Color Texture Classification using Modified Local Binary Patterns based on Intensity and Color Information

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***Abstract*—This paper presents a color texture descriptor, Modified Local Binary Pattern (MLBP) based on combined intensity and color information. It establishes the existence of correlation between the intensity and color channel information along with their corresponding neighbors. Bin values of MLBP image histogram are used as color texture descriptors. The classification performance of the proposed color texture descriptor is evaluated on VisTex and Outex datasets, for different color spaces, namely RGB, HSV, YC_bC_r , La*b* using k-nearest neighborhood classifier. The classification results obtained by the proposed texture descriptor are compared with the results obtained by the conventional Local Binary Patterns (LBP) method. The experimental results indicate that the proposed color texture descriptors enhance the classification performance.**

Keywords- Color texture; Texture classification; Intensity and color channel; Histogram features

I. INTRODUCTION

In many machine vision and image processing applications, texture analysis is an important and useful facet of study. Texture analysis methods have been exploited in various applications that involve automated inspection, document image processing and remote sensing [1]. Over the past decade, the study of joint color texture has been a popular approach to color texture analysis. The extra information present in color images compared to their gray image equivalent allows constructing an image analysis system with higher performance [2, 3]. That is why a wide variety of gray scale texture descriptors have been extended to classify color textures [4-8]. The Local Binary Pattern (LBP) operator, first proposed by Ojala [9], describes the local properties of textures present in gray level images.

In recent years, Local Binary Patterns (LBP) is the most successful approach employed in many areas of pattern recognition and computer vision [10-12]. Maenppa and Pietikainen [13] have extended gray scale approach to color images, where color channels are combined at feature level by concatenating LBP histogram from color channels and processed separately using LBP. An approach based on separate processing of complementary color and pattern information is proposed by Pietikainen, Mäenpää and Viertola [14], wherein they have used color histograms to discriminate color information and LBP to provide texture information. Porebski, Vandenbroucke and Macaire [15] have proposed an approach for color texture classification by using Haralick features extracted from co-occurrence matrices computed from LBP images. Zhu, Bichot and Chen [16] implemented color orthogonal combination of LBP, descriptor by concatenating color orthogonal combination of LBP histograms and color channels. The extension of the conventional LBP method to a three Dimensional Local Binary Patterns descriptor produces three new color images for encoding both color and texture information of an image using the different color channels [17].

The aim of the present research work is to analyze the similarity of the colors and their distributions at the same time by proposing a color texture descriptor. A color texture descriptor based on combined intensity and color information called Modified Local Binary Pattern (MLBP) is proposed. MLBP image histogram bin values are used as the color texture descriptors. The classification performance of the proposed color texture descriptor is evaluated on a set of VisTex [18] and Outex [19] color images, for different color spaces namely RGB, HSV, YC_bC_r and La*b*. The experimental results obtained by using the proposed descriptor are compared with the results obtained by using the conventional LBP method [8].

This paper is organized as follows: The section II briefly introduces Local Binary Patterns. The proposed color texture feature computation method Modified Local Binary Pattern (MLBP) is discussed in the Section III. In the Section IV, the texture training and classification are explained. Experiments and classification results are presented in the Section V. Finally, the Section VI concludes the discussion.

II. LOCAL BINARY PATTERNS

Let texture T in a local N-neighborhood of a pixel f_c is defined as the joint distribution function of all pixels in local texture region of a gray image. T is represented as in (1),

$$T = t(f_c; f_0, f_1, \ldots, f_i, \ldots, f_{N-1}) \qquad (1)$$

where f_c is the gray value of the center pixel of local texture region, f_i is the gray value of ith neighboring pixel of local texture region. For N=8, the Fig.1 depicts the 8-neighborhood of pixel f_c.

	f_3	f_2	f_1	
	f_4	f_c	f_0	
	f_5	f_6	f_7	

Figure 1. 8-neighborhood of pixel f_c.

Next the factorized joint distribution function obtained by subtracting the center pixel value f_c from each pixel value in circular neighborhood can be represented by (2),

$$T \approx t(f_c)t(f_0 - f_c, f_1 - f_c, \ldots, f_{N-1} - f_c) \qquad (2)$$

In (2), $t(f_c)$ distribution is not useful for texture analysis. The joint difference distribution, which is independent of $t(f_c)$, can be used as texture representation in (3),

$$T \approx t(f_0 - f_c, f_1 - f_c, \ldots, f_{N-1} - f_c) \qquad (3)$$

The T can be represented by using the (4),

$$T \approx t(g(f_0 - f_c), g(f_1 - f_c), \ldots, \ldots, g(f_{N-1} - f_c)) \qquad (4)$$

$$\text{where } g(p) = \begin{cases} 0, & p < 0 \\ 1, & p \geq 0 \end{cases}$$

Equation (4) generates the local binary pattern (LBP) around the center pixel f_c. Further, the sum of product of binary values and corresponding weighted values of all surrounding pixels, as given in (5), is set as the new center pixel value P_c in T.

$$P_c = \sum_{i=0}^{N-1} g(f_i - f_c) * 2^i \qquad (5)$$

III. FEATURES FROM MODIFIED LOCAL BINARY PATTERN (MLBP) IMAGE BASED ON INTENSITY AND COLOR INFORMATION

The color texture image contains R, G and B channels. These channels are used to transform color image to intensity image using the (6) [8],

$$I = 0.299 * R + 0.587 * G + 0.114 * B \qquad (6)$$

Let us consider a pair of images (I, R), for a central pixel I_c in I and its corresponding central pixel R_c in R. Consider their 8-neighborhood I_N, R_N respectively as shown in the Fig. 2,

I_4	I_3	I_2
I_5	I_c	I_1
I_6	I_7	I_8

I

R_4	R_3	R_2
R_5	R_c	R_1
R_6	R_7	R_8

R

Figure 2. 8- neighborhood of pixel I_c in I and its corresponding pixel R_c in R.

The modified local binary pattern g is constructed using I and R as shown in the (7),

$$g_i = \begin{cases} 1; if \ \max(\min(I_c, R_i), \min(R_c, I_i)) = \min(I_c, R_i) \\ 0; otherwise \end{cases} \quad (7)$$

where i= 1,2,…,N and N=8 is number of neighboring pixels. The new central pixel value P_c is computed using the (8),

$$P_c = \sum_{i=1}^{N} g_i * 2^{i-1} \quad (8)$$

The Fig. 3 illustrates the above procedure to calculate the central pixel value P_c which obviously lies in the range 0 to 255.

137	147	120
134	148	140
158	168	153

I

139	146	140
132	135	163
145	155	98

R

0	0	1
1		0
0	0	1

*

8	4	2
16		1
32	64	128

Binary Pattern Weights

P_c = (2+16+128) = 146

Figure 3. Calculation of central pixel value P_c .

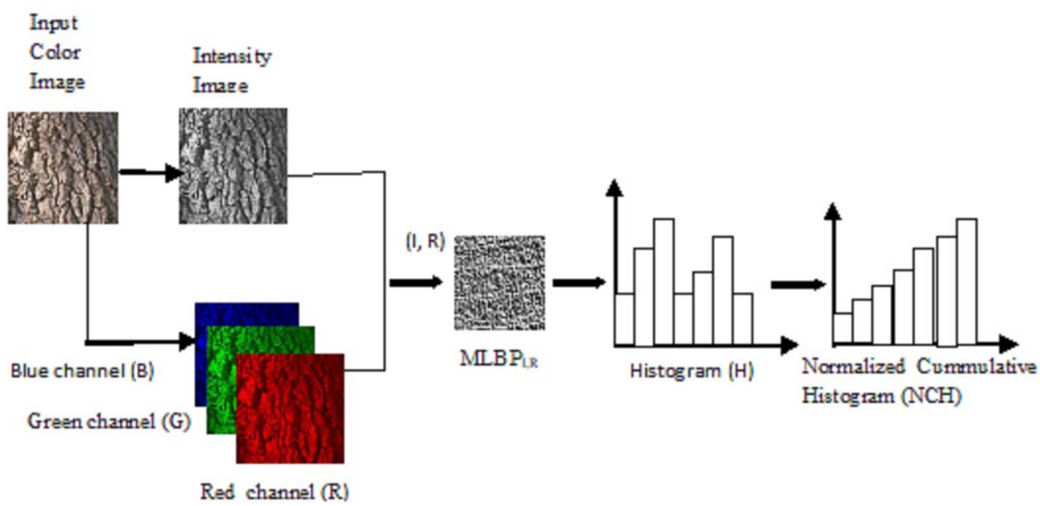

Figure 4. Schematic diagram of the proposed color texture feature extraction using MLBP method.

The above procedure is repeated for all the pixels of the entire image, which results in Modified LBP image (MLBP) $MLBP_{I,R}$ based on the combination of Intensity (I) and Red color (R) information. Similarly, we construct MLBP images using the other two combinations, namely $MLBP_{I,G}$, $MLBP_{I,B}$.

The features are extracted from MLBP image as described below:

1) Construct Histogram (H) for the MLBP image.
2) Obtain the Cumulative Histogram (CH) for H.
3) Construct Normalized Cumulative Histogram NCH = CH/Sum (CH).

The bin values of NCH form the texture feature vector $v=(b_0,b_1,b_2,\ldots,b_{255})$. The Fig. 4 depicts the proposed color texture feature extraction using MLBP method. The features are extracted from the combinations of intensity and color information of HSV, YC_bC_r and La*b* color spaces. The results are compared with RGB color space.

IV. TEXTURE TRAINING AND CLASSIFICATION

In texture training phase, texture features are extracted from training sample using the proposed feature extraction method MLBP. These texture features are stored in the feature library, which are further used for texture classification.

In texture classification phase, the texture feature vector q is extracted from the test sample using the proposed feature extraction method MLBP, and then compared with the corresponding feature vector p of all the texture samples stored in the feature library using l_1*-norm* as the distance metric [20] given by (9),

$$D(p,q) = \sum_i |p_i - q_i| \tag{9}$$

where p_i , q_i are the i^{th} components of feature vectors p and q respectively. The test sample is classified using the k-nearest neighbor (k-NN) classifier. In the present study, it is chosen as k = 1 [21].

V. EXPERIMENTS AND DISCUSSION

Experiments are performed on three different color texture datasets. The sets include 164 color textures of size 128*128 available from the Vision Texture (VisTex) dataset [18], training and testing samples are chosen as in [22], and two sets of 68 color textures (Outex_TC_00013 and Outex_TC_00014) from the Outex texture dataset[19]. The different color spaces, namely RGB, HSV, YC_bC_r, and La*b* are considered for the evaluations of the proposed method. The results based on different sample sizes are presented for comparative analysis of texture classification.

TABLE I. CLASSIFICATION ACCURACY (%) OF COLOR TEXTURE USING PROPOSED MLBP METHOD.

Color Spaces	**MLBP based features with intensity and color channel combinations**	**Datasets**		
		VisTex	***Outex _TC_00013***	***Outex _TC_00014***
RGB	$MLBP_{I,R}$	95.54	67.50	24.04
	$MLBP_{I,G}$	94.22	69.71	18.53
	$MLBP_{I,B}$	95.54	58.08	12.21
	$MLBP_{I,R}$, $MLBP_{I,G}$	96.43	78.82	17.35
	$MLBP_{I,R}$, $MLBP_{I,B}$	97.05	76.03	18.75
	$MLBP_{I,G}$, $MLBP_{I,B}$	96.68	74.12	14.26
	$MLBP_{I,R}$, $MLBP_{I,G}$, $MLBP_{I,B}$	97.23	82.33	16.76
HSV	$MLBP_{I,H}$	79.28	63.97	13.82
	$MLBP_{I,S}$	94.18	55.44	12.50
	$MLBP_{I,H}$, $MLBP_{I,S}$	95.59	76.18	15.51
YC_bC_r	$MLBP_{I,Cb}$	79.23	31.03	19.34
	$MLBP_{I,Cr}$	78.41	45.29	18.24
	$MLBP_{I,Cb}$, $MLBP_{I,Cr}$	84.59	40.00	18.01
La*b*	$MLBP_{I,a*}$	76.86	45.44	21.62
	$MLBP_{I,b*}$	75.77	31.47	19.93
	$MLBP_{I,a*}$, $MLBP_{I,b*}$	80.31	39.26	19.04

TABLE II. COMPARISON OF CLASSIFICATION ACCURACY (%) OBTAINED BY USING PROPOSED MLBP METHOD AND CONVENTIONAL LBP METHOD FOR VISTEX DATASET.

Size of sample	**Proposed MLBP method**	**LBP method[8]**
120	98.96	97.62
110	98.44	96.42
100	97.23	93.52
80	95.82	91.20
50	89.24	79.49
20	38.96	28.01
10	11.06	7.70

The classification results of experiments are presented in the Tables I and II. The entries in the table shows the classification accuracy (%) averaged over 10 experiments for different combinations of intensity and color channels, for an angle=0° and distance=1. In the Table I, first column indicates the different color spaces used in the experiments; second column shows the combinations of intensity and color channels. The third, fourth and fifth columns show the classification accuracy (%) on VisTex, Outex _TC_00013 and Outex _TC_00014 datasets respectively. The results show that maximum classification accuracy of 97.23% and 82.33% is obtained for VisTex and Outex_TC_00013 datasets in RGB color space. The maximum of 24.04% classification accuracy is obtained when the intensity and red color channel of RGB color space is used for Outex_TC_00014. It is clearly seen in Table I, that the proposed method gives the better results in RGB color space as compared to other color spaces.

The Table II shows the comparative results obtained using VisTex dataset for the proposed method ($MLBP_{I,R}$, $MLBP_{I,G}$, $MLBP_{I,B}$) and the conventional LBP method (LBP_R , LBP_G , LBP_B) [8], here all the color channels of RGB color space are used. It is observed from the results that the combinations of intensity with color channels improve the classification accuracy. It reveals that the proposed method outperform LBP method for different sample sizes. Even if the 50% of the pattern image is considered, the better classification can be expected using the proposed method as compared to the conventional LBP method. Thus it establishes the existence of correlation between intensity and color channel information along with their corresponding neighbors.

VI. CONCLUSION

A color texture descriptor based on combined intensity and color information called Modified Local Binary Pattern (MLBP) is proposed. MLBP image histogram bin values are used as the color texture descriptors. The experiments are performed on benchmark datasets, namely, VisTex and Outex datasets, for different color spaces, namely, RGB, HSV, YC_bC_r and La*b*. The proposed color texture descriptors give the better classification results for RGB color space along with intensity values and it also outperform the conventional Local Binary Patterns (LBP) method. The results suggest that the proposed color texture descriptors have the potential for use in real-world applications involving recognition of patterns in digital images.

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