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A New Logical Compact LBP Co-Occurrence Matrix for Texture Analysis

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Abstract— Texture is an important spatial feature, useful for identifying objects or regions of interest in an image. Statistical and structural approaches have extensively studied in the texture analysis and classification whereas little work has reported to integrate them. One of the most popular statistical methods used to measure the textural information of images is the grey-level co-occurrence matrix (GLCM). The present paper combines the Logical Compact LBP with OR operator (LCLBP-OR), which is derived on textons, with GLCM approach and LCLBPCM using three stages. The LCLBP-OR reduces the texture unit size from 0 to 255 to 0 to 15 and achieves much better rotation invariant classification than conventional LBP. The LCLBP-OR values are obtained by applying the logical OR operator in between relative positions of LBP window. To evaluate micro texture features in stage one textons are evaluated. To make texture features relatively invariant with respect to changes in illumination and image rotation LCLBP-OR images are applied on LBP images of texton shapes in stage-two. Later in stage three the GLCM is constructed on LCLBP-OR and first and second order statistical features are evaluated for precise and accurate classification. The experimental results indicate the proposed LCLBPCM method classification performance is superior to that LBP, Gabor and other methods.

Keywords: Texton, LBP, First and Second order statistical features, LCLBP-OR.

1 INTRODUCTION

Texture analysis is one of the most important techniques used in image processing and pattern recognition. In texture analysis, the first and most important task is to extract texture features which efficiently embody information about the textural characteristics of the original image. These features can then be used for the description or classification of different texture images. Many researchers have put forward various algorithms for texture analysis, such as the gray co-occurrence matrixes [1], Markov random field (MRF) model [2], simultaneous auto-regressive (SAR)model [3], Wold decomposition model [4], Gabor filtering [5,6] and wavelet decomposition [7,8] and so on.

Initially, texture analysis was based on the first order or second order statistics of textures [1, 9, 10, 11]. In statistical approaches, textures are considered to be formed by certain random processes. The types of textures were analyzed by studying the statistical properties of the intensity values of pixels or the coefficients of certain filter banks. Haralick et al. [1] calculated second-order grayscale statistics using gray-level co-occurrence matrix (GLCM) and defined the statistical moments as a texture descriptor for which the correct classification rate of 60% to 70% was only reported in the literature.

However, the method is computationally inefficient. You and Cohen extended Laws' masks for rotation-invariant texture characterization in their "tuned" mask scheme [12]. In their experiments, a high accuracy rate was achieved. However, there are some limitations to many of the existing techniques for rotation-invariant texture classification.

In structural approaches, texture is considered to consist of textural primitives, often called textons, which are located on the texture with certain placement rules. Texton is a very useful concept in texture analysis and has been utilized to develop efficient models in the context of texture recognition or object recognition [13, 14]. The texton co-occurrence matrices (TCM) proposed in [15] can describe the spatial correlation of textons for image retrieval. It has the discrimination power of color, texture and shape features. This paper put forward a new method of GLCM approach on LCLBP-OR for texture classification to describe image features. This method can express the spatial correlation of textons. During the course of feature extracting, we have quantized the original images into 256 colors and computed color gradient from the RGB vector space, and then calculated the statistical information of textons to describe image features.

The rest of this paper is organized as follows. The Section 2 describes the proposed method. Section 3, refers to the experimental evaluation and the classification results obtained. Section 4 concludes the paper.

2 LCLBPCM ON TEXTONS

The proposed LCLBPCM approach on textons for effective texture analysis consists of five steps as shown in the block diagram of Fig.1.

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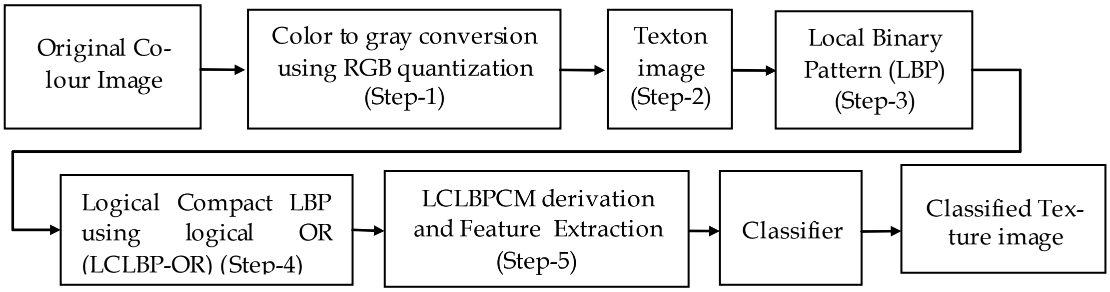

Fig.1 Gray Level co-occurrence matrix on LCLBP-OR: LCLBPCM approach.

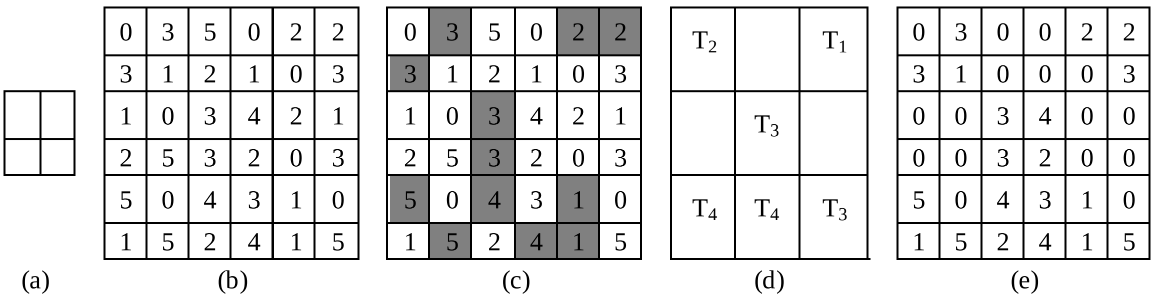

Fig.3 Illustration of the Texton detection process: (a) 2×2 grid (b) Original image (c) & (d) Texton location and Texton types (e) Texton image.

2.2 Step-1: Color Quantization in RGB Color Space

To convert color images into grey level image the present paper utilized RGB color quantization method. Color provides powerful information for texture classification and recognition even in the total absence of shape information. In order to extract grey level features from color information the present paper utilized the RGB color space which quantizes the color space into 8-bins to obtain 256 grey levels. The index matrix of 256 color image is denoted as C(x, y). Let I(R), I(G), I(B) be the index value of unit vectors along the R, G and B axes of RGB color space, as follows:

$$C(x,y) = 32*I(R) + 4*I(G) + I(B) \quad (1)$$

where

$$I(R)= 0,\ 0 \le R \le 32,\quad I(R)= i,\ ((32*i)+1) \le R \le (32*(i+1)) \quad i = [1, 2, 3, \ldots, 7] \quad (2)$$

$$I(G)= 0,\ 0 \le G \le 32,\quad I(G)= i,\ ((32*i)+1) \le G \le (32*(i+1)) \quad i = [1, 2, 3, \ldots, 7] \quad (3)$$

$$I(B)= 0,\ 0 \le B \le 64,\quad I(B)= i,\ ((64*i)+1) \le B \le (64*(i+1)) \quad i = [1, 2, 3] \quad (4)$$

Then each value of C(x, y) is 8-bits binary code, ranging from 0 to 255 respectively.

2.2 Step-2: Texton detection

In step two textons are defined which are having a close relationship with image features and local distribution. Textons are considered as texture primitives which are located with certain placement rules. The textons are defined as a set of blobs or emergent patterns sharing a common property all over the image [16, 17]. The different textons may form various image features. If the textons in the image are small and the tonal difference between neighbouring textons is large, a fine texture may result. If the textons are larger and concise of several pixels, a coarse texture may result. If the textons in image are large and consists of a few texton categories, an obvious shape may result. If the textons are greatly expanded in one orientation, pre-attentive discrimination is somewhat reduced. If the elongated elements are not jittered in orientation, the texton gradients at the texture boundaries are increased. To achieve this present paper utilized four texton types on a 2×2 grid as shown in Fig.2. In Fig.2 the four pixels of a 2×2 grid are denoted as V_1, V_2, V_3 and V_4. If two pixels are highlighted in gray color of same value, the grid will form a texton. The four texton types are denoted as T_1, T_2, T_3 and T_4 respectively as shown in Fig.2. The working mechanism of texton detection is illustrated in Fig.3.

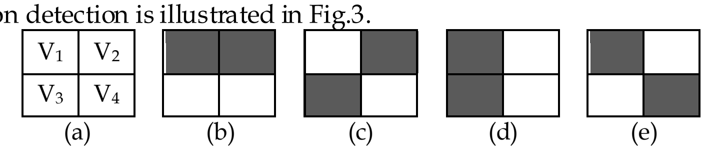

Fig.2 Four special types of Textons: (a) 2×2 grid (b) T_1 (c) T_2 (d) T_3 and (e) T_4.

2.3 Step-3: Local Binary Pattern

In step3 LBP is evaluated on the texton image for obtaining local information in a precise way. Local Binary Pattern (LBP) is based on the concept of texture primitives. This approach provides a theoretically, computationally simple and efficient methodology for texture analysis. To represent the formations of a textured image, the LBP approach, models 3×3 textons as illustrated in Fig.4. A 3×3 texton consists of a set of nine elements, $P = \{p_c, p_0, p_1, \ldots, p_7\}$, where p_c represents the gray level value of the central pixel and p_i $(0 \le i \le 7)$ represent the gray level values of the peripheral pixels. Each texton then, can be characterized by a set of binary values b_i $(0 \le i \le 7)$ where

$$b_i = \begin{cases} 0 & \Delta p_i \geq 0 \\ 1 & \Delta p_i < 0 \end{cases} \quad (5)$$

and $\Delta p_i = p_i - p_c$.

For each 3×3 texton a unique LBP code can be derived by these binary values, as follows:

$$LBP = \sum_{i=0}^{i=7} b_i \times 2^i \quad (6)$$

Every pixel in an image generates an LBP code. A single LBP code represents local micro texture information around a pixel by a single integer code LBP Є [0, 255].

p_0	p_1	p_2
p_3	p_c	p_4
p_5	p_6	p_7

→

b_0	b_1	b_2
b_3		b_3
b_5	b_6	B4

×

2^0	2^1	2^2
2^3		2^4
2^5	2^6	2^7

→ LBP

Fig. 4 Representation of LBP.

2.4 Step-4: Logical Compact LBP with Logical OR Operation (LCLBP-OR)

In step-4 LCLBP-OR is applied on LBP image, which converts a 3×3 neighbourhood with a value that ranges from 0 to 15. The image classification is a data generalization process; a preprocessing that reduces the data variability to some extent should not seriously influence the classification accuracy. According to Narayanan et al. [18], reducing the data down to 4 bits would still preserve more than 90 percent of the information content. In LCLBP-OR, the logical OR operation is used on relative position neighbours of LBP to compress 8-bit binary code into 4-bit binary code. The LCLBP-OR is different from CLBP. CLBP is purely based on the principle of homogeneous neighbours where as LCLBP-OR is based on logical OR of relative positions of LBP.

For each position (n_1, n_2 n_3, n_4) of LCLBP-OR the relative positioned values of the 3×3 LBP mask is chosen as shown in Fig.5. From this, LCLBP-OR unit is evaluated as given in the Eqn. (7). The transformation process of LBP to LCLBP-OR is given in Fig 5. The Fig.6 illustrates an example of evaluating LCLBP-OR unit using relative position of LBP.

$$LCLBP = \min\left(\sum_{i=0}^{3} n_i \times 2^i\right) \quad (7)$$

b_0	b_1	b_2
b_7		b_3
b_6	b_5	b_4

(a)

$b_0 \mid b_4$ n_1	$b_1 \mid b_5$ n_2
$b_3 \mid b_7$ n_3	$b_2 \mid b_6$ n_4

(b)

Fig.5 Transformation from LBP to LCLBP-OR: a) a 3×3 LBP mask b) a 2×2 LCLBP-OR mask.

In order to reduce the complexity of computation and to achieve rotation invariance the LCLBP-OR considered the minimum value pattern from the 4 bits. On the obtained minimum value patterns, weights are applied to achieve LCLBP unit, which is the minimum LCLBP-OR unit. For example in the Fig.6 the pattern 1011 is considered as 0111 and weights are applied to obtain the LCLBP-OR unit, which results a value 7.

1	0	1
1		0
1	0	0

(a)

1|0=1	0|0= 0
0|1=1	1|1=1

(b)

$(1011)_2$ (c)

$(0111)_2$ (d)

Fig. 6 An example of evaluating LCLBP unit using relative position of LBP: a) a 3×3 LBP mask b) a 2×2 DCLBP mask c) Obtained Pattern d) Minimum 4-bit valued pattern.

2.4 Step-5: Gray Level Co-occurrence Matrix on Logical Compact LBP using Logical OR (LCLBP-OR)

Grey level co-occurrence matrices is constructed on LCLBP-OR. This matrix is named as LCLBPCM. The LCLBPCM will have grey levels ranging from 0 to 15, thus it will reduce computational cost. On LCLBPCM the first and second order statistical features are evaluated. The first order statistical features are skewness and kurtosis as given in Eqs (8) and (9) whereas second order statistical features such as energy, entropy, contrast, local homogeneity, correlation, cluster shade and cluster prominence are calculated using Eqs (10) to (16) respectively.

$$Skewness = \frac{\sum_{i=0}^{L-1}(z_i - m)^3 * p(z_i)}{\sigma^3} \quad (8)$$

$$Kurtosis = \frac{\sum_{i=0}^{L-1}(z_i - m)^4 * p(z_i)}{\sigma^4} \quad (9)$$

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij} \quad (10)$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} (P_{ij})^2 \quad (11)$$

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \quad (12)$$

$$\text{Local Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (13)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (14)$$

where P^{ij} is the pixel value in position (i, j) in the texture im-

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age and N is the Number of gray levels in the image

$$\mu = \sum_{i,j=0}^{N-1} iP_{ij}$$ is the texture image mean

$$\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}(i-\mu)^2$$ is the texture image variance.

$$\text{Cluster Shade} = \sum_{i,j=1}^{N} (i - M_x + j - M_y)^3 P_{ij} \quad (15)$$

$$\text{Cluster Prominance} = \sum_{i,j=1}^{N} (i - M_x + j - M_y)^4 P_{ij} \quad (16)$$

$$M_x = \sum_{i,j=1}^{N} iP_{ij} \quad \text{and} \quad M_y = \sum_{i,j=1}^{N} jP_{ij}$$

In the classification phase, an unknown texture is used and its features are extracted and compared with the corresponding feature values stored in the features library using a distance vector formula given in Eqn. (17).

$$D(i) = \sqrt{\sum_{j=0}^{n} abs[f_j(x) - f_j(i)]} \quad (17)$$

where n is the total number of features used, i = 1 to Q (Q is the number of images in the database), $f_j(x)$ represent the j[th] feature of unknown texture image (x) and $f_j(i)$ represents the j[th] feature of texture belonging to i^{th} texture if the distance $D(i)$ is minimum among all textures, available in the library. The success of classification is measured using the classification gain (G) and is calculated using Eqn. (18).

$$G(\%) = \frac{C_{corr}}{M} \times 100 \quad (18)$$

where C_{corr} is the number of sub-images correctly classified and M is the total number of sub-images, derived from each texture image.

3 Experimental Results

The proposed method is experimented with VisTex [19] and Google [20] color image databases, each of size 512×512. For comparative analysis, texture classification is done using different feature vectors for two different feature datasets. Dataset-1 and Dataset-2 contains 50 original color texture images each, every texture image is subdivided into 4 (256×256), 16 (128×128) and 64 (64×64) non-overlapping image regions, so that a total of 4200 (50×84) regions are obtained.

The classification is done for all 84 (4+16+64) sub-image regions derived from each texture image in Dataset-1 and 2 using three different feature vectors (F_1, F2 and F3). Feature vector F_1 contains the first order statistics with two features while feature vector F2 contains second order statistics with seven features. Feature vector of each image is calculated from LCLBPCM. In order to improve the classification gain the combination of feature vectors F_1 and F_2 are also used as feature vector F_3.

The classification results are summarized in Table 1, where each entry corresponds to the average correct classification rate of all the 84 image regions of different sizes. From the Table 1, it is observed that the mean success rate for feature vectors F1, F2 and F3 are 92.66%, 87.14% and 95.81% respectively. Next, classification is carried out with Dataset-2 containing Google database, using the same combination of feature vectors F_1, F_2 and F_3. The average classification rates for Dataset-2 are 92.09%, 86.33% and 94.82% for feature vectors F_1, F_2 and F_3 which are shown in Table 2 respectively.

The proposed integrated method is compared with logical transform [21], SGLDM [1], Wavelet algorithm [22], Laws [21], and Gabor algorithms [23] and LCLBP-OR [24] approaches as shown in Table 3. Table 3 clearly indicates that the proposed LCLBPCM method outperforms the existing methods.

Table 1: VisTex Database: Mean percentage of classification rate of each group of textures.

Texture Name	% Classification Rate		
	F1	F2	F3
Bark	94.98	87.8	94.91
Brick	91.32	94.68	96.32
Leaves	89.74	77.25	95.53
Fabric	92.38	89.47	95.75
Stone	94.9	86.54	96.54
Average	92.66	87.14	95.81

Table 2: Google Database: Mean percentage of classification Rate of each group of textures.

Texture Name	% Classification Rate		
	F1	F2	F3
Bark	91.96	85.15	94.9
Granite	94.68	90.74	94.89
Leaves	90.56	80.07	92.67
Marble	91.92	89.71	96.71
Stone	91.35	86.02	94.94
Average	92.09	86.33	94.82

4 Conclusions

The present paper proposed an effective texture descriptor called LCLBPCM on texton images. The proposed approach has the advantage of discriminating power of the local structural textons. The LCLBP-OR reduces the texture unit size from 0 to 255 to 0 to 15 and achieves much better rotation invariant classification than conventional LBP. This makes the LCLBPCM as compact with gray levels ranging from 0 to 15

Table 3: Comparison of Texture classification Methods.

Textured Name	% Correct Classification (PCC) results

Brodatz Textures with Texture ID's	Logical Transform	SGLDM	Wavelet Algorithm	Laws	Gabor Algorithm	LCLBP-OR	Proposed LCLBPCM approach
D94	93	67	63	52	62	93.75	93.98
D28	96	84	62	84	70	96.88	97.88
D90	88	64	62	47	67	97.50	97.96
D105	89	59	53	46	55	95.67	96.67
D28-1	99	67	65	77	63	89.13	89.78
D103	90	77	58	58	59	92.86	93.86
Average % of Classification	93	70	61	61	63	94.30	95.02

and greatly reduces the computation time. The proposed method is different from other methods because this method is having discrimination power of shape features by textons and invariant features with respect to change in illumination and image rotation by LCLBP-OR and overcomes the problem of sensitive to noise and captures important texture information by using LCLBPCM. The proposed method shows better classification rate than the existing methods as shown in Table 3. It is found that the success rate is improved much by combining statistical and structural approaches.

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