Semi-Supervised Change Detection Method using Phase Congruency and Local Binary Pattern (PC-LBP)

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Abstract **- Several feature extraction methods are available for the application of change detection using remote sensing images. In this paper an efficient feature extraction technique is proposed by combining the phase congruency (PC) and local binary pattern (LBP) to extract the features in the images. The congruency amplitude and orientation is first determined for the two-multi temporal images and the LBP features are extracted. From the feature vectors of two images, neural networks (NN) classify the region into changed and unchanged. The deterministic method developed in this paper exploits improved accuracy in the change detection results. From the performance evaluation, it is noted that proposed method shows high accuracy and better kappa coefficient, which yields good change detection results.**

Keywords - phase congruency, local binary pattern, remote sensing, change detection

I. INTRODUCTION

Change detection in remote sensing platform offers a detailed study about environmental issues; land use and land cover changes, impact of urbanization etc. [1]. Change detection of multi temporal images can be done using supervised or by unsupervised classification methods. In supervised method of change detection, training data with ground truth is desirable whereas in unsupervised method training data with ground truth is not necessary [2]. Another technique is proposed [3] by combining a sparse fusion method for semi supervised change detection. In change detection methods spatial domain features explores more to depict perfect analysis of changes. Texture is an important spatial domain feature having innate property of analyzing the structural information of the surface. In order to make the method invariant to illumination and contrast changes phase congruency method is adopted to detect the corners and edges in an image [4]. Wang [13] proposed a feature extraction method of modified phase congruency by combining Hilbert transform. In satellite images boundary detection is one of the important area and phase congruency method combining local energy model is proposed by Ahmed [14]. A gray scale invariant method called Local Binary Pattern (LBP) is used for better change detection result [5]. Another feature extraction method called Law's texture measure [6] that performs line and edge detection in two directions. For human detection Histogram of Oriented Phase (HOP) method is employed by Ragb [15]. Haralick [7] proposed GLCM feature Extraction method, which is widely used in the field of medical and remote sensing applications.

II. SEMI-SUPERVISED CHANGE DETECTION METHOD

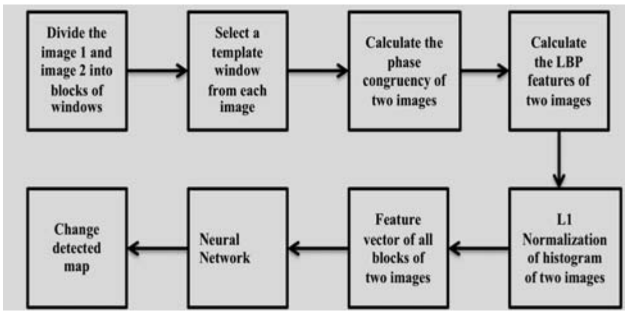

Fig 1. Proposed Methodology for change detection

Fig. 1 shows the block diagram of proposed method. Two multi temporal images are taken for the year 2013 and 2015 and the dataset is Bay Area California and the image has 224 spectral bands. The proposed method composed of mainly 5 stages such as (i) Divide the image into blocks (ii) Calculation of phase congruency (iii) Calculation of LBP features (iii) L1 Normalization (iv) Classification using neural network and (v) Change detection map.

The input database consists of two images (image 1 and image 2) and the images are divided into blocks of windows. Then select a template window from each image and phase congruency is calculated. Then the LBP features are extracted and L1 normalization is done. Then feature vectors of all blocks are calculated for two images and given to the neural network for classifying the image into changed and unchanged regions. Then an accuracy assessment is

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carried out to validate the effectiveness of the proposed method by comparing with LBP and HOP methods.

A. Phase Congruency (PC)

Phase information is an effective measure in the domain of image analysis. Phase congruency is important for image perception because it reflects the significance of phase and also invariant to illumination and contrast changes. It mainly focused on detection of corners and edges where Fourier components are maximum in phase. Since the phase congruency is sensitive to noise, Kovesi [8] proposed a more localized method of phase congruency.

Phase congruency is evaluated using a filter called log Gabor filter [9] generates even and odd symmetric wavelets. The DC component is absent in the log Gabor filter and it overcomes the shortcomings of Gabor filter. The convolution of even and odd symmetric wavelets in different angles results in projections of horizontal and vertical directions.

The phase congruency of a signal g(x) is given by

$$PC = \max_{w(x)\epsilon[0,2\pi]} \{\textstyle\sum_n Y_n(x)\cos\big(w_n(x) - \overline{w}(x)\big) / \sum_n Y_n(x)\} \quad (1)$$

Where Y_n denotes the amplitude of nth Fourier component and w_n is the local phase.

The log Gabor filter is represented by:

$$G_{log}(w) = \exp\left(\frac{-\left(\log\left(\frac{\alpha}{\alpha o}\right)\right)2}{2\left(\log\left(\frac{g}{\alpha o}\right)\right)2}\right) \quad (2)$$

The orientation of the phase congruency is given by

$$\theta = \arctan(s,t) \quad (3)$$

Where:

$$s = \textstyle\sum_{\phi}(odd(\emptyset)cos\emptyset \quad (4)$$

$$t = \textstyle\sum_{\phi}(odd(\emptyset)sin\emptyset \quad (5)$$

Where $odd(\emptyset)$ is the odd symmetric component of log Gabor filter.

B. Local Binary Pattern (LBP)

The template window is divided into bocks and each block is divided into cells [10]. Each pixel in a cell is compared with its neighbors following either in clockwise or anti clockwise direction. If the pixel value of the center is greater than the neighbor, represent the value as '1' and if the pixel value of center is less than 1, represent the value as '0'. All the values in the neighborhood generate an 8 digit binary number that can be converted to decimal which is depicted in Fig.2. Then the histogram is calculated for each cell and concatenates the histogram of all blocks and normalize using L1 normalization to get a feature vector.

$$LBP_{R,G}(x,y) = \sum_{i=0}^{G-1} k(g_i - g_c)2^i, k(x) = \begin{Bmatrix} 1, x \geq 0 \\ 0 \quad ow \end{Bmatrix} \quad (6)$$

In the 8 neighborhoods LBP operation, g_c represents the gray level value of center pixel and R is the radius of the G equally spaced pixel and its gray level is denoted as g_i.

- Basic LBP operator

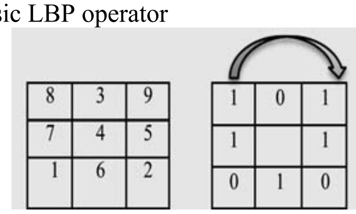
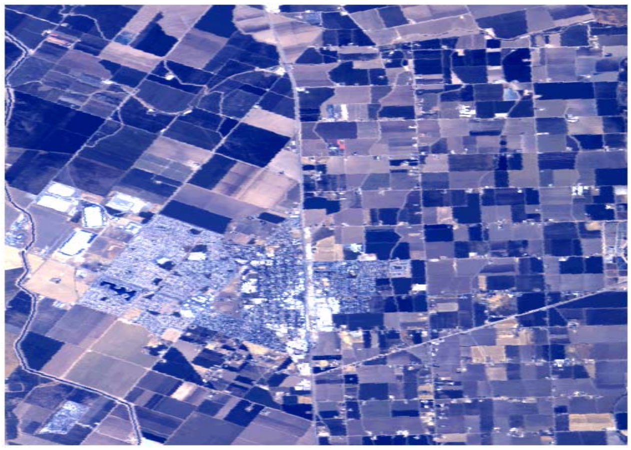
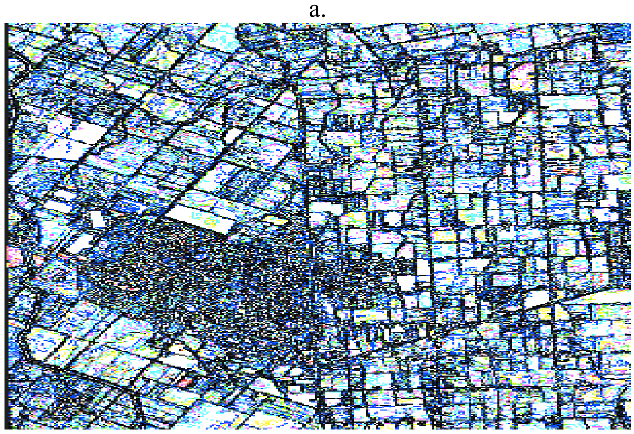


Fig 2: Basic LBP operator

Binary value: 10110101



a.



b.

Fig 3. Illustrative example of LBP

C. Neural Network (NN)

The PC-LBP feature vectors are given to NN for classifying the image into changed and unchanged regions. A straightforward neural network is used in the proposed method. NN [11] refers to one of the most appropriate classification method and the most important strategy is the training and testing sets [12]. It mainly consists of three layers namely input layer, hidden layer and output layer. The feature vectors of both the images (2013 and 2015) are given to the input layer of NN. To validate the feature vector 70% of data is given for training. After the training phase, the neural network will assign the weight for changed pixels. The expected result in the output of neural network is given in Equation (7).

$$K = \sum_{j=1}^{C} w_x \left\{ \frac{1}{1 + exp\left(-\sum_{i=1}^{P} H_i \omega_{xy}\right)} \right\} \quad (7)$$

In the above equation w_x is the weight allotted to output layer and hidden layer and ω_{xy} is the weight allotted to input layer and hidden layer. H_i is the feature vector which is give to input layer.

III. ALGORITHM FOR PC-LBP METHOD

Step 1: Two multi temporal images are given as input

Step 2: Select a template window from the image blocks

Step 3: Calculate the phase congruency amplitude and orientation for each pixel of the images.

Step 4: Local binary pattern features are extracted

Step 5: Feature vectors are normalized by L1 normalization of the histogram of all the cells.

Step 6: Feature vectors are given to NN classifier to classify the region into changed and unchanged areas.

Step 7: The accuracy assessment is done by evaluation the parameters like Kappa coefficient and Overall accuracy. Kappa Coefficient and overall accuracy is evaluated by using the True Positive (Tp), True Negative (Tn), False Positives (Fp) and False Negative (Fn) values with respect to the reference image.

IV. RESULTS AND DISCUSSIONS

Fig 4 (a) and (b) shows two multi temporal images of the year 2013 and 2015 taken from the Bay Area dataset, California.

By analyzing the classification accuracy and kappa coefficient that is shown in Table.1 reveals that proposed method shows better results than the LBP and HOP feature extraction methods. In the change detection result the black portion denotes the changed area and white portion denotes the unchanged area.

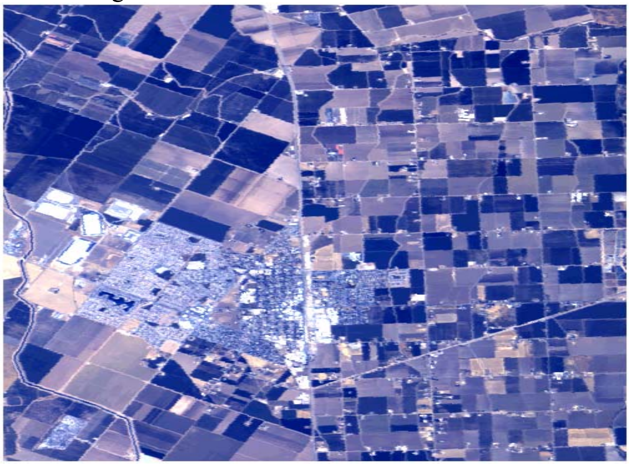


Fig 4. (a) Input image (2013)

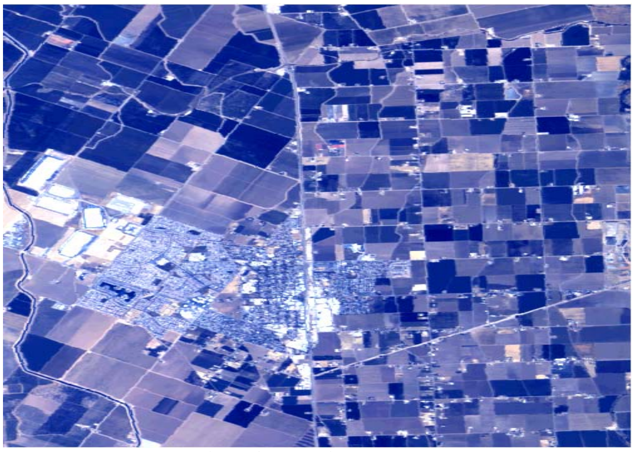


Fig 4. (b) Input image (2015)

The two input images are preprocessed and calculate the phase congruency amplitude and orientation. Then PC-LBP features are extracted.

Fig 5: Change Detection results

Then the feature vector is given to neural network and change detection is performed. Change detection results are illustrated in Fig 5.

The experimental evaluation is done by analyzing certain performance measures

Tp- the pixels of changed area are identified correctly as changed.
Tn- the pixels of unchanged area are identified correctly as unchanged.
Fp- the pixels of changed area are wrongly identified as unchanged area.
Fn- the pixels of unchanged area are wrongly identified as changed area.

Kappa Coefficient- Measure of accuracy of changed area (2015) with respect to a reference image (2013).

$$Kc = \frac{PCC-PRE}{1-PRE} \tag{8}$$

Where PRE is given by

$$PRE = \frac{(Tp+Fp)Mch+(Fn+Tn)Mun}{(Tp+Fp+Fn+Tn)^2} \tag{9}$$

And PCC (Percentage Correct Classification) or Overall Accuracy is given by

$$PCC = \frac{Tp+Tn}{Tp+Tn+Fp+Fn} \tag{8}$$

TABLE 1. PERFORMANCE MEASURES

Metrics	HOP	LBP	Proposed Method
Kappa Coefficient	85.12	86.27	89.52
Overall accuracy (%)	85.22	89.87	92.37

V. PERFORMANCE EVALUATION

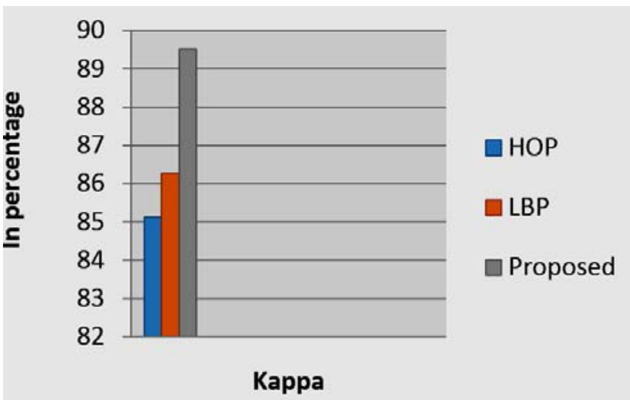


Fig 6: Kappa coefficient

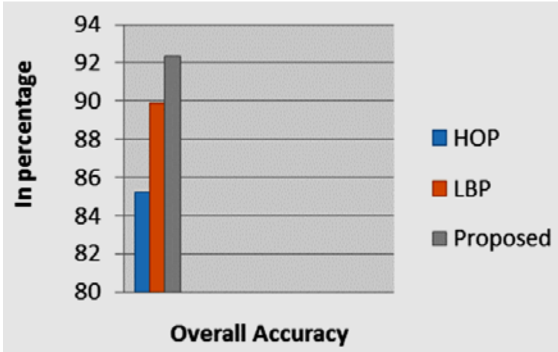


Fig 7: Overall Accuracy

VI. CONCLUSION

In this paper we proposed an efficient feature detection method for change detection in the domain of remote sensing. The proposed PC-LBP technique illustrates the importance of phase information for extracting the features. Three main approaches discussed here are Phase Congruency, Local Binary Pattern and Neural Network. In the change detection results, high intensity pixels denote the changed area and low intensity pixels denote the unchanged area. Based on the performance evaluation of Kappa Coefficient and Overall Accuracy, the proposed method confirms the effectiveness of improved model of change detection.

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