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IMAGE RETRIEVAL BASED ON HYBRID FEATURES

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ABSTRACT

The present paper put forward efficient content-based image retrieval (CBIR) system by extracting structural, texture and local features from images. The local features are extracted from local directional pattern (LDP). The LDP produces a steady local edge response in the presence of noise, illumination changes. The LDP coded image is converted in to a ternary pattern image based on a threshold. The structural features are derived by extracting textons on the "local directional ternary pattern (LDTP") image. The texture features are derived by constructing grey level co-occurrence matrix (GLCM) on the derived texton image. Image retrieval results on various data base images based on various classifiers have proved the discrimination power of the proposed method over existing methods.

Keywords: local binary pattern, local directional pattern, textons, GLCM features.

1. INTRODUCTION

In image retrieval systems, a client puts forward a query image to the system. The system extracts the image features such as shape, texture, or color depending on the type of CBIR model used. These image features are examined and compared with the data base image features. Based on this, the CBIR model retrieves similar images from image database. The comparison of image features between query image and the data base images is made based on a distance function. Then the CBIR model displays those images of the data base that have the closest similarity with the query image. CBIR is an active, ongoing research and still under investigation. Different researches suggested that various algorithms are for content based retrieval and mostly they are based on one feature and only show good results on a particular type of images [1-7].

Shape is considered as the best visual feature, among the other features, for image retrieval, classification and analysis. Shape is a rotational invariant and has high reliability on geometric measurements and transformation, whereas the rest of the features are affected by these transforms. The recent CBIR approaches used color histogram [3, 8, 9, 10, 11] and they provided important information for computing the resemblance between two images based on color component. The texture of image represents the spatial association of gray level image surface [12]. GLCM features are used as bench mark representation of texture. It is derived based on orientation and distance between image pixels. The GLCM features are widely used for image classification, analysis, recognition and retrieval purposes [13, 14, 15, 16, 17, 18]. There are other CBIR models based on colour and/or texture features [9, 10]. Motif Co-occurrence Matrix (MCM) is also proposed in the literature for CBIR [19]. The MCM distinguish between pixels; and change them to a basic graphic. It computes the probability of its happening. Qasim Iqbal also developed a new system [20] based on important image attributes. A multi texton and texton co-occurrence matrix are also proposed in literature for an efficient CBIR [21, 22]. The proposed method considers hybrid features of the images derived from texture and shape in the form of LDP, GLCM features and textons. The rest of the paper organized as follows: The section 2 review the related work. The section 3 and 4 describes the proposed method and results with discussions respectively. The section 5 describes the conclusion.

2. RELATED WORK

2.1 Local binary pattern (LBP)

The LBP was proposed long back [23] and it plays a crucial role in texture classification [24], age classification [25], face recognition [26, 27, 28], image retrieval [29, 30] and texture segmentation [31, 32]. The main reason for this is its simplicity, ability to capture local information more significantly and rotational invariant feature. Various LBP variants are proposed in the literature to improve its performance further [33]. One of the main disadvantages of the LBP is it is prone to error. LBP provides invariant depiction in the occurrence of a monotonic variation. LBP operator is a gray-scale invariant texture primitive that is capable to describe texture of an image more precisely. LBP operator derives the micro-level information efficiently. LBP labels each neighboring pixel (g_p) of an image window by p-neighboring value. This is accomplished by using a threshold with the center pixel value (g_c). This finely converts the image neighborhood into a LBP code by using equation 1 and 2

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} S(g_p - g_c) * 2^P \quad (1)$$

$$S(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (2)$$

LBP suffers much in non-monotonic illumination variation and random noise. A small fluctuation may lead

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to abnormal variation of LBP code as shown in Figure-1 and Figure-2.

141	143	141
141	142	143
141	141	141

Fig. 1 :(a) Actual LBP image

0	1	0
0		1
0	0	0

1(b) : Generation of Binary Patterns Based on Equation 1

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

1 (c):Corresponding Weights

10

1 (D): LBP Code

141	143	141
141	140	143
141	141	141

Figure 2 (A) : LBP Window With Error

1	1	1
1		1
1	1	1

2(B) Generation of Binary Patterns Based On Equation 1

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

2 (c):Corresponding weights

255

2 (d) : LBP code

A small change in the central pixel of the above LBP window of Figure-1 (a) converts an LBP code of 10 into 255, as shown in Figure-2. This also converts (in this case) a non-uniform LBP into uniform LBP [26]. A

LBP is treated as uniform, if it contains a maximum of two transitions from 0 to 1 or 1 to 0 in a circular manner. To come out of this disadvantage recently error free LBP operators are proposed in the literature [34, 35]. To address this problem local directional pattern (LDP) is also introduced in the literature.

3. PROPOSED METHOD

The present paper proposes a new integrated method called "local derivative ternary pattern texton matrix (LDTPTM)" for image retrieval. The local features in the form of edge responses in eight directions are obtained based on LDP coded image. The ternary patterns are derived on LDP. This results into a local derivative ternary pattern (LDTP) image. Then the local shape features in the form of textons are evaluated on LDTP. This results LDTP-texton (LDTPT) image. Finally texture features are obtained by constructing "co-occurrence matrix on LDTPT (LDTPTM)". For effective retrieval, various machine learning classifiers are used on the derived feature set of LDTPTM and retrieval rates are measured.

The proposed LDTPTM method of retrieval consists of the following steps.

Step 1: The color image is converted in to grey level images using RGB color space.

Step 2: The grey level image is converted in to local directional pattern (LDP) coded image. The formation process of LDP is explained below.

3.1 Local directional pattern (LDP)

The LDP is an eight bit binary code which describes the relative edge value of a pixel in different directions [36]. The present paper evaluates edge responses in eight directions on a central pixel of a 3 x 3 neighborhood using Kirsch masks. The masks are applied in eight different orientations (M0~M7). These masks are shown in the Figure-3.

-3	-3	5
-3	0	5
-3	-3	5

M_0

-3	5	5
-3	0	5
-3	-3	-3

M_1

5	5	5
-3	0	-3
-3	-3	-3

M_2

5	5	-3
5	0	-3
-3	-3	-3

M_3

5	-3	-3
5	0	-3
5	-3	-3

M_4

-3	-3	-3
5	0	-3
5	5	-3

M_5

-3	-3	-3
-3	0	-3
5	5	5

M_6

-3	-3	-3
-3	0	5
-3	5	5

M_7

Figure-3. Kirsch edge response masks in eight directions.

We define our directional number as

$$P^i_{dir}=\arg\max I\{\ I_i|\ 0\le i\le 7\}, \qquad (3)$$

Where P^i_{dir} is the principal direction number, Ii is the absolute response of the convolution of the image I with the ith Kirschcom-passmask. Mi defined by

$$I_i=|I*M_i| \qquad (4)$$

Applying the above eight masks, eight edge response value m0, m1…m7 are obtained. Each of these represent edge significance in these directions. Out of eight (mi/i=0, 1, ….7) only the k-most significant edges are given a value 1 and the remaining are set to zero. The proposed method take the three greatest responses, i.e. k=3 in the present paper. The reason for this is the occurrence of corner or edge indicates a huge edge response value in a particular direction. Using this, LDP code is derived by the following equation 5. The LDP code generation on a 3x3 neighborhood is shown below in Figure-4.

$$LDP\ (x_c, y_c) = \sum_{i=0}^{7} m_i * 2^i \quad (5)$$

Step 3: Conversion of LDP coded image in to ternary form based on a threshold. This converts the original image in to "Local direction ternary pattern (LDTP)" image. This mechanism simplifies the extraction of textons that represent shape of the texture in the next step. This also makes the present LDTP process to be resistant to lighting effects, noise and other illumination changes.

The LDP coded image of the step two is converted in to a ternary or 3-valued code (LDTP). For this the neighborhood pixel (p_i) values of LDP coded image are compared with central pixel (i_c) using a lag limit value *'l'*. The neighborhood values are assigned to one of the ternary values T_i. (Equation 6).

$$LDTP(T_i) = \begin{cases} 2 & P_i \geq (i_c + l) \\ 1 & |P_i - i_c| < l \\ 0 & P_i \leq (i_c - l) \end{cases} \quad (6)$$

25	28	65
35	85	75
50	48	65

Mask index	m7	m6	m5	m4	m3	m2	m1	m0
Mask value	331	131	-109	-293	-469	-229	171	467
Rank	2	4	5	7	8	6	3	1
Code bit	1	0	0	0	0	0	1	1
LDP code	131							

Figure-4. Transformation of LDP Code For K=3.

The process of generation of LDTP is illustrated in Figure-6 with l=3. The LDTP generates a total of 0 to 3n-1 codes and this is considered as the main disadvantage. This is not considered as the disadvantage in the present paper, since we are not deriving LDTP coded image. The present paper only derives local ternary patterns (0 or 1 or 2) on LDP coded image (LDTP), to derive shape features on them in the next step.

85	32	26	
53	50	10	LBP=00111000
60	38	48	LDP=00010011

85	32	26	
49	50	10	LBP=00101000
60	38	48	LDP=00010011

Figure-5. Stability of LDP vs. LBP (a) Original image (b) Image with noise.

(a)Sample neighborhood (Intensity values)

38	+	101	100	20
20	25	33	67	109
53	65	43	111	117
65	132	125	145	36
120	100	65	42	144

(b)LDP code of image (a)

49	146	26
44	37	7
41	100	138

(c) LDTP image

2	2	0
2	1	0
2	2	2

Figure-6. Transformation of LDTP image.

Step 4: Derivation of local shape features in the form of textons on the LDTP image. The method of deriving textons on LDTP image is given below. This results "LDTP texton (LDTPT)" image

The basic unit of an image is Pixels and its intensity and experiments based on this have not resulted into any satisfactory results. In order to progress the performance the pattern and shape based methods are employed. A pattern and shape consists of group or set of neighboring pixels with similar intensity levels. One of such popular measure is "texton" proposed by Julesz [37]. Textons are defined as emergent patterns or blobs. These emerging patterns "textons" share a common property all over the image. They are very useful for texture analysis [38], classification [39], face recognition [40, 41], age classification [42], image retrieval [43] etc. Based on textons one can say whether texture is fine or coarse or in any other form. Textons can be derived on a 2x 2 or on a 3x3 or on any neighborhood window. Number of textons will grow if we increase the size of the window. A 2 x2 window neighborhood may generate many types of textons in images. The present paper utilized all texton patterns that contain two and four pixels on a 2×2 grid. This will derive seven textons on a 2 x 2 grid, out of this six textons are formed with different combinations of two adjacent pixels and one with four pixels and the formation of the textons are shown in Figure-7. The considered texton patterns will have either two or four pixels of the 2×2 grid with same intensity values. In Figure-7 (a) the

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P1, P2, P3 and P4 denote the pixel intensities. The TP1, TP5 and TP3, TP6 represents the two horizontal and vertical textons. The two diagonal textons (DT1, DT2) are shown in 7 (c) and 7 (e) and the blob texton is in 7 (h).

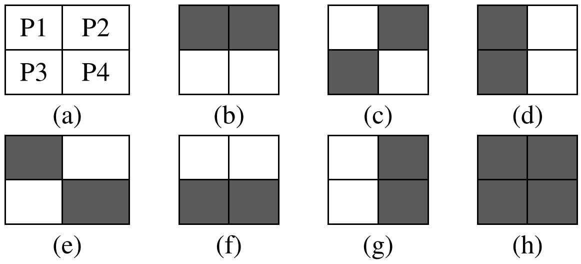

Figure-7. Seven special types of textons on LDTP image grid: a) 2×2 grid b) TP1 c) TP2 d) TP3 e) TP4 f) TP5 g) TP6 and h) TP7.

The derivation of texton image with the above 7 local shape features (textons) is shown below Figure-8.

3	1	1	2	1	3
3	2	3	2	3	1
1	2	4	2	3	2
1	3	1	3	2	1
2	2	2	1	3	2
2	2	3	1	3	1

(a)

3	1	1	2	1	0
3	2	0	2	3	1
1	2	0	2	0	2
1	0	0	3	2	0
2	2	2	1	3	0
2	2	0	1	3	0

(c)

Figure-8. Transformation of texton process: a) Original image (b) Textons identification (c) Texton image.

Step 5: Construction of "LDTPT Matrix (LDTPTM)" and derivation of GLCM features. GLCM features are computed on the derived LDTPTM to generate LS-GLCM.

The Grey Level Co-occurrence Matrix (GLCM), a second order statistical method, was introduced by Haralick *et al.* [44] and able to characterize textures based on the spatial relationship between grey tones in an image [45]. In general, GLCM could be computed as follows. First, an original texture image D is re-quantized into an image G with reduced number of grey level, Ng. Then, GLCM is computed from G by scanning the intensity of each pixel and its neighbor, defined by displacement d and angle ø. A displacement, d could take a value of 1, 2, 3…n whereas an angle, ø is limited 0°, 45°, 90° and 135°. The following Figure-9 illustrates the formation of GLCM with different angles (0°, 45°, 90° and 135°) from a given window.

3	3	3
1	3	3
1	3	2

0°	1	2	3
1	0	0	2
2	0	0	0
3	0	1	3

45°	1	2	3
1	0	0	2
2	0	0	0
3	0	0	2

90°	1	2	3
1	1	0	1
2	0	0	1
3	0	0	3

135°	1	2	3
1	0	0	0
2	0	0	1
3	0	0	2

Figure-9. An example of GLCM formation.

The proposed LDTPTM evaluated all 16 features as proposed by Haralick *et al.* [44] for effective image retrieval.

Step 6: usage of machine learning classifiers for image retrieval on the derived features of LDTPTM.

4. RESULTS AND DISCUSSIONS

To estimate the performance of the proposed LDTPTM approach thoroughly, the present paper used the WANG and Corel data-sets. The COREL data base images are collected from COREL photo gallery [46]. There are 10,800 images in COREL data base and they are divided into 80 concept groups. Each group consists of more than 100 images. The group consists of images from various concepts like elephant, bonsai, dog, stalactite,, steam-engine, primates, waterfall, train, autumn, aviation, cloud, ship, tiger etc. The advantage of considering COREL data base is, it consists of dissimilar images in the same group and also different semantic content images are also in the same group. The WANG database contains 10 classes and each class is represented by 100 images [47]. WANG images are subset of Corel stock photo database. We have considered 1000 images and 500 from each database. We have not included all the results of all queries in the paper due to space limitation, but included in Recall and Precision metrics of this paper.

The retrieval performance of the LDTPTM is judged in terms of precision and recall using various classifiers like Naive Bayes, LibLinear, Multilayer Perceptron, Ibk and J48. Precision is the ratio of the number of retrieved images that are relevant to the number of retrieved images. Recall is the ratio of the number of retrieved images that are relevant to the total number of relevant images. They are defined as follows:

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Precision: P = RR/NR (7)

Recall: R = RR/M (8)

where RR is the number of relevant images retrieved, NR is total number of images retrieved or total number of trials made and M is the total number of relevant images.

The proposed LDTPTM method is experimented with different lag values (l=0, 2, 3, and 4). The proposed LDTPTM has given the best results on all classifiers for l=3. The LDTPTM method also experimented by using LBP instead of LDP in step two. The precession and recall graphs for the two datasets are shown below. The graphs clearly indicate the proposed LDTPTM with l=3 out performs the LBP and the proposed method with l=0. The Multilayer Perceptron and J48 classifiers has shown high retrieval rate on both the data bases.

We have also calculated accuracy based on the following equation 9

Accuracy = (Precision+ Recall)/2 (9)

The present paper plotted the average accuracy rate for 1000 images using the proposed LDTPTM using on l=3 and for existing methods (Figure-14). The graph clearly indicates a high accuracy rate for the proposed method than the existing methods.

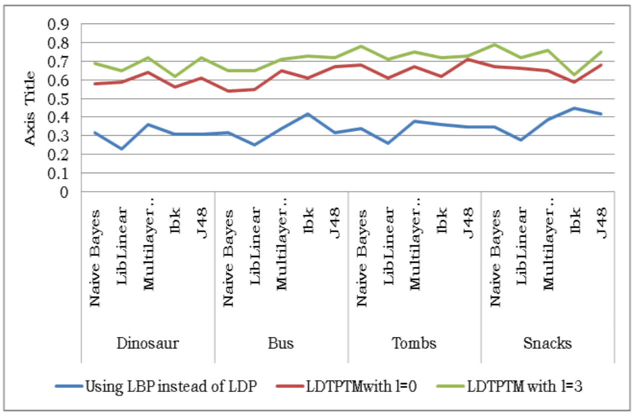

Figure-10. Precision graph for proposed method on WANG database.

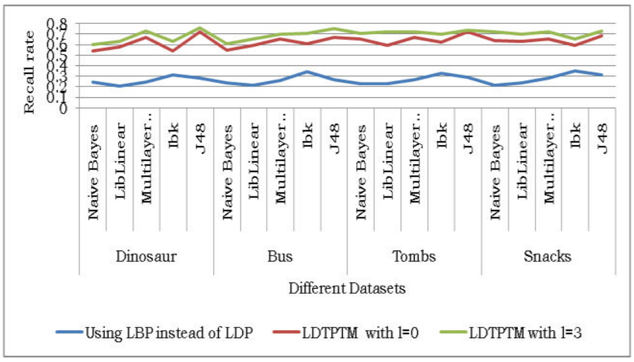

Figure-11. Recall graph for proposed method on WANG database.

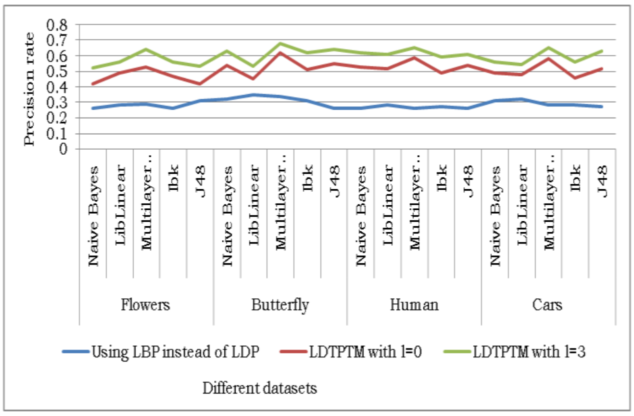

Figure-12. Precision graph for the proposed method on COREL database.

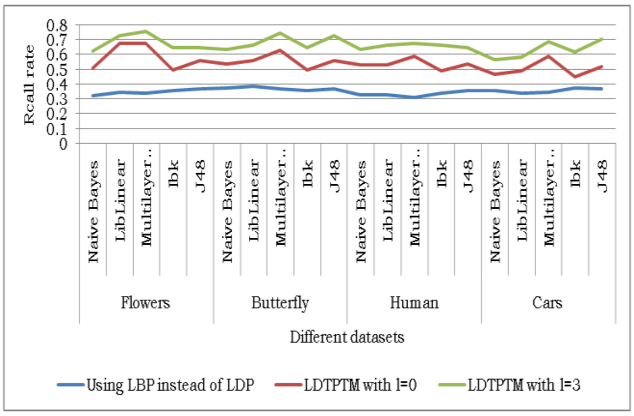

Figure-13. Recall graph for the proposed method on COREL database.

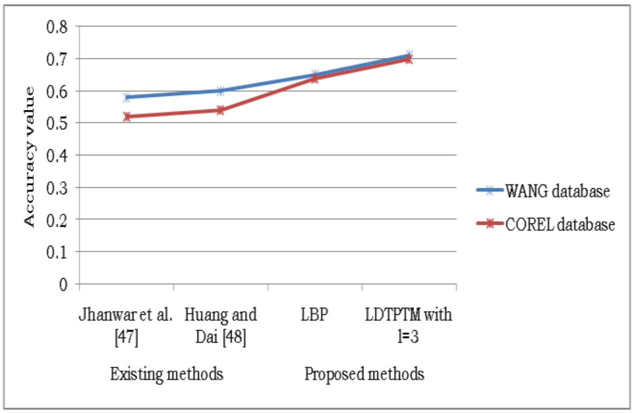

Figure-14. Accuracy graph.

5. CONCLUSIONS

The present paper has proposed and successfully implemented the new hybrid approach for image retrieval i.e. LDTPTM on two databases using various machine learning classifiers. The proposed LDTPTM captured the local peak edge responses using LDP with l=3. To derive shape features on the edge responses the LDP coded image is converted into a ternary pattern image using a random threshold. The GLCM features are evaluated and retrieval performance is noted using precision, recall and accuracy parameters. The proposed method using Multilayer Perceptron and J48 classifiers have shown a good retrieval rate than the other Naivee Bayes, Liblinear and Ibk classifiers. The proposed method is also implemented using LBP and with different thresholds and the results are compared. The proposed method also compared with the existing methods and the accuracy graph indicates the high performance of the proposed method than the existing and LBP approaches.

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