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# Land Cover Classification using Opponent Texture Pattern with Multi-Color Model Histogram

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***Abstract:*** - **Remote sensing image classification plays a vital role in a wide range of applications and classifies the multispectral remotely sensed image into various land covers such as urban, vegetation, forest, water, etc. Feature extraction is an important step in multispectral remote sensing image classification before classifying the image. In the case of classification of remotely sensed images, colour and texture models should have the capacity of capturing and discriminating even minute pattern differences. In this paper, features are extracted using opponent color, texture pattern with different color space histograms. HSV and LUV color histogram and the opponent patterns in the feature space are used to train a random forest classifier. The performance can be evaluated based on several metrics such as accuracy, specificity, sensitivity and f-score. An IRS LISS IV orthorectified dataset is used as the input image for this experiment.**

***Keywords:*** **Color space, multispectral remotely sensed image, random forest classifier, opponent color texture pattern.**

## I. INTRODUCTION

Land cover is the biophysical characteristics of the surface of the earth. Land cover classification refers to the classification of multispectral remotely sensed image into various land covers such as urban areas, vegetation, water body, forest, etc. Remote sensing image scene classification is an active research topic in the field of aerial and satellite image analysis to categorize scene images into a discrete set of meaningful LULC classes according to the image contents. During the past decades, remarkable efforts have been made in developing various methods for the task of remote sensing image scene classification. The classification accuracy depends on the selection of feature vector space and the classifier employed [1]. Color histograms have valuable information about color images. The color dissimilarity measure known as histogram intersection and its successors have been broadly used for object recognition and image retrieval [2]. The basic RGB color space can be transformed into other color spaces such as HSV, CMY, LUV, etc. The HSV color space is used in this paper due to its ability to reduce the size of color and gray scale values of an image [3]. In the LUV color space, the three channels L, U and V encodes luminance, saturation and hue angle [4]. Bianconi et al. explored the importance of color in texture classification and proposed taxonomy for classifying the color and texture descriptors in the state of the art. These descriptors have also been evaluated on a standard data set. The results exhibit that color is a very important feature for texture classification [5]. Texture feature is often used with color information for classifying the image in a better level than with color alone. Texture features are very important cue in computer vision and pattern recognition. Many features have been proposed to define texture properties. Tamura proposed six texture features such as contrast, coarseness, contrast, direction, line-likeness, smoothness and roughness [6]. Ojala et al. proposed a Local Binary Pattern (LBP) approach that provides highly discriminative texture information. The major advantages of LBP are its invariance to any monotonic change in gray level and its computational simplicity. Histograms of LBP patterns are used for texture description and these features can be extended to take into account color information also. This LBP approach can be applied to the red, green, and blue components of the RGB image or to the components of any other color space [7]-[10]. An Opponent color LBP (OCLBP) approach is an extension of LBP in which the center pixel is taken from one

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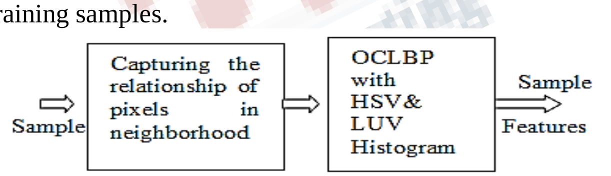
channel and the neighboring pixels are taken from the other. LBPs are extracted from each color channel independently, and then for vector pair. In general, six histograms are computed: three for the R, G and B components independently and three for the combinations of R/G, R/B and G/B. The feature vector is formed by concatenating the histograms and the cross-channel information can be incorporated in the LBP framework [5]. Random forest (RF) algorithm proposed by Breiman et al., a well-known state of the art classifier, is used in this experiment. Ensemble learning algorithms such as random forest, bagging and boosting have acknowledged great interest as they are more accurate and robust to noise when compared with single classifiers. The philosophy behind ensemble classifiers is based on the principle that a set of classifiers classify better than an individual classifier does. Breiman suggested that the random forest classifier presents many advantages for its application in remote sensing [11].

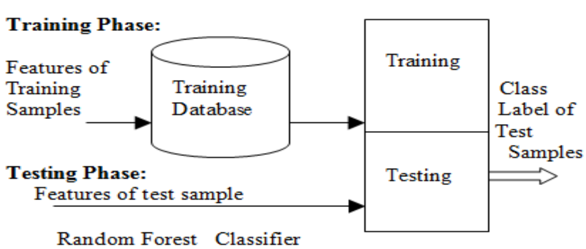
## II. METHODOLOGY

### A. Block Diagram

The proposed approach has texture feature extraction part and classification part as shown in Fig-I. During feature extraction, the centre pixel of every 3x3 neighborhood of the sample is dispensed a pattern label using the texture descriptor. The multiclass RF classifier works in two phases. In the training phase, training samples are randomly selected from distinct land cover classes of remotely sensed images. Texture feature histograms of training samples are used to train RF classifier. In the testing phase, test samples center around each pixel of remotely sensed image are extracted, and given as input to RF. The RF classifier returns the class labels based on its prior learning of training samples.




Classification:




### B. Feature extraction using Opponent Color Local Binary Pattern

In this paper, the classification performance of the Opponent Color LBP texture descriptor is analyzed on the IRS and the Pavia university datasets with HSV and LUV color spaces. The LBP describes local patterns in a texture as binary codes. The 3X3 pixels neighborhood is threshold by the gray level of the central pixel. The pixel values in the threshold neighborhood are multiplied by the respective weights as in fig-II. The eight gray level differences within a pixel neighborhood are recorded by equation-1 and the center pixel neighborhood is defined as in fig-III.

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 8 | | 16 |
| 2 | 64 | 128 |

Fig- II

| | | |
|---|---|---|
| $g_1$ | $g_2$ | $g_3$ |
| $g_4$ | $g_0$ | $g_5$ |
| $g_6$ | $g_7$ | $g_8$ |

Fig- III

$$LBP = \sum_{i=1}^{8} S(g_0\ , g_1\ ) 2^{i-1}$$

$$\text{Where } S(g_0, g_1) = \begin{cases} 1 \text{ if } g_i > g_0 \\ 0 \text{ if } g_i < g_0 \end{cases} \qquad (1)$$

This LBP pattern can be extended to the red, green and blue channels of the RGB image or any other color spaces [12]. In the Opponent Color LBP (OCLBP) method, the center pixel is taken from one channel and the neighboring pixels are taken from the other. LBP histograms are extracted by incorporating the cross channel information from the combinations of R/G, R/B and G/B color channels [5]. In this experiment, the opponent color LBP with HSV color space histogram takes 24+ 3*256 = 792 bins of feature vector. The data are taken from the ground truth of distinct land cover classes of remotely sensed images. The 10-fold cross validation method is used to estimate the result. The standard ensemble classifier random forest with 160 trees is used to classify the land cover dataset.

## III. EXPERIMENTS AND RESULTS

### A. Study Area and Datasets

An IRS dataset and a hyper spectral airborne dataset are taken for the study purpose.

i) An IRS (Resouresat2 Satellite), LISS-IV remotely sensed orthorectified image supplied by National Remote Sensing Centre (NRSC), Hyderabad, India, is taken for this study.

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This image covers the area in and nearer to Nagercoil city located in the District of Kanyakumari, TamilNadu, India. It was taken in January 2012 with a spatial resolution of 5.8m and 552 X 414 pixels size. The region covers the latitude of 8.2145236 to 8.195756 and longitude of 77.4189782 to 77.443809. The RGB image is formed by combining bands 2, 3 and 4 of LISS-IV data (Green, red and near IR respectively). The ground truth of the study area has been taken from ENVI. Labeled ground truth is provided in 5 land cover classes and a snapshot of the dataset is provided in Fig- IV.

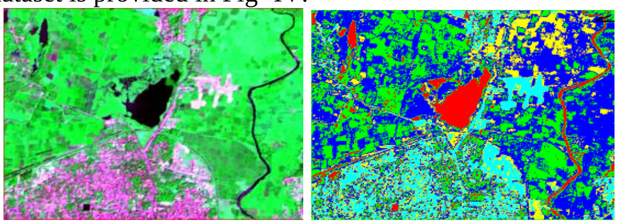

*Fig-IV IRS RGB image and its Labeled Ground Truth*

Water Uncultivated land Vegetation land

Bare soil Urban

ii) A readily available hyper spectral dataset of 103 bands image of the University of Pavia (Pavia University) with a spatial dimension of 610 X 340 pixels and its ground truth is also taken for study. A snapshot of the labeled ground truth of Pavia dataset with 9 land cover classes is provided in Fig-V.

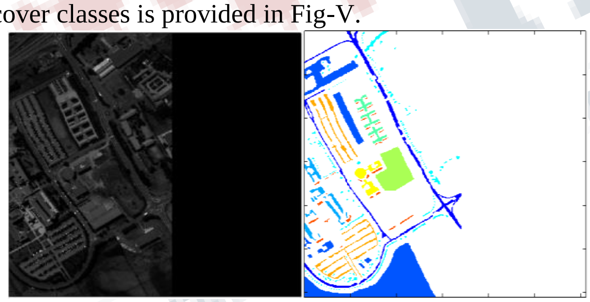

*Fig-V Pavia University Dataset and its labeled ground truth*

Asphalt Meadows Bare soil Trees

Painted metal sheets self Blocking Bricks

Shadows Bitumen Gravel

**B. Performance Metrics**

The classification based on HSV color space and LUV color model is analyzed using Random forest classifier. The Opponent Color Local binary pattern (OCLBP) based classification is also analyzed with HSV and LUV color spaces. The performance of these classification methods are evaluated using various metrics such as accuracy, specificity, sensitivity and f-score. The average values of accuracy, precision, specificity, sensitivity and f-score for all the classes of IRS and Pavia University dataset are tabulated. Kappa coefficient is also used to analyze the efficiency of the classification technique and all the metrics are shown in the following tables (Table 1 & Table 2). The misclassification is also identified with confusion matrix. The performance of all these classification methods on the IRS and hyper spectral Pavia datasets are compared and represented in the form of graphs (Fig I & Fig II).

*Table-1 Performance comparison of OCLBP – IRS Dataset*

| RANDOM FOREST - IRS DATASET | | | | |
|---|---|---|---|---|
| **Metrics** | **HSV** | **HSV-OCLBP** | **LUV** | **LUV-OCLBP** |
| Accuracy | 0.87184 | 0.85046 | 0.86794 | 0.84852 |
| Sensitivity | 0.71622 | 0.60924 | 0.72402 | 0.52396 |
| Specificity | 0.91738 | 0.92096 | 0.91442 | 0.9153 |
| Precision | 0.62892 | 0.4786 | 0.62122 | 0.48116 |
| F score | 0.65182 | 0.43274 | 0.64812 | 0.45436 |
| kappa | 0.558 | 0.4583 | 0.5464 | 0.4561 |

*Table-2 Performance comparison of OCLBP – Pavia Dataset*

| RANDOM FOREST - PAVIA UNIVERSITY DATASET | | | | |
|---|---|---|---|---|
| **Metrics** | **HSV** | **HSV-OCLBP** | **LUV** | **LUV-OCLBP** |
| Accuracy | 0.974222 | 0.960889 | 0.965333 | 0.964444 |
| Sensitivity | 0.691978 | 0.534211 | 0.435111 | 0.67551 |
| Specificity | 0.984644 | 0.979367 | 0.975078 | 0.981733 |
| Precision | 0.545178 | 0.281189 | 0.420756 | 0.333633 |
| F score | 0.601356 | 0.324278 | 0.424922 | 0.416711 |
| kappa | 0.6998 | 0.4394 | 0.6091 | 0.5163 |

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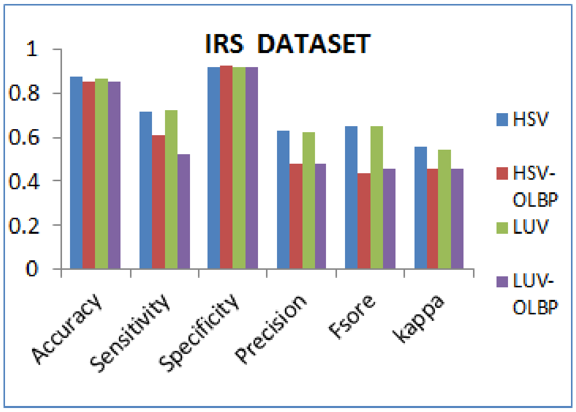


*Fig-VI comparison of various classification methods – IRS Dataset*

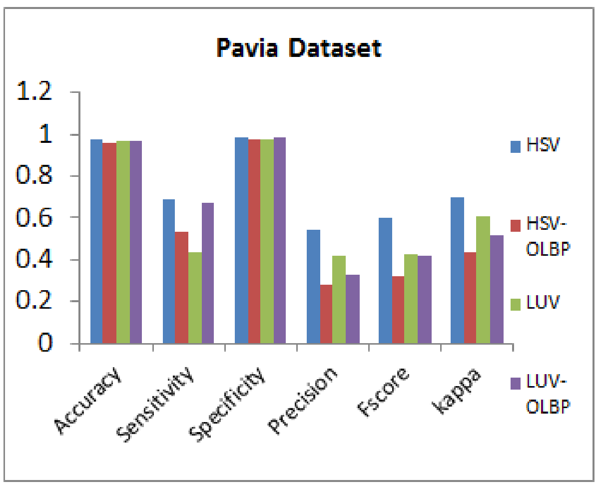


*Fig-VII Comparison of various classification methods – Pavia Dataset*

## IV. CONCLUSION

In this paper, the Opponent Color LBP based classification with HSV and LUV color spaces is analyzed on LISS IV IRS dataset and the hyper spectral dataset. Results obtained on both the datasets indicate that the Opponent LBP texture pattern incorporated with HSV color space based classification produces good quantitative results compared to the LUV color space. There are remarkable differences in the classification performance between these two color spaces. In future we will perform image classification with different texture patterns for a color image on the HSV color space.

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