Efficient Post Classification Change Detection of land cover images using Multi-Scale Segmentation and Self Organizing Feature Map

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Abstract- **Remote sensing is the most reliable and effective way of classifying the land use and land cover images. In the present day world, this land use and land cover mapping is of great significance in scientific, research, planning and management. Based on remotely sensed data it could be quite possible to classify the land into various classes. This paper proposes a novel method for classifying the land based on Object Based Segmentation and Robust Local Texture Pattern. In urban areas, classifying the land and detecting the usage of the land is highly essential. In this paper, a novel Object Based Segmentation to segment the image is performed initially on the given image to identify the objects present in the image. Local Texture Pattern is applied on the segmented objects to identify the texture of the objects so that the objects can be distinguished effectively. Also UDWT transform domain approach to construct post-classification change detection binary map is performed on two co-registered images. Unsupervised Self Organizing Map (SOM) neural network classification was applied individually on two multitemporal images and then resultant classified images are exploited for Post classification process to generate change matrix. Finally the changes are labeled by comparing binary change map and change matrix.**

Keywords— Land Use Land Cover (LULC), Object Based Segmentation(OBS), robust Local Texture Pattern (rLTP), Self Organizing Map (SOM)

I. INTRODUCTION

In urban areas, regional land use patterns reflect the characteristics of interaction between human and environment interms of man's basic economic and social activities. Remotely sensed satellite images provide a synoptic overview of the whole area in a little time span, which leads to quick and truthful representation of the real world data in the best possible manner. Classification is very essential process for identifying the land use and land cover classes which is helpful for observing the objects present in the land. Several applications are evolved based on remote sensing namely land cover monitoring, land cover change detection, classification, impact assessment and infrastructure planning. The main advantage of remote sensing is that recent information over a large geographical area, acquisition of data from inaccessible regions, easy to manipulate and combine that information with other medium like GIS (Geographic Information System). In general, classification of land images can be separated into two major groups namely; 1) pixel based classification 2) object based classification approaches. In pixel based approach, each pixel of the image is classified and it mainly focuses on textural and spectral properties. But in case of object based approach, each individual object is classified and it focuses on textural, spatial and contextual properties. In this paper, an object based segmentation based on watershed transform and region merging to segment the image to detect the objects was performed initially on given land cover image. Robust LTP is applied next segmented image to detect the textural patterns. For understanding the interactions and relationships between natural phenomena and human, the periodic monitoring of change detection of earth surface is extremely important. Post-classification change detection method can provide information about what kind of transitions has occurred on the ground. Because this method involves classification of remote sensing images. In this paper, a novel UDWT is used to produce multi-resolution representation of the difference image. UDWT and binary map was performed on two co- registered images. Classification is applied next on the two temporal images by using SOM. As a result, class transition change is produced.

II. RELATED WORKS

The literature survey deals with the olden techniques that were used for classifying the land such as HMM and Transductive SVM.

Uijwal Maulik. B et al. (2013) constructed Transductive SVM for classification of land. The classifier filters between the Transductive sets to select the effective samples from unlabeled data, a process called Successive filtering TSVM to reduce the misclassifications.

Ataollah Haddadi *et al.* (2013) proposed a new technique of multi-scale segmentation by combining wavelet and watershed transform. The wavelet transformer produces initial images and then watershed algorithm was applied for segmentation of the initial image, then by using inverse wavelet transform, the segmented image was projected up to a higher resolution to capture larger objects. Finally, the region merging was done to obtain larger objects.

Surulliandi and Rmar (2009) proposed LTP, in which the texture pattern around a pixel in an image is computed with the pattern units P obtained for its eight neighbors. A pattern string is then formed by collecting the P values of the eight neighbors starting from any position. Uniformity measure is computed and the patterns are relabeled to form continuous numbers from 1 to 46.

Cludio Rosito Jung (2005), proposed a new multi-scale method for watershed segmentation using wavelets. The background noise tends to produce spurious gradients, causing over segmentation and degrading the result of watershed transform. A new technique was presented to improve robustness of the segmentation using watersheds, which attenuates the over segmentation problem. A redundant wavelet transform is used to de noise the image, enhance the edges and obtain an enhanced version of image gradients. The watershed transform is applied to the obtained gradient image and the segmented regions that don't satisfy the criteria are removed or merged.

Krahulec M (2009) proposed a new post processing technique for merging the smaller objects into larger ones. The merging can be done with all regions with an area below an assigned threshold. When deciding which neighboring regions to merge these small regions into, the quality of edges in between the neighboring regions and the region to be merged are considered. By looking at which edge has the lowest average height, it can be chosen as the region to be merged into.

Uma Shankar. B et al. (2011) constructed a wavelet feature based fuzzy classify for land cover detection in multispectral images. The extracted features can acquire the information about the pixel along its neighbors both in spectral and spatial domains. It can be utilized effectively for improving accuracy in classification. Mourad Bauziani et al. (2010) [4] proposed an automatic multispectral segmentation algorithm inspired by the specific idea of guiding a classification process for a high-spatial-resolution remote sensing image of an urban area using an existing digital map of the same geographical area. The classification results might be used for change detection studies.

III. METHODOLOGY

To classify the remotely sensed land use and land cover image, the methodology followed in this work includes three tasks such as i) Multi-Scale segmentation iii) Classification using SOM.

To classify the image, the objects of the image are extracted using Multi-Scale segmentation. Change map generation using post-classification change detection. In the post-classification change detection method, classify the classes of the temporal images. Change/ no change map are generated by using post-classification change detection.

Input Images at time T1 ,T2

Multi-Scale Segmentation, Feature Extraction, Classification

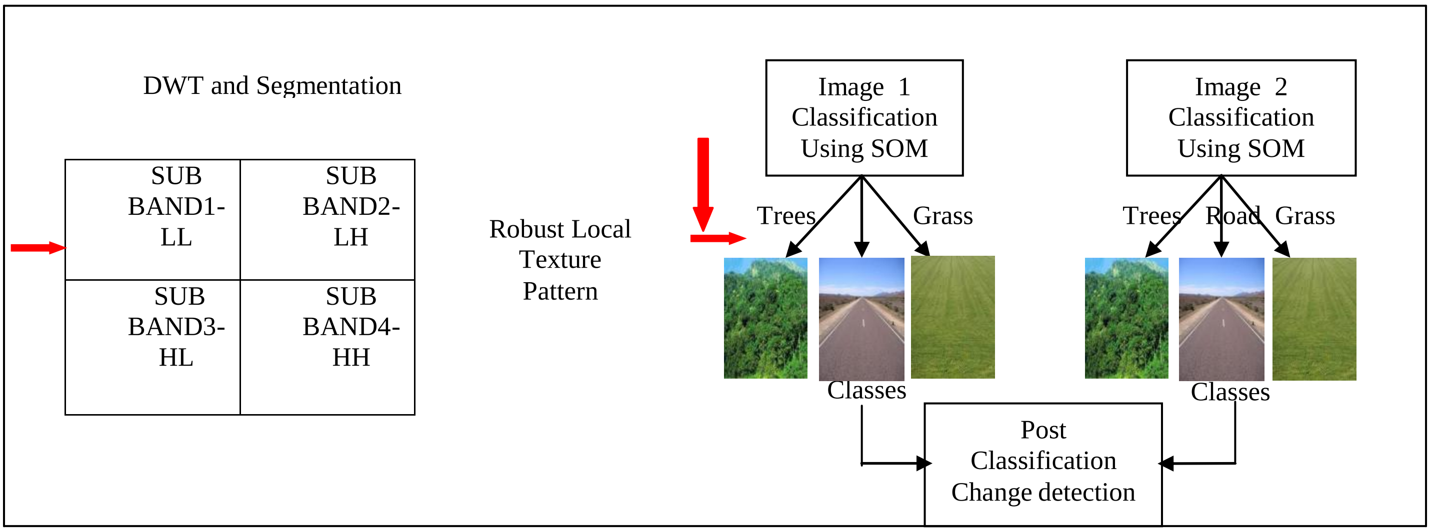


Fig.1 Proposed System Architecture

A. Multi-Scale Segmentation Approach

The approach involves the decomposition of the input image into various levels using Wavelet Transform. The image is decomposed into four levels, thus producing a Multi-Scale representation. The wavelet eliminates the noise in the image.

1) Discrete Wavelet Transform: The wavelet transform is localized in both time and spatial frequency domain. The Discrete Wavelet Transform (DWT) is based on the sub-band coding and it is found to yield a result with fast computation. DWT is computed with a cascade of filtering such as a high pass and low pass respectively followed by Sub Sampling. At first, DWT is performed for all rows and then for all columns. Multi-Scale representation function is one of the main features of DWT. There are a number of basic functions in Wavelet Transform and that can be used as the mother wavelet for wavelet decomposition. All wavelet functions are mostly produced by mother wavelet and it determines the characteristics of the resulting wavelet decomposition. Commonly used wavelet functions are Haar wavelet, Daubachies wavelet and symlet. Daubachies are characterized by a maximal number of vanishing moments. Here, the dwt2 is used and it is a two dimensional wavelet transformation function. DWT decomposes the image into Approximation Image (cH1), Vertical Image (cV1) and Diagonal Image (cD1). The image obtained at the LL sub-band is called Approximation Image and the images obtained at LH, HL and HH sub-bands are referred as Detail Images. Also, due to the smoothing properties of the low pass filters and high pass filters used in wavelet, it eliminates the noise and acts as a preprocessing step for watershed segmentation.The reversible type of wavelet transform is used so that the size of the image can be recovered after it has been transformed.

2) Edge Detection Using Sobel Operator: Edges characterize boundaries and are therefore they are considered as fundamental importance in image processing. Edges are areas with strong intensity contrasts – a jump in intensity from one pixel to the next. Edge detecting in an image significantly reduces the amount of data and filters out useless information, while preserving the structural properties in an image. There are two major ways to perform edge detection. They are gradient and laplacian. The Laplacian method searches for Zero crossings in the second derivative of the image to find the edges. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. The derivative shows a maximum located at the center of the edge in the given signal. This method of locating an edge is characteristic feature of the "gradient filter" family of edge detection filters and includes the Sobel method. In the proposed method, the edge detection is implemented using the Sobel operator. Since, the Sobel operator works only on grayscale images, and hence the original rgb color image is converted into grayscale image. The sobel operator is applied on the Approximate Image. The Sobel operator performs a 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial frequency that correspond to edges. It is used to find the approximate absolute gradient magnitude at each point in the given grayscale image. The operator consists of a pair of 3X3 convolution kernels. One kernel is simply the other kernel rotated by 90^0. The following figure 2 shows the convolution filters of Sobel operator.

-1	0	+1
-2	0	+2
-1	0	+1

+1	+2	+1
0	0	0
-1	-2	-1

Fig. 2 Convolution masks GX and GY of Sobel Operator

These kernels are designed to respond maximum to edges running vertically and horizontally relative to the pixel grid, one kernel separately for each of the two perpendicular orientations. The kernels are applied separately to the input image, to produce GX and GY of the gradient component in each orientation. They can be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is described by:

$$|\mathbf{G}| = \sqrt{(\mathbf{G_X}^2 + \mathbf{G_Y}^2)}$$

Where GX = $\mathbf{(Z_7 + 2Z_8 + Z_9) - (Z_1 + 2Z_2 + Z_3)}$ and GY = $\mathbf{(Z_3 + 2Z_6 + Z_9) - (Z_1 + 2Z_4 + Z_7)}$. (1)

3) Watershed Segmentation: In order to segment the different regions, segmentation is used in Image Processing. It consists of constructing a symbolic representation of the image: the image is described as homogenous areas according to one or several a priori attributes. In general Image Segmentation approaches are based on either homogeneity and or discontinuity of the gray level values in a region. The discontinuity based methods tends to partition an image by detecting points, lines and edges according to abrupt changes in gray levels. The homogeneity based methods include watershed, thresholding, region growing, region splitting and merging. The proposed method deals with a new method for object based image segmentation using the gradient approach and the watershed transformation. The major advantages of the proposed method are that it always provides closed contours, which is very useful in image segmentation. Another advantage is that the watershed transformation requires low computation times in comparison with other segmentation methods. This method also eliminates the over segmentation problem of watershed, by proposing a new method based on the gradient algorithm and a watershed transformation.

Watershed algorithm is based on morphological process, in which watersheds are the ridge line that divides different areas called catchment basins drained by different river systems. In mathematical morphology, a gradient image may be considered as a topological surface where the numerical value of each pixel indicates the evaluation of their points. The set of pixels along which the gray level changes sharply gives rise to an edge. The proposed method of watershed segmentation uses the Distance Transform approach. The distance transform of a binary image is the distance from every pixel of the object component which is black pixels to the nearest white pixel. In binary images there are only two gray levels 0 and 1 where 0 stands for black and 1 stands for white. The distance transform used in the proposed method is Euclidean Distance. The Euclidean Distance between two pixels [i1, j1] and [i2, j2] is calculated by,

$$\mathbf{D_{Euclidean}([i1, j1], [i2, j2]) = \sqrt{[(i1-i2)^2 + (j1-j2)^2]}} \quad (2)$$

The function L=Watershed (image, connectivity) computes a label matrix identifying the watershed regions of the input image matrix, which can have any dimension. The elements of L are integer values greater than or equal to 0. The elements labeled 0 don't belong to unique watershed region. These are called as watershed pixels. The elements labeled as 1 belong to the first watershed region, the elements labeled as 2 belong to the second watershed region, and so on.

4)Inverse Discrete Wavelet Transform: As the invertible wavelet transform is used, the wavelet transform image can be reversed. The Watershed segmented Approximate Image is projected to high resolution using the Inverse Discrete Wavelet Transform; here the detail regions of the image (LH, HL, HH) are also updated using Inverse Discrete Wavelet Transform to reconstruct the original image. The function IDWT2 (cA, cH, Cv, cD,'Wname') helps in reconstruction of the image. A process by which components can be assembled back into the original signal without loss of information is called Inverse Discrete Wavelet Transform. This process is called reconstruction, or synthesis and the mathematical manipulation that effects synthesis is called IDWT. IDWT reconstructs a signal from the approximation and detail coefficients derived from decomposition. IDWT requires Upsampling and filtering, in which Upsampling, known as interpolating, does the insertion of zeros between samples in the image. The analysis filter bank reduces the rate of an input signal and produces multiple output signals with varying rates.

5)Post Processing Using Region Merging: The post processing step of watershed segmentation deals with extracting larger objects, so that the features can be easily from these regions in the further steps. Region merging operations eliminate false boundaries and spurious regions by merging adjacent regions that belong to the same object. The region merging process avoids the over-segmented regions of watershed and produces larger meaningful object. The goal of the merging procedure is to minimize the weighted heterogeneity of the image.

The general process of region merging is summarized as:

Step 1: Form initial regions in the image.

Step 2: Build a Region Adjacency Graph (RAG)

Step 3: For each region do:

a. Check the area of the region with the threshold.

b. If the area is less than the threshold, merge them and modify the RAG.

Step 4: Repeat until all the regions are covered.

In the proposed work, the number of regions formed in the reconstructed image is found and the region properties of each region are calculated using region properties function. The connected components labeling is used to assign each region a unique label, so that the objects can be distinguished. The algorithm of connected component makes two passes over the image. The first pass is to assign temporary labels and record equivalence classes. The second pass to replace each temporary label by the smallest label of its equivalence class. The feature selected from each region is Area. The Area of a region is defined as the number of pixels in the region. The area of each region is calculated using the Area () function. A threshold value is set manually, such that the areas of the regions that are greater than the threshold value are merged.

B. Feature Extraction

Texture feature is used in land cover classification to differentiate terrains such as grasses and trees. In the proposed work, Local Texture Pattern descriptor is employed which includes the local description of a small region is computed and a pattern label is assigned to that region. LTP operator is designed in which the local image information can be extracted to form a neighborhood of 3x3 local regions. Let g1, g2… g8 are the pixel values of its 8 neighborhood and gc be the center pixel. The pattern unit P is defined as

$$p(gi, gc) = \begin{cases} 0 \ if \ gi < \varepsilon \\ 1 \ if \ gi = \varepsilon \\ 9 \ if \ gi > gc \end{cases} \quad (3)$$

The Uniformity measure is calculated as

$$U = s\big(P(g8, gc), P(g1, gc)\big) + \sum_{i=2}^{8} s(P(gi, gc), P(gi - \quad (4)$$

Where s is calculated as

$$s(X, Y) = \begin{cases} 1 \ if \ |X - Y| > 0 \\ 0 \ \ otherwise \end{cases} \quad (5)$$

The LTP value is calculated as

(6)

$$LTP = \left\{ \sum_{I=1}^{8} P\ (gi, gc)\ if\ U \leq 3 \atop 73\ \ otherwise \right\}$$

U is the uniformity measure. The uniform patterns can have values in the range 0 to 73. The LTP is not robust to noise and illumination changes. To make LTP robust to noise and illumination changes, a novel method is developed in this paper, in which the center pixel gc of every 3x3 neighbors is replaced by the mean of the local region every time and then the LTP is calculated. These features are used for the input of direct change detection and classification.

C. Classification

Classification is a process of assigning individual pixel of a multispectral image to discrete categories. It analyzes the numerical properties of various image features and organizes the data into categories. Classification algorithm employs two phases of processing. They are training and testing. In training phase, properties of typical image features are isolated and, based on these, a unique description of each classification category, i.e., training class is created. In testing phase, these feature-space partitions are used to classify the image features. In the classification process it produces the different classes such as building, forest, road, grass, shadow, tree, water etc., The classification process is performed by using SOM.

Self Organizing Map (SOM)

Unsupervised Classification is performed using SOM (Self Organizing Map). SOM is a type of Artificial Neural Network (ANN) that is trained using unsupervised learning to produce a low-dimensional, discretized representation of the input space of the training samples called a map. SOM are different from other ANN, that they use a neighborhood function to preserve the topological properties of the input space. SOM is operating in two modes. They are training and mapping. The purpose of SOM is to produce a classified image. The learning process of SOM is as follows

a) Initialize each node's weights and neighborhood distance.

b) Choose a random vector from training data and present it to the SOM.

c) Find the Best Matching Unit (BMU) by calculating the distance between the input vector and the weights of each node. The formula of calculating the distance is as follows

$$\text{Euclidean Distance} = \sum_{k=1}^{n} (i_{l,k} - w_{j,k}(t))^2 \qquad (7)$$

where i_l is an input sample

w_j is a weight vector

d) The radius of the neighborhood around the BMU is calculated. The size of the neighborhood decreases with each iteration.

e) Each node in the BMU's neighborhood has its weights adjusted to become more like the BMU. Nodes closest to the BMU are altered more than the nodes furthest away in the neighborhood. Update weights to all nodes within a topological distance are calculated as

$$w_j(t+1) = w_j(t) + \eta(t) \quad (i_l - w_j(t)) \qquad (8)$$

f) Repeat from step b for enough iteration for convergence.

The following Figure3 shows a self organizing map that artificial neurons have one or more input signals (x_1, x_2, ... ,x_n) and one output signal. Each input signal is associated to a weight (w_1, w_2, ... , w_n) that indicates how important that input is to the neuron activation level. The input signal value is multiplied by the associated weight and the resulting sum (Σ) is the neuron stimulus signal (net input). The stimulus signal produces an output according to the neuron internal activating function and its sensibility (threshold). The activating function will produce an output when the received information (net input) transposes an established threshold-value. Similarly to what occurs in the brain, artificial neurons interconnect to form networks. The neuron with the weight vector that is similar to the input is called as the best matching unit (BMU). Weights of the BMU and the nodes closer to it are to be considered and in this process the node with the smallest value is declared as the winner node. The winning node thus determines the spatial location and topological neighborhood of the existing neurons. SOM is trained in such a way to generate a low dimensional representation of the input space of the training samples. It is also useful for visualizing low-dimensional views of high-dimensional data. The topological relationships between the input data are preserved when mapped to a SOM network.

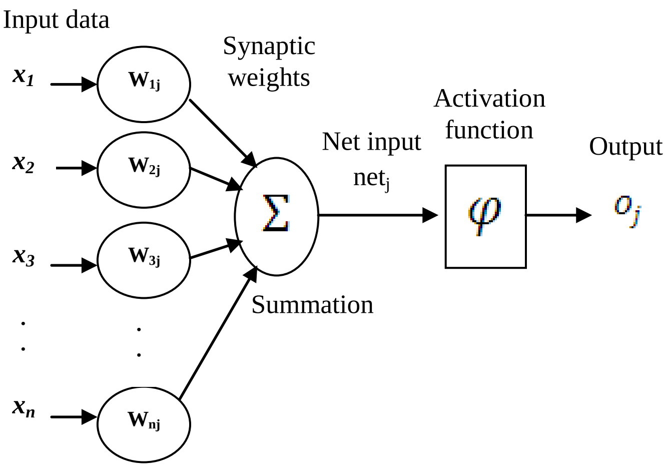


Fig. 3 A Self Organizing Map

Therefore SOM is used in Unsupervised Classification to produce the classified image.

IV.EXPERIMENTAL RESULTS

The following Fig. 3 shows the remotely sensed land cover input image. These images are taken in the place of SriLanka. The image type is a land cover image.

Fig. 4 Input images of two different time

The following Fig. 4 shows the results of final multi-scale segmentation which includes DWT to remove noise and for multi scale representation and edge detection to find contours and watershed segmentation and IDWT for reconstruction and finally connected component labeling and region merging to make larger and meaningful objects.

Fig.5 Final Segmented Image

The Fig. 6 shows the analysis chart of number of objects obtained during segmentation using the existing method (watershed segmentation of original image) and the proposed segmentation method (wavelet, watershed and region merging- Multi scale segmentation). The graph shows that segmentation using the proposed method yields larger number of objects, thus confirming that the proposed method segments the image in a very finer way extracting even the minute objects present in the image.

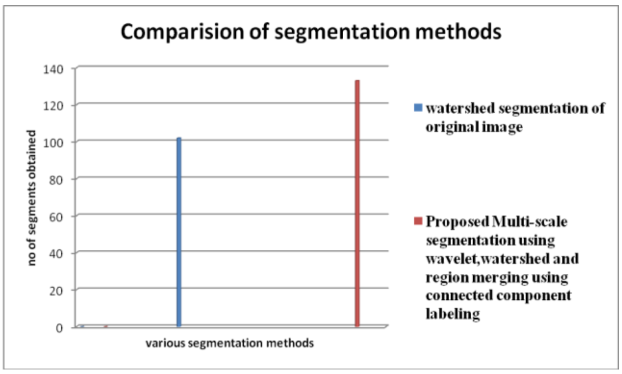


Fig. 5. Comparison of watershed segmentation and proposed Multi scale segmentation

The Fig. 6 shows chart that in the existing Local Texture Pattern method, it is illumination variant and the Local Texture pattern tends to change each time when the illumination of the same image changes.

The Fig. 7 shows chart in which the proposed Local Texture Pattern method, it is illumination invariant and the Local Texture pattern remains the same each time when the illumination of the same image changes.

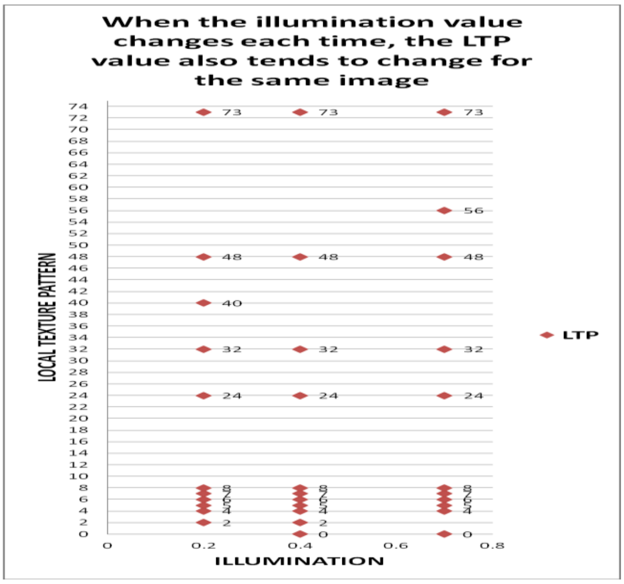


Fig.6.In existing algorithm, when the illumination value of the image changes, the LTP value also changes.

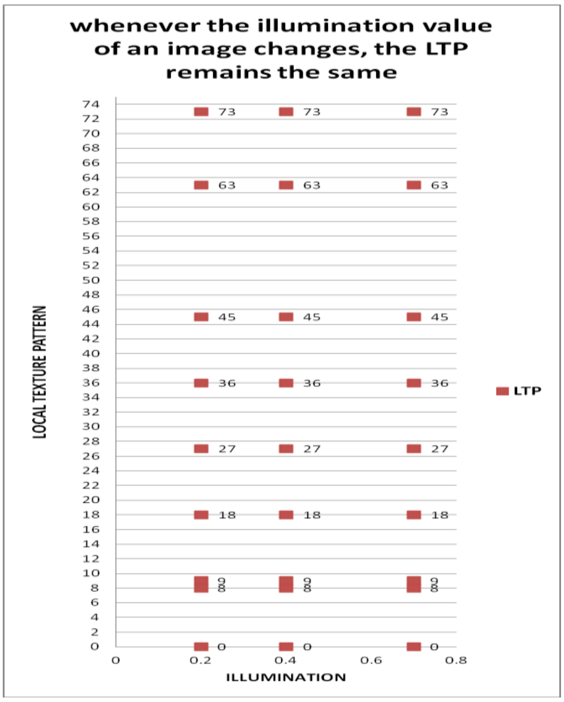
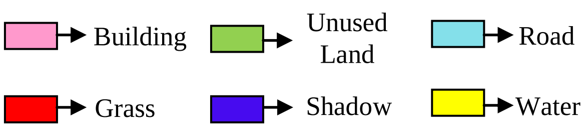
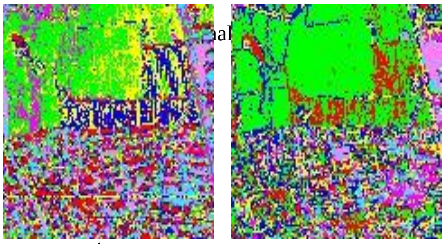


Fig.7. In proposed algorithm, when the illumination value of the image changes, the LTP value remains the same.

The following Fig. 8 (a) and (b) shows the output performance T1 and T2 image classification. It segments the image into each class with different colors. The colors are as follows





(a (b)

Fig. 8 Classification Results of (a)T1 image (b)T2

The Proposed methodology is evaluated against the quantitative measures for the input images. The quantitative measures are False Alarm (FA). The probability of FA is PFA can be calculated as

$$PFA=FA/N_1*100\% \quad (9)$$

where N_1 is the total number of unchanged pixels counted in reference change detection map. Miss Detection (MD). The probability of MD is PMD can be calculated as

$$PMD=MD/N_0*100\% \quad (10)$$

where N_0 is the total number of changed pixels counted in reference change detection map. Total Error (TE). The probability of TE is PTE can be calculated as

$$PTE= ((FA+MD)/ (N_0+N_1)) *100\% \quad (11)$$

The Confusion matrix for both classified images shown in TABLE II and TABLE III.

TABLE I. Confusion Matrix for the Classified Image$_1$

	Grass	Unused Land	Tree	Building	Road	Shadow	Total	User's Accuracy %
Grass	58232	0	4336	0	0	90	62658	93
Unused Land	0	38570	0	720	1240	0	40530	95
Tree	2232	0	21520	0	0	150	23902	90
Building	0	179	0	18342	2896	0	21417	86
Road	0	109	0	512	9641	112	10704	89
Shadow	86	0	120	0	0	1292	1498	77
Total	60555	38858	26046	19574	13777	1644	160807	88
Producer's Accuracy %	96	99	82	94	70	78	87	88

TABLE II. Confusion Matrix for the Classified Image$_2$

	Grass	Unused Land	Tree	Building	Road	Shadow	Total	User's Accuracy %
Grass	58232	0	4336	0	0	90	62658	93
Unused Land	0	38570	0	720	1240	0	40530	95
Tree	2232	0	21520	0	0	390	24142	89
Building	0	179	0	18342	2896	0	21417	86
Road	0	109	0	512	9641	112	10704	89
Shadow	86	0	120	0	0	1292	1498	77
Total	60555	38858	26046	19574	13777	1884	161047	88
Producer's Accuracy %	96	99	82	94	70	69	85	87

V.CONCLUSION

In this paper, an efficient post-classification change detection method is proposed and implemented in land use and land cover images. The core idea of the system is to classify the given remotely sensed image into several classes. The system extracts the objects using Multi-Scale segmentation. From the obtained objects, the different classes that exist in the land cover image are identified using Support Vector Machine. Good classification accuracies are reached with the selected features using SOM. Finally post conflict change classification performance reaches the optimal results. In future work, this land use land cover classification will be carried out using real time data and will be used for Change Detection especially, in flood affected areas.

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