_{end}]$ by way of assigning new starting and ending point values by using the following equations as follows:

$i_{start} = (i-1)_{end} + 1$ (6)

$i_{end} = i_{start} + range_i$ (7)

Where, 'i' denotes the corresponding **i-th** sub-histogram, for this case the value of i varies from 1 to 3, i_{start}denotes the value which is initialized to the minimum intensity value of the new dynamic range and i_{end}denotes the value which is initialized to the maximum intensity value of the new dynamic range
5) Histogram equalization: After the new dynamic ranges have been resolved for all the quadrant sub-histograms, the last step in the MDHE is to match each sub-histogram independently. The output of histogram equalization, $y\ (x)$ of this partition can be determined by using the transfer mapping function:
$Y(x) = [(i_{start} - i_{end}) * CDF(X_K)] + i_{start}$ (8)
Where, K = 1, 2 and 3 and denotes Cumulative density function of a sub-histogram.
This method is proposed to enhance the contrast of the image which is taken in the dim-light environment. The proposed method eliminates over-enhancement, noise amplification and intensity saturation problems and also produces better enhancement for smaller gray levels unlike in QDHE [27]. Finally, two enhanced images of the histogram are fused to give a single image.

Modified Marker Controlled Watershed Segmentation: Segmentation, in particular, has always performed a fundamental role for remote sensing applications, and numerous powerful techniques have been proposed over the years [28], offering regularly very good results in challenging real-world problems. Before performing watershed segmentation, a Modulated intensity gradient based method is used to convolve gradient operators with the image. The high value of gradient magnitude can be points (edge pixels) with an abrupt change between intensities of the two regions and can be linked together to form closed boundaries. Then, the use of markers, on the other hand, allows us to reduce the over segmentation typical of watersheds, providing thus a compact object layer. Markers of two kinds are described, primarily based on spectral and morphological residences. The former is used prevalently in low-detail areas of the image, whereas the latter is more vital in high-detail regions, wherein the spectral information is much less reliable.
The segmentation process is divided into two steps:
1) Finding the markers and the segmentation.
2) Performing a marker-controlled watershed with those factors.
The over-segmentation could be reduced by suitable filtering, but the exceptional results are acquired by marking the patterns to be segmented before performing the watershed transformation of the gradient. Unfortunately, maximum instances the real watershed transform of the gradient present many catchment basins, each one corresponds to a minimum of the gradient that is produced by small variations, mostly due to noise. This leads to over segmentation problem.
The algorithm for over segmentation solution is as follows:
$W_{i+1}(g) = IZ_{Z_{i+1} \cup M}\big(W_i(g)\big)$ (9)
Where, $W_i(g)$ - section at level i of the new catchment basins of g
M = $W_{-1}(g)$, Initialization

Classification: Quantitative information is extracted from remotely sensed data via classification which consists of the following steps, 1) Feature extraction 2) Training and 3) Labeling. In feature extraction step, the multispectral image is transformed to a feature image by a textural or spectral transform. In the training phase, homogeneous pixels are selected to represent the desired classes. The feature space is then partitioned by determining the decision boundaries based on the trained pixel properties.ANN is an non-parametric classifier used where no assumption is made about the data distribution.

Change Feature Extraction: Many strategies have been used to extract features from images via the use of spectral and textural information of the corresponding pixels, which might be employed to highlight the changed areas between the multispectral image pair. The spectral information of pixels is the average gray value within the pixels in different wavebands of the image. An ultimate level to gather such features through texture analysis process is called as texture feature extraction. GLCM is a matrix that describes the frequency of one gray level acting in a unique spatial linear relationship with another gray level inside the location of investigation [29].Given an image, each with an intensity, the GLCM is a tabulation of how frequently distinctive combinations of gray levels can occur in an image. Therefore, we choose the GLCM mean feature to measure the textural difference between the high-resolution images. It is given by:

(Textural feature) j = (Y2) j – (Y1) j (10)
Where (Y1) j and (y2) j denote the *j* th pixel of the GLCM mean feature.

Neural Network Classifier: It is well known that neural network is an effective tool to excavate the intrinsic relationship of images and accumulate large amount of useful knowledge. Nowadays, it has achieved great success in machine learning due to its excellent performance of data representation and powerful learning ability from the chaotic data. The Neural network has the ability to learn the abstract high-level representation of the input data from lower layers. In this proposed model, the process of learning the enhancement techniques from the multispectral images can be divided into two parts, the training phrase by using layer-wise supervised learning and fine-tuning the whole network by the RBM algorithm [30].Algorithm 1 shows that RBM algorithm and it is used in neural network classifier to obtain changed values from the training samples.

Algorithm 1 Restricted Boltzmann learning Algorithm

```
Initialize node outputs to random values
Separate Visible units into Input & Output units
Until Convergence (Δw < ε)
For each pattern in training set
Clamp pattern on all visible units
Anneal several times and gather p+ij
End
Average p+ij for all patterns
Unclamp all visible units
Anneal several times and gather p-ij
Update weights
End
```

5.2.1 Brief Description of Restricted Boltzmann Machine

Boltzmann machine learning may be considered as an unsupervised learning process for modeling a distribution that is exact by using the clamping patterns. A restricted Boltzmann machine (RBM) consists of a layer of visible units and a layer of hidden units with no visible-visible or hidden- hidden connections. A Restricted Boltzmann Machine (RBM) [31] is a two-layer connectionist system characterized by an energy function E,

$$E(v,h) = -\sum_{ij} v_i w_{ij} h_j - \sum_{i} a_i v_i - \sum_{j} b_j h_j \qquad (11)$$

According to the learning rule, the network can be trained by the training samples. After completing this step, a BP algorithm is applied to fine-tune the whole network from top to bottom.

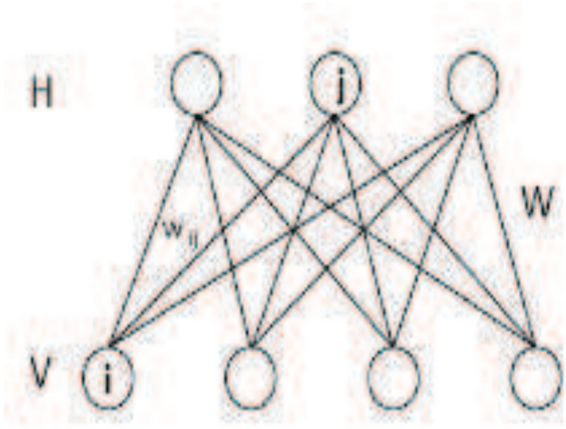


Fig. 3: Structure of RBM

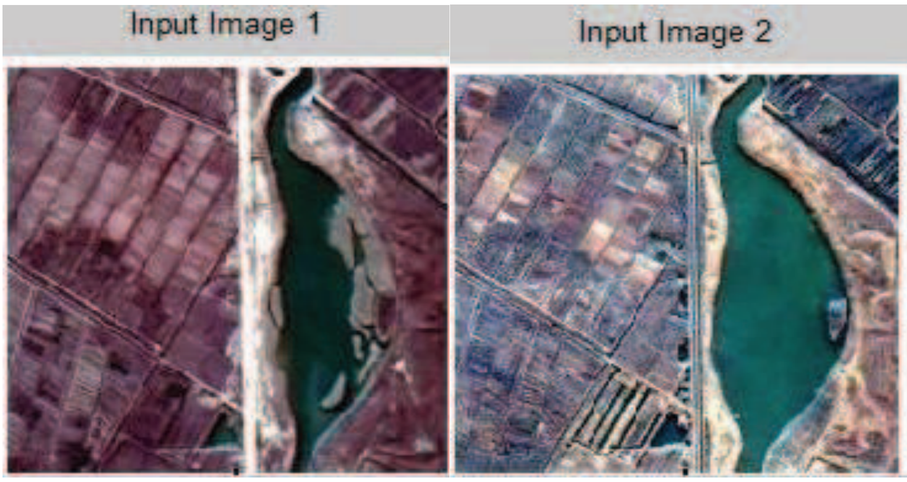
In Fig. 3, layer 'v' describe the states of the visible layers (Pixels),'h' describe the states of the hidden layers (Feature Detectors) and 'w' represents connection weights, and a ;b hold biases for visible and hidden layers respectively. Since, all units in one layer are independent of each other, the state of a hidden unit depends only on the states of visible units and vice versa. The hidden units are conditionally unbiased stated the visible states. So can rapidly get an independent sample pattern from the posterior distribution when given a data-vector. This is a big advantage over directed belief nets.

Supervised Classification: Land covers, may be recognized and differentiated from each other by their exclusive spectral response patterns.**Supervisedclassification** may be used to improve the spectral responses of known categories, such as training site improvement and then the software assigns each pixel within the image to the cover type to which its spectral response is maximum comparable.

Sources for Deriving Ground Truth Data: When performing Land Use Land Cover classifications, one needs ground truth data to provide an unbiased reference necessary to conduct accuracy assessments. Because landscapes can exchange rapidly, it's far critical that training data and ground truth data are acquired at dates as near to each other as possible. When the instrumentation cannot be located directly at the point of interest, substitution can be done by direct observations with imagery that has a much higher spatial/spectral resolution than the imagery used for the LULC classifications.

Accuracy Assessment: The improved usage of remote sensing data and techniques has made spectral analysis faster and further powerful, but the increased complexity also creates increased possibilities for error. In the past, accuracy assessment was no longer a concern in image classification studies. Because of the increased possibilities for error presented by using digital imagery, however, accuracy assessment has become more important than ever. The complete accuracy of the classified image compares how each of the pixels is classified against the real land cover conditions acquired from their corresponding ground truth data.

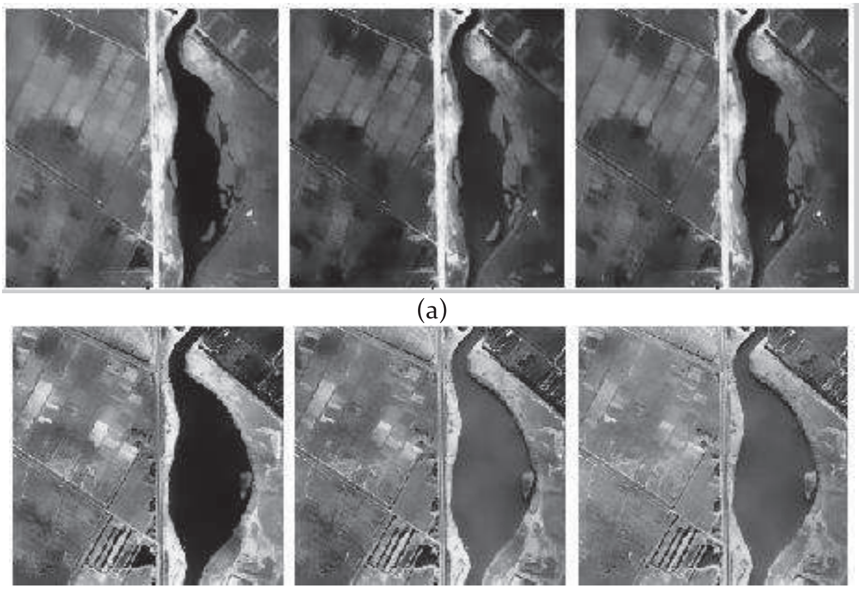
Experimental Settings: To validate the effectiveness of the proposed methods, the challenges were made for multispectral change detection on a real data set. Fig. 4, describes the riverway changes of Hongqi Canal along the Xijiu village, and with the same size of 539 × 543 pixels framing in green. The experiments will be applied to demonstrate the superiority of the proposed technique based on MDHE and modified watershed segmentation. At first, the evaluation criteria of change detection using proposed techniques will be described in detail.



(a) (b)

Fig. 4. Multispectral images of Hongqi Canal data set. (a) Image acquired on December 9th, 2013. (b) Image acquired on October 16th, 2015.

Result Analysis: In the above multispectral input images, preprocessing (RGB to Grayscale conversion) was done in both input images. In Fig.5, Bilateral Filtering is applied to produce higher-dimensional representation of image.



(a)

(b)

Fig 5: (a) Bilateral Filtering applied for input image 1, (b)Bilateral Filtering applied for input image 2

After preprocessing, Fig. 6. And Fig. 7. Shows the Modified Dynamic Histogram equalization of two input images which is used to enhance the contrast of the image which is taken in the dim-light location.

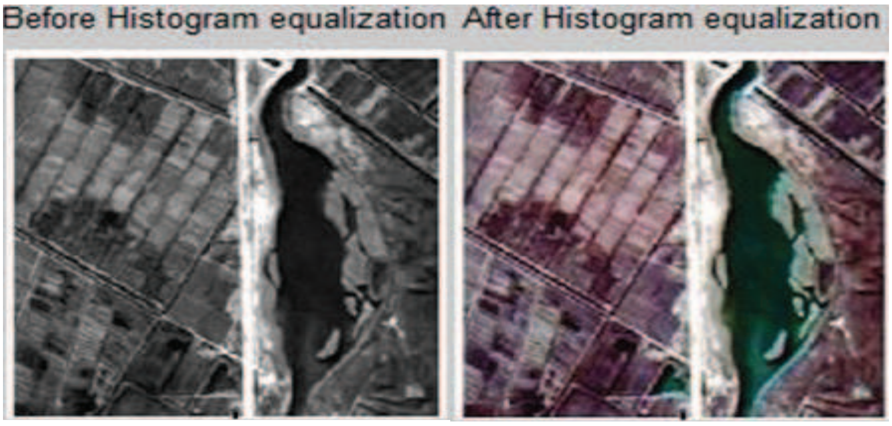
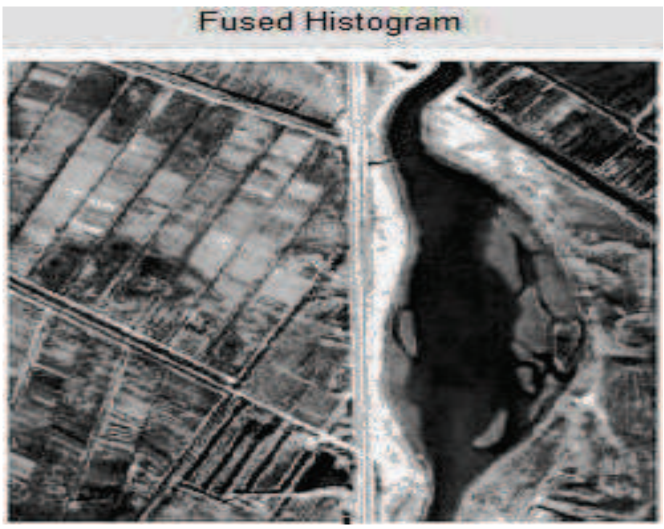
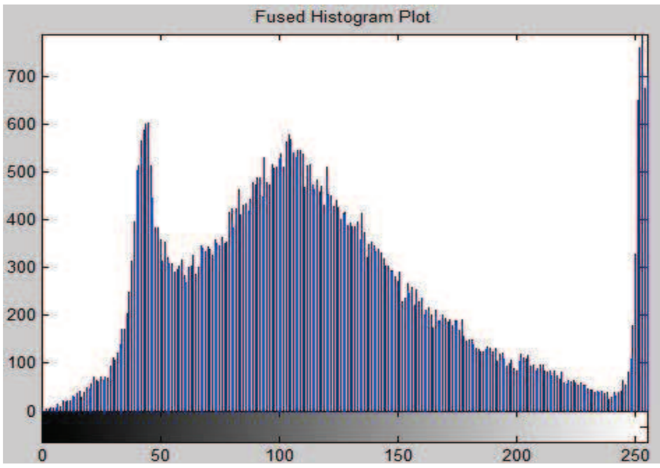


Fig. 6. Modified Dynamic Histogram Equalization of Input Image1
Fig. 7. Modified Dynamic Histogram equalization of Input Image2

The above figures show that the histogram equalization is done by transforming and computing the two input image to give a contrast image. After performing equalization, fusion is done by using high and low pass filters. Fusion of two histogram images eliminates over-enhancement, noise amplification and intensity saturation problems. Fig.8. Shows that two histogram images are fused to give a single enhanced image and its histogram plot.



(a)



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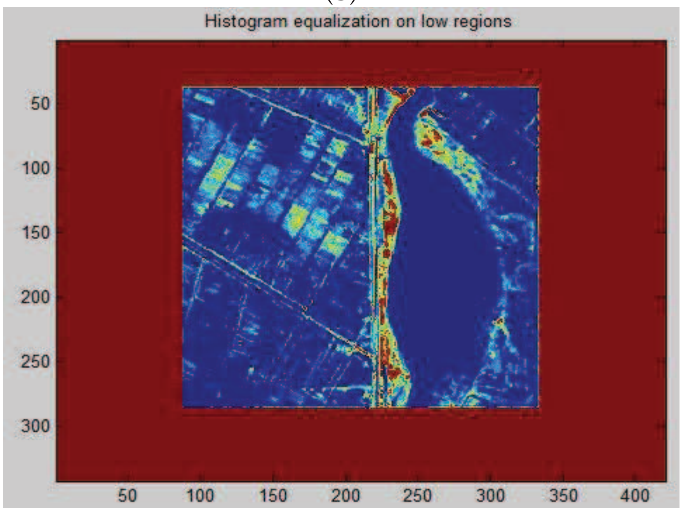

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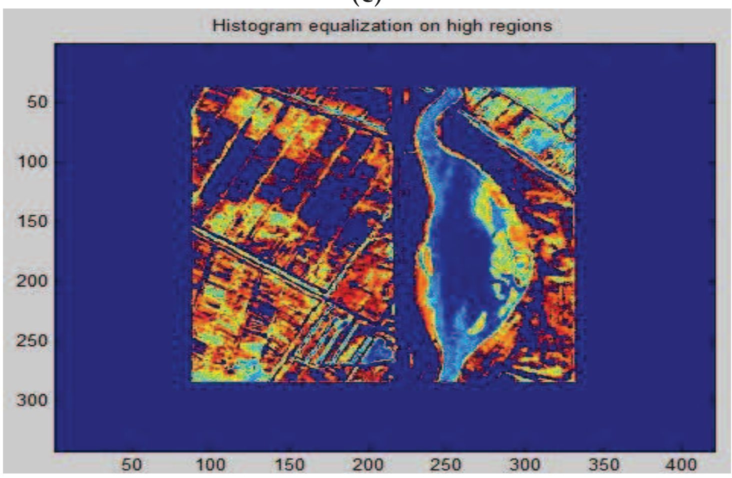
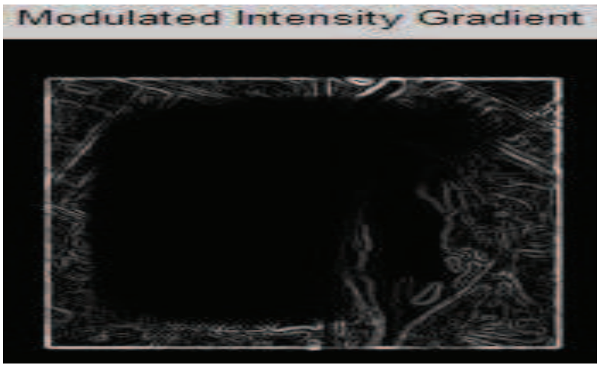


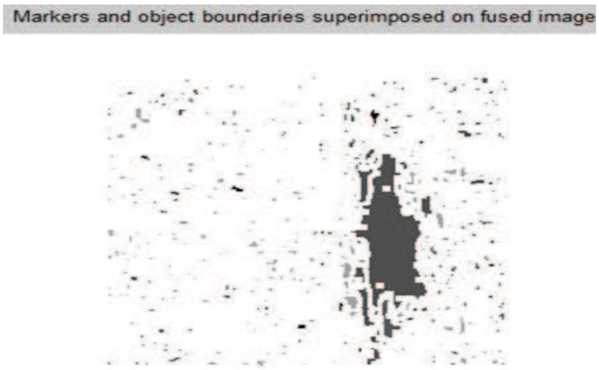
(d)

Fig.8. (a) Fusion of Histogram Equalized images and (b) MDHE Plot (c) MDHE on Under Enhanced Region (d) MDHE on Over Enhanced Region.

Under enhanced and over enhanced images can be created by dividing the histogram into two regions (by taking the average intensity value of histogram image) and perform histogram stretching on both the regions to improve the contrast in the image. Modulated Intensity Gradient Based Segmentation is used, when there is an abrupt change in the intensity near edge and then the high value of gradient magnitude between intensities of the two regions can be linked together to form closed boundaries. In the following Fig 9, (a) and (b) shows that Modulated Intensity Gradient Based Segmentation and markers super imposed on fused image respectively.



(a)



(b)

Fig.9.(a) Modulated Intensity Gradient Segmentation and (b) Markers and object boundaries

In Fig. 9, (b) illustrates how the locations of the foreground and background markers affect the result. In a couple of locations, partially occluded darker objects were merged with their brighter neighbor objects because the occluded objects did not have foreground markers. After recognizing markers on fused image, watershed segmentation is applied to reduce over segmentation problem which was shown in Fig. 10.

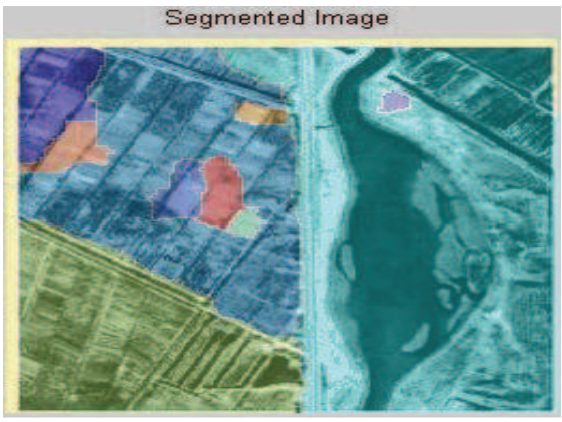


Fig. 10. Watershed Segmentation

Finally, the entire framework has been thoroughly processed and the change detected areas are identified by the white bordered regions which were shown in Fig. 11.

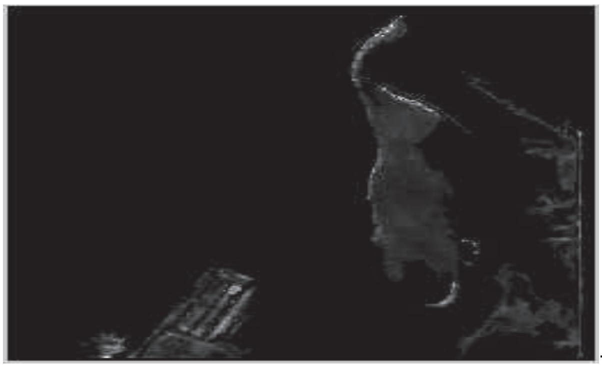


Fig. 11. Change Detected Image

Therefore, supervised classification is advantageous because it will use a relatively small number of classes in future work to determine the appropriate land cover for each pixel.

Conclusion: In this paper, a novel change detection framework for high-resolution multispectral images has been presented. Results obtained shows that the algorithm used in this paper can effectively improve the overall brightness and enhance the contrast of the image. Furthermore, the proposed methods can overcome the limitation of existing equalization methods and obtain change feature images, by exploiting corresponding spectral and textual features. However, these change features are insufficient to accurately highlight the changes between the multispectral image pair. The upcoming work focuses on the change detection problem which will be transformed into a classification one through neural network, utilizing its strong ability. The experimental results on real data set have demonstrated its effectiveness and reliability of the proposed technique for change detection in high-resolution multispectral imagery.

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