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Color Directional Binary Code for Image Indexing and Retrieval

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Abstract— This research paper proposes a novel algorithm meant for image indexing and retrieval, by integrating color and texture features. First, the RGB image is converted to HSV space, then these space features are collected by constructing H & S space histograms and texture features, which are collected from V space of an image by Directional Binary Code (DBC). In the proposed algorithm both, color histograms and texture feature, are then concatenated to generate the feature vector. Using feature vector of query image, similar images are then extracted using different distance measures. The retrieval results for this proposed algorithm is tested over Corel 1000 image database. After investigation, results demonstrate the substantial improvement in terms of retrieval precision and recall as equated to LBP, DBC feature algorithms.

Keywords— Feature Extraction, Local Binary Patterns, Directional Binary Code, Texture, Pattern Recognition, Image Retrieval.

I. INTRODUCTION

In the present scenario there is a momentous expansion of digital libraries which makes handling these datasets extremely difficult by text based human annotations. Hence, there is an urgent need of expert search technique viz content based image retrieval (CBIR). Feature extraction is a key step and the success of CBIR system depends heavily upon methods of feature extraction. The CBIR exploits the visual contents of an image such as color, shape, texture, etc. in order to represent and index of the image. Classification of these visual features may further be possible into domain specific general features such as finger prints and human faces. Still there is no single best representation for all perceptual subjectivity, because the images present in the database may be in different conditions. Extensive and comprehensive literature survey on CBIR is present in [1]–[4].

In 1991, M. Swain et al. introduces color histogram concept and also proposed the histogram intersection distance that measures distance between the histograms of different images [5]. M. Stricker et al. used the central moments for image retrieval called as mean, variance and skewness of each color [6]. G. Pass et al. proposed Color Coherence Vector (CCV) [7]. CCV partitions each histogram bin into two types, i.e., coherent or incoherent. A histogram bin is coherent if it belongs to a large uniformly color region. J. Huang et al. used a new color feature called color correlogram [8] which characterizes not only the color distributions of pixels, but also spatial correlation of pair of colors. Z. Lu et al. presented color feature in Discrete Cosine Transform (DCT) domain which uses vector quantized index histograms [9].

Texture is another principle and vital feature for CBIR. J. Smith et al. used the first and second moment in the wavelet domain as texture features for image retrieval [10]. A. Moghaddam et al. introduced the Gabor wavelet correlogram (GWC) for image content representation [11, 12]. Texture classification using Wavelet Transform is then proposed by A. Ahmadian et al. [13]. H. Moghaddam et al. proposed new algorithm called wavelet correlogram (WC) [14]. Using genetic algorithm and by optimizing quantization threshold, the performance of WC technique is then improved by M. Saadatmand et al. [15, 16]. L. Birgale et al. [17] and M. Subrahmanyam et al. [18] integrates the color (histogram) and texture (wavelet transform) features for CBIR. S. Murala et al. introduced correlogram algorithm using wavelets and rotated wavelets (WC+RWC) [19] for image retrieval.

LBP is used for texture description by T. Ojala et al. [20]. These LBPs are then converted for texture classification to rotational invariant [21]. Using feature distributions, M. Pietikainen et al. proposed rotational invariant texture classification [22]. LBP operator was then used by T. Ahonen et al [23] and J. Zhao et al. [24] for facial expression recognition and analysis. By using LBP M. Heikkila et al. proposed background detection and modelling [25]. For shape localization X. Huang et al. utilized the extended LBP [26].

M. Heikkila et al. used LBP in their paper for interest region description [27]. M. Li et al. combined LBP and Gabor filter for texture segmentation [28]. Face recognition using local derivative pattern [29] is proposed by B. Zhang et al. in which they considered LBP as a non-directional first order local pattern. B. Zhang et al. have introduced the directional binary code (DBC) [30] for face recognition. The DBC represents the directional edge information in a specified neighbourhood.

N. Jhanwara et al. [31] have proposed the motif co-occurrence matrix (MCM) for content based image retrieval. The MCM is derived from the motif transformed image which is calculated by dividing the whole image into non-overlapping 2×2 pixel patterns. Jhanwar et al. [31] introduced the motif co-occurrence matrix (MCM) in their paper for image retrieval. Further by applying MCM on each color planes (R, G, and B) they proposed color MCM. C. Lin et al. [32] integrates color feature, texture feature and k-mean color histogram (CHKM), MCM and the difference of pixels of scan pattern.

We concatenates, in this paper, color (histogram of H and S space) and texture (DBC of V space) feature on HSV space image to improve the retrieval accuracy. The performance of the proposed algorithm has been tested on Corel 1000 image database [33] for proving the worth of this algorithm. After analysing the results with respect to retrieval accuracy and recall significant improvement in the performance is observed as compared to LBP and DBC.

Rest of the paper is organized as follows. The following Section II contain the concise review of local binary patterns and describes directional binary code (DBC). Section III contain the proposed system framework. In section IV the experimental results and discussion about the same is given. Finally section V concludes the research work with future directions.

II. RELATED WORK

2.1 Local Binary Patterns

For texture classification, the LBP operator was proposed by T. Ojala *et al.* [20]. This operator proved its successful use in terms of efficiency and performance in many active research areas like, face recognition, object tracking, texture classification, fingerprint recognition, and bio-medical image retrieval.

LBP operator value is calculated by comparing a canter pixel value in a specified neighbourhood with its neighbours. The equations to compute LBP is given by Eq. (1) and Eq. (2):

$$LBP_{P,R} = \sum_{i=1}^{P} 2^{(i-1)} \times f(I(g_i) - I(g_c)) \quad (1)$$

$$f(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & otherwise \end{cases} \quad (2)$$

Where P and R denotes the number of neighbours and radius of neighbourhood respectively, $I(g_c)$ denotes the gray value of canter pixel, and $I(g_i)$ is the gray scale value of its neighbour. A sample example of computation of an LBP value using a 3 x 3 pattern is shown in Fig. 1 as given below. The LBP value histograms of these neighbourhoods extracts distribution of edge information in an image [20].

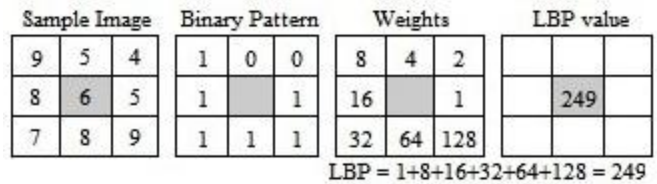

Figure 1: LBP calculation for 3×3 pattern

2.2 Directional Binary Code

B. Zhang et al. [30] have introduced the DBC for face recognition in their paper. DBC is used to represent directional edge information in a specified neighbourhood. In an image *I*, first-order derivatives along 0º, 45º, 90º and 135º directions is denoted as $I^1_{\alpha,d}$, where α = 0º, 45º, 90º and 135º, and *d* is the distance between given point and its neighbouring point. In Fig. 2, for example, the distance between canter pixel and its four neighbours is 1(i.e. *d* = 1 in all four directions). If $Z_{i,j}$ be a point in *I* then all four directional derivatives at $Z_{i,j}$ are

$$\begin{aligned} I^1_{0°,d} &= I(Z_{i,j}) - I(Z_{i,j-d}) \\ I^1_{45°,d} &= I(Z_{i,j}) - I(Z_{i-d,j+d}) \\ I^1_{90°,d} &= I(Z_{i,j}) - I(Z_{i-d,j}) \\ I^1_{135°,d} &= I(Z_{i,j}) - I(Z_{i-d,j-d}) \end{aligned} \quad (3)$$

A thresholding function, $f(I^1_{\alpha,d}(Z))$, is applied to all four directional derivatives to get a binary code in the given direction:

$$f_1(I^1_{\alpha,d}(Z)) = \begin{cases} 1, & if\ I^1_{\alpha,d}(Z) \geq 0 \\ 0, & otherwise \end{cases} \quad (4)$$

Then DBC is defined as:

$$DBC(I(g_c))\big|_{\alpha} = \left\{ I^1_{\alpha,d}(g_c); I^1_{\alpha,d}(g_1); \ldots I^1_{\alpha,d}(g_8) \right\} \quad (5)$$

Fig. 2 below shows the DBC computation in 0º direction.

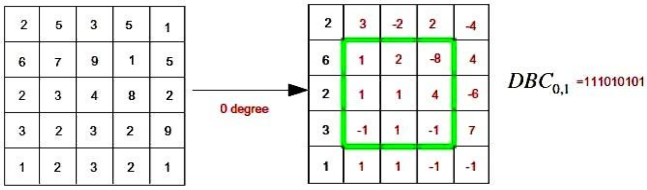

Figure 2: Example showing DBC computation in 0º direction

III. Methodology

This paper emphasises the new algorithm by using color and texture features for CBIR. First, RGB image is converted into HSV space, then the histogram calculation is performed for H image and S image by quantizing into Q levels. Also the local region of V image is represented by DBC patterns, which are evaluated by taking consideration of local difference between the pixels. Thus, feature vector is constructed by concatenating the features collected on HSV spaces and further used for image retrieval.

Algorithm: Color DBC
Input: Query Image
Output: Image Retrieval results
Steps:

1. Input query image.
2. Convert RGB to HSV image.
3. Perform quantization on H and S spaces.
4. Generate the histograms of quantized H and S spaces.
5. Calculate DBC patterns on V space.
6. Construct the feature vector by concatenating the color and texture features.
7. Find the best matches using distance metrics.
8. Retrieve number of top matches.

3.1 Similarity Measurement

In the work presented in this paper *four* types of similarity distance measures are used as given below:

Manhattan Distance [6]

Manhattan distance measure is less expensive in computation because it considers only absolute differences in each feature. This distance metric is also known as L_1 distance or city-block distance and defined as

$$D(Q,T) = \sum_i \left| f_i(Q) - f_j(T) \right| \quad (6)$$

Euclidean Distance [6]

For p=2 in the equation (6) give the Euclidean distance and defined as:

$$D(Q,T) = \left(\sum_i \left| f_i(Q) - f_j(T) \right|^2 \right)^{1/2} \quad (7)$$

Euclidian distance computation is the most expensive as it requires to find square root value. This distance metric is also known as L_2 Distance.

D_1 Distance [6]

$$D(Q,T) = \sum_{i=1}^{Lg} \left| \frac{f_{T,i} - f_{Q,i}}{1 + f_{T,i} + f_{Q,i}} \right| \quad (8)$$

Canberra Distance [6]

$$D(Q,T) = \sum_{i=1}^{Lg} \frac{\left| f_{T,i} - f_{Q,i} \right|}{\left| f_{T,i} + f_{Q,i} \right|} \quad (9)$$

Where Q and T are the query image and image in database respectively, Lg denotes feature vector length; $f_{I,i}$ is i^{th} feature of image I in the database, $f_{Q,i}$ is i^{th} feature of query image Q.

IV. Results and Discussion

For the work proposed in this paper, image retrieval tests are conducted on Corel 1000 database and results are presented in the following subsections.

3.1 Corel 1000 Database

Corel 10000 database [33] contains huge amount of images of different contents ranging from outdoors and animals to nature and human face. These images are pre-classified into various categories of size 100 by domain experts. In this paper, we collected the database which contains 1000 images of 10 different categories (groups G). Total ten categories are present in this database namely Africans, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, food and mountains. Each category contains 100 images ($N_G = 100$) and all these images have either 384×256 or 256×384 sizes. Fig. 3 shows the sample images (one image from each category) from Corel 1000 image database.

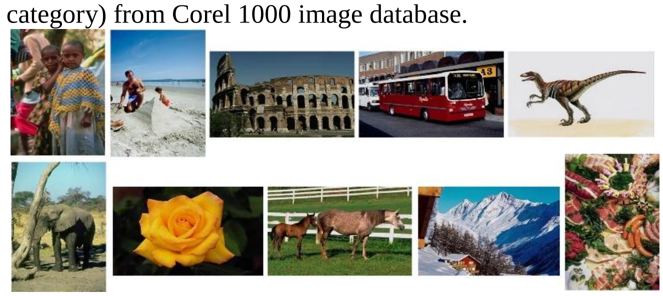

Figure 3: Sample images (one image/category) from Corel 1000 database

The performance of the proposed method is measured in terms of precision and recall by Eq. (10) and (11) respectively.

$$Precision = \frac{Number\ of\ Relevant\ Images\ Retrieved}{Total\ Number\ of\ Images\ Retrieved} \times 100 \quad (10)$$

$$Recall = \frac{Number\ of\ Relevant\ Images\ Retrieved}{Total\ Number\ of\ Relevant\ Images\ in\ Database} \times 100 \quad (11)$$

Table 1 and 2 summarizes the retrieval results of the proposed method (Color-DBC), LBP and DBC methods in terms of average retrieval precision and recall respectively.

Table 1: Precision results on Corel 1000 image database

Category	Precision (%)		
	LBP	*DBC*	*Color-DBC*
Africans	65.4	61.4	71.7
Beaches	56.4	58.1	61
Buildings	65.4	73.1	77.5
Buses	97.4	97.9	98.7
Dinosaurs	98	97.9	98.8
Elephants	52.2	55.4	61
Flowers	92	89.9	92.5
Horses	77.6	80.1	86.3
Mountains	46.4	38.6	42.6
Food	84.7	88.8	90.7
Average	73.55	74.12	78.08

From Table 1 and 2, it is clear that the proposed algorithm shows category wise better performance as compared to LBP and DBC methods with respect to average retrieval precision and recall.

Table 2: Recall results on Corel 1000 image database

Category	Recall (%)		
	LBP	*DBC*	*Color-DBC*
Africans	33.3	33.54	38.09
Beaches	33.39	36.12	37.99
Buildings	33.71	35.64	37.68
Buses	60.41	64.17	63.85
Dinosaurs	81.68	84.04	86.27
Elephants	29.06	29.75	31.72
Flowers	73.15	70.61	71.02
Horses	41.94	37.78	41.57
Mountains	26.08	23.33	24.83
Food	47.19	50.28	53.2
Average	45.99	46.52	48.62

Table 3: Results of Average Retrieval Precision on Corel 1000 image database

No. of Top Matches	LBP	DBC	Color-DBC
10	73.55	74.12	78.08
20	66.84	67.71	71.54
30	62.66	63.63	67.21
40	59.76	60.43	63.58
50	56.85	57.49	60.48
60	54.43	54.88	57.74
70	52.16	52.64	55.29
80	50.00	50.58	53.01
90	47.95	48.66	50.86
100	45.99	46.52	48.62

Table 4: Results of Average Retrieval Rate on Corel 1000 image database

No. of Top Matches	LBP	DBC	Color-DBC
10	7.35	7.41	7.80
20	13.56	13.54	14.30
30	18.79	19.09	20.16
40	23.9	24.17	25.43
50	28.42	28.74	30.24
60	32.66	32.93	34.64
70	36.51	36.85	38.70
80	40.00	40.47	42.41
90	43.16	43.79	45.78
100	45.99	46.52	48.62

Table 3, 4 and Fig. 4 (a) & (b) illustrate the performance comparison of "Color DBC algorithm" with LBP and DBC in terms of average retrieval precision and average retrieval recall respectively. From Table 3 & 4 and Fig. 4 (a) & (b), it is found that the proposed method shows the better performance as compared LBP and DBC. The performance of the proposed algorithm when tested with different distance measures, it concludes that the Manhattan distance outperforms other distances as shown in Table 5 and Fig. 5.

Table 5: Results of "Color DBC algorithm" with respect to Average Retrieval Precision on Corel 1000 image database

No. of Top Matches	Distance Measures			
	Manhattan	*Canberra*	*Euclidean*	d_1
10	81.38	77.9	71.4	78.08
20	76.28	71.39	64.90	71.54
30	72.72	67.11	61.27	67.21
40	69.96	63.48	58.41	63.58
50	67.54	60.37	56.06	60.48
60	65.19	57.69	53.88	57.74
70	62.79	55.15	51.78	55.29
80	60.50	52.90	49.65	53.01
90	58.14	50.73	47.70	50.86
100	55.71	48.52	45.79	48.62

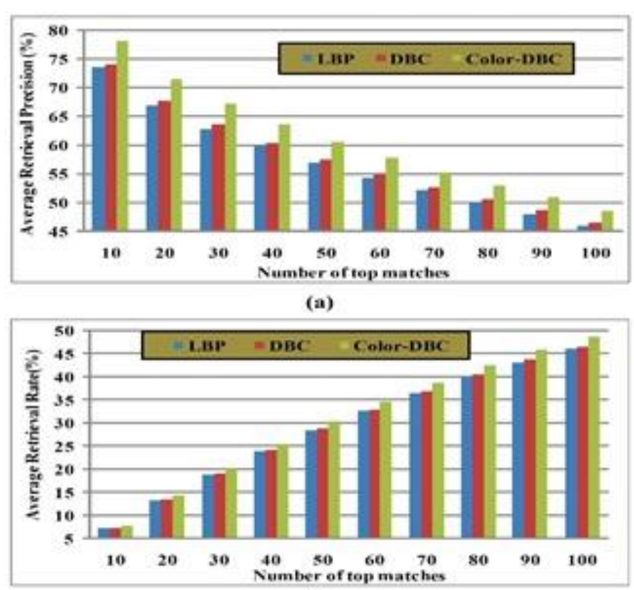

Figure 4. Comparison of "Color DBC algorithm" with LBP and DBC with respect to: (a) average retrieval precision, (b) average retrieval rate

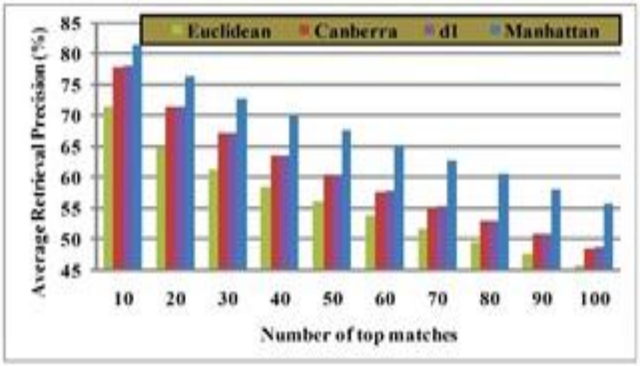

Figure 5. Average retrieval precision using various distance measures for "Color-DBC algorithm".

V. CONCLUSION AND FUTURE SCOPE

A new algorithm meant for image indexing and retrieval proposed in this paper by combining quantized color histogram features on H and S spaces and DBC patterns on V space. The experiment has been carried out on Corel 1000 database to prove the worth of proposed algorithm. The results after being investigation show a significant improvement in terms of their evaluation measures as compared to LBP and DBC. In future, rotation invariant texture features can be extracted and used for image retrieval.

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