Image Retrieval based on LBP Transitions

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ABSTRACT
One of the current theoretically significant, simple and very effective texture descriptor that describe local structure efficiently and precisely is the '*Local Binary Pattern'* (LBP). Today LBP and its variants are applied in many areas. One of the disadvantage with LBP is it derives a total of 256 patterns out of which 58 are the Uniform LBP (ULBP) and remaining are Non Uniform LBP (NULBP).The ULBP holds the fundamental characteristic and most of the textures predominantly contain ULBP . The disadvantage with ULBP is one should consider 58 pattern features for any classification or retrieval etc. The ULBP approaches completely ignored the NULBP and grouped them into mislenious class. This leads to lot of complexity. To overcome this, present paper designed a new method for retrieval based on histogram of transitions from 0 to 1 or 1 to 0 on LBP. LBP contains only 5 such transitions (0 or 2 or 4 or 6 or 8). The proposed method is experimented on various images collected from Google data base. The experimental result indicates the efficiency of the proposed method over the various methods.

Keywords
Histogram, Transitions, NULBP, ULBP, Texture descriptor.

1. INTRODUCTION
Invention of the digital camera and also cell phones with powerful cameras with moderate and low pricing system has given the common man the privilege to capture his world in pictures anywhere, at any time, and conveniently share them with others. This has resulted the generation of volumes of images by common man especially when he or she participating in a function, visiting a new place, meeting friends at different places, when eating new dish etc... The low cost storage devises like pen drives, cell phones and easy Web hosting has made the user community to place a very huge number of photographs or images in these devices. All these factors have created numerous possibilities and finally created interest among the researchers towards the design of an efficient and accurate Content Based Information Retrieval (CBIR) system. That's why the technological advances and growth in CBIR has been unquestionably rapid during the last five years. The general overviews on CBIR are given in [1, 2, 3, 4, 5]. Basically there are, two different approaches in CBIR: a discrete approach and a continuous approach [6]. A comparison of these two models is presented in [6]. The first systems that were available were the QBIC system from IBM [7] and the Photo book system from MIT [8]. QBIC uses color histograms. Photo book uses appearance features, texture features, and 2D shape features. Another well known system is Blobworld [9], developed at UC Berkeley. Recently, local image descriptors are getting more attention within the computer vision community. The underlying idea is that objects in images consist of parts that can be modelled with varying degrees of independence. These approaches are successfully used for object recognition and detection [10, 11, 12, 13, 14, 15] and CBIR [16, 17, 18, 19]. The present paper uses an LBP based approach for efficient image retrieval. LBP approach captures the local features of the image efficiently, accurately and significantly.

LBP is proved as an extreme

ely versatile and significant descriptor. LBP based models often shows promising performances in texture analysis and have been widely used in related applications, such as texture segmentation [20], facial expression recognition [21], shape localization [22] texture classification [23, 24], face recognition [25], dynamic texture recognition [26], and object recognition [27]. Based on LBP new operators are derived such as Local Ternary Patterns (LTP) [28], Local Quinary Patterns (LQP) [29], Centralized Binary Patterns (CBP) [30] etc. In this paper we studied about efficient methodology for image retrieval based on bit wise transitions on LBP. In section 2, we have given clear information about LBP. In section 3 we have highlighted the proposed method and the section 4 describes results and discussions. Finally we concluded the paper in section 5.

2. LBP APPROACH
In the LBP operator, a gray-scale invariant texture primitive, has gained significant popularity for describing texture of an image discussed by Ojala etal. [29]. LBP characterizes the spatial structure of the local image texture in a significant manner. A pattern number in LBP is evaluated by comparing the centre pixel value of a 3 x 3 neighborhood with the neighboring pixels as given in Equation (1). Pattern numbers in LBP can be evaluated even on a 5 x 5 neighborhood. This refers to the third order neighborhood.

$$\mathrm{LBP}_{P,R} = \sum_{P=0}^{P-1} S(g_P - g_c)2^P,$$
$$S(t) = \begin{cases} 1 & t \geq 0 \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

where g_c corresponds to the gray value of the center pixel of the local neighborhood and g_p (p= 0,1,...,P-1) correspond to the gray values of P equally spaced pixels on a circle of radius R (R>0) that form a circularly symmetric neighbor set. Suppose the coordinates of g_c are (0, 0), then the coordinates of g_p are given by (–Rsin(2Πp/P), Rcos(2Πp/P)). The gray value of neighbor points which do not fall exactly in the centre of a pixel is calculated by linear interpolation of the corresponding pixels. The basic form of an LBP operator on a 3×3 square second order neighborhood labels the each pixel value into some binary value (either 0 or 1) by comparing it with some threshold value. Fig.1 shows an exemplary illustration for generation of LBP code. In Fig.1 the threshold is measured as the gray value of central pixel. If the neighboring pixels gray value is greater than or equal to central pixel value then it is made as 1 otherwise zero. The

LBP code is formed by multiplying corresponding LBP weights with the corresponding LBP pixel value. The present paper considered the weights starting from the top left corner and moving towards right in a clock wise direction on a 3x3 neighborhood. The calculation of LBP code is described in Fig.1 and LBP weights can be ordered differently and they can be ordered in 8 different ways as shown in Fig.2.

69	97	12
85	64	24
4	9	65

⇨

1	1	0
1		0
0	0	1

⇨

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

a.Original 3x3 graylevel neighbourhood

b.Local binary pattern(LBP)

c.LBP Weights

d) LBP code = $1*2^0+ 1*2^1+ 0*2^2+0*2^3+1*2^4+0*2^5+0*2^6+1*2^7$ =147

Fig.1: The basic LBP operator.

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

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

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

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

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

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

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

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

Fig.2: Different ways of representing LBP weights.

3. PROPOSED TRANSITION BASED LBP FOR IMAGE RETRIEVAL

To overcome the problem of assigning weights in eight different ways, the present paper measured various transitions on LBP. The LBP generates a total of 256 patterns ranging from 0 to 255. Considering such a huge number of patterns for image retrieval, classification or any other purpose is a very complex task and tedious process. The formation of ULBP and NULBP over comes this. A pattern is considered 'Uniform' (U) if the number of transactions in the sequence between 0 and 1 is less than or equal to two. It was observed by Ojala et al. [29] that certain patterns seem to be fundamental and essential properties of texture, these patterns are called ''uniform'' because they have at most two one-to-zero or zero-to-one transitions in the circular binary code defined in Equation (2). That is, the larger the uniformity value U is, the more likely is that spatial transition occurs in the local pattern.

$$U(LBP_{P,R}) = |s(q_{P-1} - q_c) - s(q_0 - q_c)| + \sum_{P=1}^{P-1} |s(q_P - q_c) - s(q_{P-1} - q_c)| \qquad (2)$$

For example, patterns 0 (bitwise 00000000) and 255 (bitwise 11111111) have a U value of 0 while patterns 1(00000001), 2 (00000010), 12(00001100), 48(00110000), etc. have a U value of 2 as there are exactly two 0/1 or 1/0 transitions in the bitwise representation. Similarly, patterns 00000011, 00000111, 00001111, 00011111, 00111111, 01111111 and other circularly bitwise rotated versions have a U value of 2. There are 58 patterns out of total 256 patterns have 0 or 2 transitions on 0 to 1 or 1 to 0. The ULBP represent only 22.66% of total LBP codes. This leads a total of 256 – 58 = 198 number of NULBP's. The NULBP falls into a large category of total LBP. And the NULBP represents 77.34% of total LBP codes. An important observation was made by Ojala et al. [31] that in texture images, majority of LBP features can be categorized to be uniform. That's why only ULBP's are treated as fundamental patterns of local image texture. Based on this, all the non-uniform patterns (U>2) are grouped under a ''miscellaneous'' label, while each uniform LBP is represented into a unique histogram bin according to its decimal value. This leads to the problem that is by considering the fundamental elements of LBP i.e the ULBP, one will be counting only 23.04 % of patterns out of 256. To address this many researchers proposed many suggestions for improvement.

An improvement suggested by Zhenhua Guo, Lei Zhang. [32] is to consider only the so-called "uniform" patterns. Then merging all non-uniform patterns into one pattern (as done in the traditional LBP) or some limited patterns. These mechanisms do not describe the stochastic characteristics of texture efficiently. By this sometimes texture primitive information represented by these patterns is lost, especially when large neighborhoods are considered. This single pattern makes the uniform patterns sensitive to noise. That is a simple noise may convert ULBP into NULBP. Some authors suggested some improvement over the classical LBP operator [3] to make efficient use of non-uniform patterns in an appropriate way. Combining uniform patterns with a few non-uniform patterns was shown in [3] to improve performance. Non-uniform patterns thus appear to contain useful information. However, the existing methods still suffer much from non-monotonic illumination variation, random noise.

The above extensions of LBP [3, 31] increase the number of patterns to be considered from 58 to a large extent. This leads to lot of complexity especially in texture classification and retrieval domains. After the above study the present paper found that one should consider both uniform and non uniform patterns for an effective image retrieval, classification, recognition etc…. . The problem in considering both the uniform and non uniform LBP's is they generate a total number of 256 patterns. Even if one considers only the ULBP then it leads to 58 different patterns. This increases the dimensionality and also by missing the 77% of pattern information. Evaluating the frequency occurrences of 58 or 256 pattern leads a complex and tedious work especially for image retrieval. For each retrieval, on the test image 58 or 256 feature patterns are to be evaluated if we consider ULBP or all patterns respectively. Then these huge numbers of features i.e 58 or 256 are to be compared each of the database images and the nearest one should be picked as a matching image. To overcome this tedious task the present paper derived a method that represents a 3 x 3 LBP window by its number of transitions that occur from 0 to 1 or 1 to 0 in circular manner.

A 3 x 3 LBP can have 0 or 2 or 4 or 6 or 8 such transitions. There will be no odd number of transitions. That is the proposed method derives image retrieval method based on number of transitions, instead of LBP weights. The present paper represents all 256 LBP's (ULBP and NULBP) into 5 texture features based on the transitions in a novel way. The proposed method is rotationally invariant because it considers only transitions but not relative weights. This reduces the lot of complexity. The proposed method finds the histogram of transitions on LBP on the entire image. The five texture features i.e F_1, F_2, F_3, F_4 and F_5 represents the histogram of 0,2,4,6 and 8 transitions on LBP respectively.

4. RESULTS AND DISCUSSIONS

The proposed transitions based histogram on LBP is experimented on the Tire, Animal fur, Car and Leaf textures collected from Google data base with a resolution of 256 x 256. Fig. 3, 4, 5 and 6 shows some of the texture images of Tire, Animal fur, Car and Leaf respectively with their numbers mentioned below the texture images.

The proposed method initially evaluated histogram or frequency occurrences of 0,2,4,6 and 8 transitions from 0 to 1 or 1 to 0, on LBP i.e rotationally invariant texture features of LBP, F_1, F_2, F_3, F_4 and F_5 respectively on above considered images and placed them in the training database. The Table 1, 2, 3 and 4 shows the histogram texture features on the Animal fur, Tire, Car and Leaf textures respectively. On each probe image the texture features are evaluated in the form of histogram of the transitions from 0 to 1 and 1 to 0. Based on the nearest neighbourhood the histogram of probe image is compared with training images. The Euclidean minimum distance for image retrieval is calculated by the following equation 3.

for j=1 to N

$$new\ d_j \ = \sum_1^5 \sqrt{\left|\left(T_j F_i - P\, F_i\right)\right|^2} \tag{3}$$

where N is the number of textures in the data set(training database) , the T_jF_i refers the histogram value of the texture feature i for for the training texture T_j PF_i represents the histogram of the texture feature i for the probe texture P and d_j represents the summation of absolute difference between the corresponding texture features of the trained texture T_j and probe texture P.

The retrieved image R is obtained by the following equation 4

$$R= \min (d_j) \text{ where j is 1 to N} \tag{4}$$

If d_j value for two or more training textures (let J=2 or 4 or 8) are same then new d_j is evaluated in the following way by taking the absolute difference between texture feature 2 i.e histogram of 2 transitions on LBP.

for j=2 or 4 or 8

$$new\ d_j \ = \sqrt{\left|\left(T_j F_2 - P\, F_2\right)\right|^2} \tag{5}$$

The new R is evaluated in the following way

$$\text{new R}= \min(\text{new } d_j) \tag{6}$$

Based on R and new R the hit and miss are evaluated and represented in Table 5, 6, 7 and 8 for considered textures. A hit indicates a correct match is found and miss indicates there is miss match between the probe image and image retrieved. In the table 5, 6, 7 and 8 hit and miss are shown with binary value 1 and 0 respectively.

The overall image retrieval performance based on the proposed transitions based histogram on LBP method is shown in Table 8 and it is also shown in the form of bar graph in Fig.7.

Fig.3. Tire texture images.

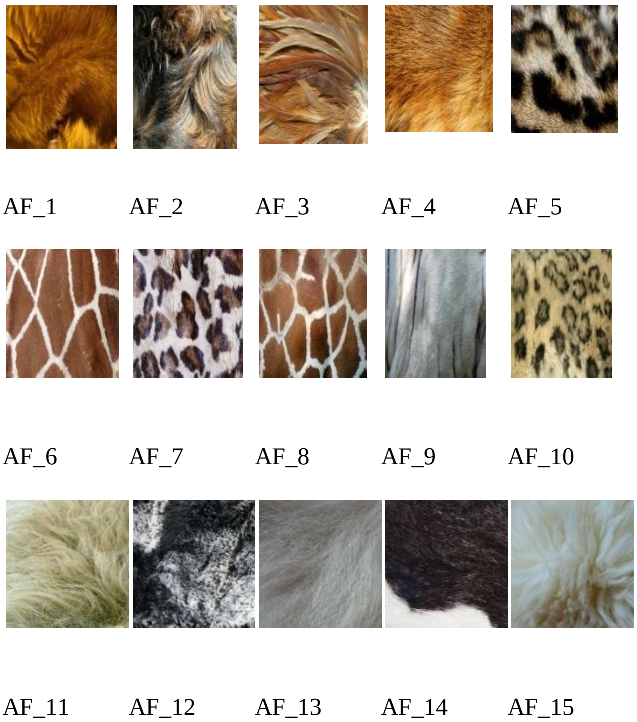

Fig.4. Animal fur textures images.

Fig.5. Car texture images.

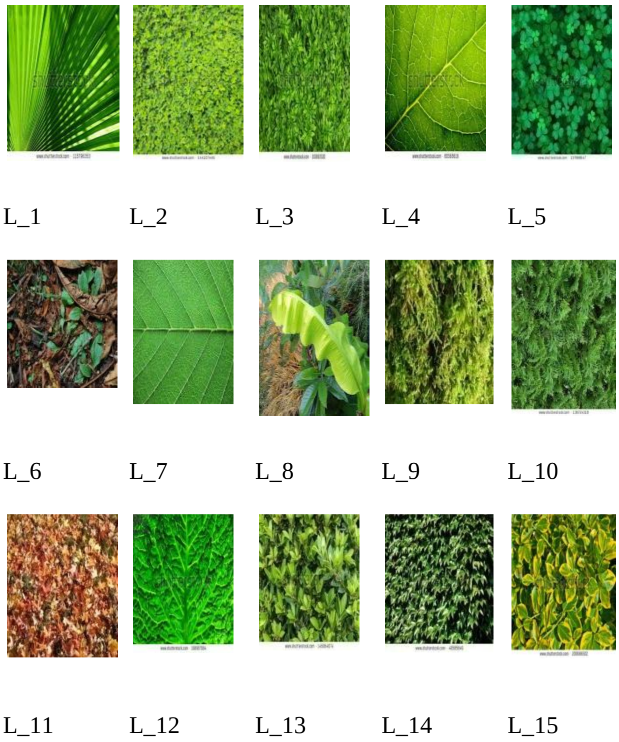

Fig.6: Leaves texture images.

Table 2: Histogram of the transitions on LBP of Animal fur texture images.

	Number of transitions				
Texture No	0	2	4	6	8
AF_1	8012	12073	16230	5794	0
AF_2	7169	14202	15524	4918	0
AF_3	8369	22223	16156	1521	0
AF_4	8369	22223	16156	1521	0
AF_5	7170	21698	17215	1905	0
AF_6	9403	11363	14429	4616	0
AF_7	9225	9221	14824	7786	0
AF_8	6894	9371	14038	9947	0
AF_9	8687	10041	15054	7094	0
AF_10	8751	11560	15113	8610	0
AF_11	5995	15039	26177	819	0
AF_12	6521	10414	14931	9028	0
AF_13	9302	11816	15372	6627	0
AF_14	9635	15539	16350	3684	0
AF_15	6287	9576	14693	10655	0

Table 3: Histogram of the transitions on LBP of Car texture images.

	Number of transitions				
Texture No	0	2	4	6	8
C_1	22246	22408	8051	4854	0
C_2	23290	22657	7957	3940	0
C_3	24811	23659	6623	3588	0
C_4	30009	20520	6398	2741	0
C_5	18995	21932	9628	5423	0
C_6	27215	13872	8882	5715	0
C_7	31025	15795	7247	4222	0

C_8	29909	18432	5225	4581	0
C_9	21217	22757	8010	4868	0
C_10	22528	25041	8301	3101	0
C_11	26009	24595	6983	2438	0
C_12	29908	19323	6431	3231	0
C_13	22296	22803	7783	4486	0
C_14	27428	21325	7362	3008	0
C_15	20803	19333	9917	4717	0

Table 4: Histogram of the transitions on LBP of Leaves texture images.

	Number of transitions				
Texture No	0	2	4	6	8
L_1	13591	13740	12868	6627	0
L_2	17911	10149	12488	5411	0
L_3	14173	11153	13353	6379	0
L_4	11639	10465	13161	6902	0
L_5	11965	10211	14433	6092	0
L_6	13213	9319	12756	6216	0
L_7	16232	8902	11875	7170	0
L_8	15025	9567	11672	7134	0
L_9	16670	11150	13257	4620	0
L_10	11030	11599	14925	6055	0
L_11	12718	11114	14772	4833	0
L_12	12804	11648	14484	5818	0
L_13	17699	13864	12502	4305	0
L_14	11036	11695	14230	6200	0
L_15	14686	15114	14242	3946	0

Table 5: Hit or Miss of Tire texture images.

Probe images (Tire)	Hit/ Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	0
10	0

Table 6: Hit or Miss of Animal fur texture images.

Probe images (Animal fur)	Hit/ Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	0
9	1
10	1

Table 7: Hit or Miss of Car texture images.

Probe images (Car)	Hit/ Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1

Table 8: Hit or Miss of Leaves texture images.

Probe images (Leaves)	Hit/ Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1

Table 9: Retrieval performance of different texture databases.

Texture Databases	Retrieval rates
Tire	80
Animal fur	90
Car	100
Leaves	100

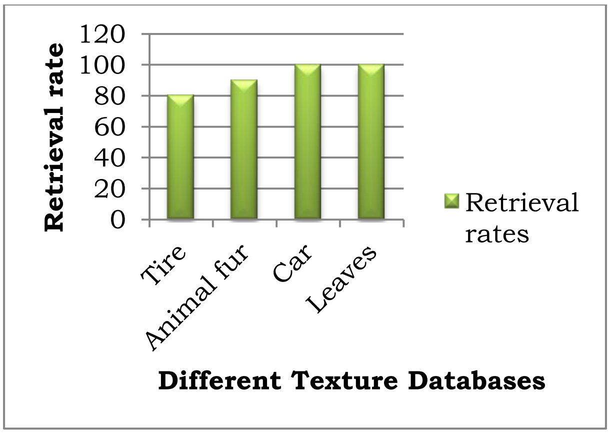

Fig.7: Bar graph representation of retrieval performance.

5. CONCLUSION

The present paper derived a simple method of image retrieval using histogram of number of transitions based on LBP. The main advantage of the present method is, it considered all the 256 LBP features by reducing them into 5 features based on the number of transitions. The present method has overcome the disadvantage of considering all NULBP into one label called mislenious. The proposed transition based LBP is rotationally invariant whereas the features based on LBP code are rotational variant because LBP weights can be represented in 8-different ways. The present method reduced lot of complexity in representing number of texture features if one considered the ULBP or NULBP. The experimental results indicate a good image retrieval rate by the present method.

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