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COLOR AND MULTI-RESOLUTION DBC CO-OCCURRENCE MATRIX FOR IMAGE RETRIEVAL

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Authors Short Profile

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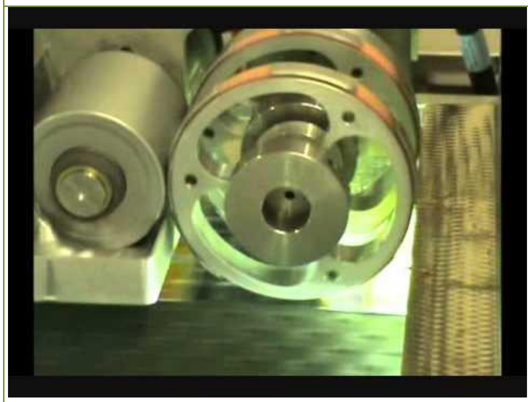


Abstract :

This paper presents a novel image indexing and retrieval algorithm using Gaussian multi-resolution directional binary code (DBC) co-occurrence matrix and color histogram. DBC histogram captures only the patterns distribution in a texture while the spatial correlation between the pair of patterns is gathered by DBC Co-occurrence. Multi-resolution texture decomposition and co-occurrence calculation has been efficiently used in the proposed method where multi-resolution texture images are computed using Gaussian filter for collection of DBCs from these particular textures. Eventually, feature vectors are constructed by making into play the co-occurrence matrix that exists between binary patterns and color histogram which is constructed from the RGB spaces of the color image. The retrieval results of the proposed method have been tested by conducting two experiments on Corel-1K and MIT VisTex texture databases. The results after being investigated show a significant improvement in terms of their evaluation measures as compared to the existing features for image retrieal.

Keywords :
Multi-resolution features; Gaussian Filter; Directional Binary Code; Texture; Pattern Recognition; Feature Extraction; Local Binary Patterns; Image Retrieval.

I. INTRODUCTION

With the growth in technology and advancement of the living world, there has been an expansion of digital database in order to meet ones' technical requirement. Handling of these databases by human annotation is a cumbersome task thereby, arousing a dire need for some familiar search technique i. e. content based image retrieval (CBIR). The feature extraction forms a prominent stair in CBIR and its effectiveness relies typically on the method of features extraction from raw images. The visual contents of an image such as color, texture, shape, faces, and spatial layout etc. are the key pillars for representing and indexing. The visual features can further regimented into general features that includes color, texture, shape and domain specific features such as human faces and finger prints. Preeminent representation of an image for all perceptual subjectivity still does not exist as the user may take photographs under different conditions (view angle, illumination changes etc.) there by making the learning of high level semantic concepts an utmost task for CBIR systems. Comprehensive and extensive literature survey on CBIR is presented in [1]–[4].

Texture analysis has been an eye catcher due to its potential values for computer vision and pattern recognition applications. The selective visual attention model (SVAM) is incorporated in [5] for the CBIR task to estimate user's retrieval concept. It distinguishes itself from the existing learning based retrieval algorithms as they need relevance feedback strategy to get user's high-level semantic information. Also, an improved saliency map computing algorithm based on the saliency map, an efficient salient edges and regions detection is proposed. The dominant set clustering (DSC) similarity for image retrieval can be seen in [6] where the low-level visual features and high-level concepts are amalgated using DSC similarity measure for the relevance feedback based image retrieval system. Retrieval performance is tested on an image retrieval system using the memorized support vector machine (SVM) relevance feedback. An efficient histogram oriented gradients (HOG) based human detection [7] reduces the features in blocks for constructing the HOG features for intersection detection windows and utilizes sub-cell based interpolation that efficiently computes them for each block.

Texture is another salient and indispensable feature for CBIR. Vo et al. [8] proposed the Vonn distribution of relative phase for statistical image modeling in complex wavelet domain. A relative phase probability density function, known as Vonn distribution, in complex wavelet domain and the maximum-likelihood method is used for estimating two Vonn distribution parameters. The rotation-invariant texture retrieval using wavelet-based hidden Markov trees can be seen in [9]. The feature extraction of the texture is performed by employing the signature of the texture, generated from the wavelet coefficients of each subband across each scale and the similarity that exists between textures using Kullback–Leibler (KL) distance measure. Smith et al. used the mean and variance of the wavelet coefficients as texture features for CBIR [10]. Moghaddam et al. proposed the Gabor wavelet correlogram (GWC) for CBIR [11, 12]. Ahmadian et al. used the wavelet transform for texture classification [13]. Moghaddam et al. introduced new algorithm called wavelet correlogram (WC) [14]. Saadatmand et al. [15, 16] improved the performance of WC algorithm by optimizing the quantization thresholds using genetic algorithm (GA). Birgale et al. [17] and Subrahmanyam et al. [18] combined the color (color histogram) and texture (wavelet transform) features for CBIR. Subrahmanyam et al. proposed correlogram algorithm for image retrieval using wavelets and rotated wavelets (WC+RWC) [19].

Ojala et al. proposed the local binary patterns (LBP) for texture description [20] and these LBPs are converted to rotational invariant for texture classification [21]. pietikainen et al. proposed the rotational invariant texture classification using feature distributions [22]. Ahonen et al. [23] and Zhao et al [24] used the LBP operator facial expression analysis and recognition. Heikkila et al. proposed the background modeling and detection by using LBP [25]. Huang et al. proposed the extended LBP for shape localization [26]. Heikkila et al. used the LBP for interest region description [27]. Li et al. used the combination of Gabor filter and LBP for texture segmentation [28]. Zhang et al. proposed the local derivative pattern for face recognition [29]. They have considered LBP as a nondirectional first order local pattern, which are the binary results of the first-order derivative in images. B. Zhang et al. [30] have proposed the directional binary code (DBC) for face recognition. The DBC is encodes the directional edge information in a neighborhood. Subrahmanyam et al. has proposed the local tetra patterns (LTrP) [31], local maximum edge binary pattersn (LMEBP) [32], directional local extrema patterns (DLEP) [33] and directional binary wavelet patterns (DBWP) [34] for image retrieval. They used the natural, texture and medical image databases for image retrieval.

To improve the retrieval performance in terms of retrieval accuracy, in this paper, we calculated the multi-resolution directional binary code (DBC) co-occurrence matrix for image retrieval. The performance of the proposed method has been tested on Corel-1K and MIT VisTex database for proving the worth of our algorithm. The results after investigation show a significant improvement in terms of their evaluation measures as compared to CC, LBP, DBC and other transform domain features.

The organization of the paper as follows: In section I, a brief review of image retrieval and related work is given. Section II, III and IV presents a concise review of local binary patterns, directional binary code (DBC) and the proposed system framework respectively. Experimental results and discussions are given in section V. Based on above work conclusions are derived in section VI.

II.LOCAL BINARY PATTERNS

The LBP operator was introduced by Ojala et al. [20] for texture classification. Success in terms of speed (no need to tune any parameters) and performance is reported in many research areas such as texture classification, face recognition, object tracking, bio-medical image retrieval and finger print recognition.

Given a center pixel in the 3×3 pattern, LBP value is computed by comparing its gray scale value with its neighborhoods based on Eq. (1) and Eq. (2):

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

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \qquad (2)$$

where $I(g_c)$ denotes the gray value of the center pixel, $I(g_i)$ is the gray value of its neighbors, *P* stands for the number of neighbors and *R*, the radius of the neighborhood.

Fig. 1 shows an example of obtaining an LBP from a given 3×3 pattern. The histograms of these patterns extract the distribution of edges in an image [20].

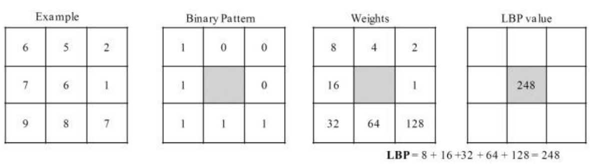


Fig. 1: LBP calculation for 3×3 pattern

III. DIRECTIONAL BINARY CODE

B. Zhang et al. [30] have proposed the directional binary code (DBC) for face recognition. The DBC is proposed to encode the directional edge information in a neighborhood. Given an image *I*, they denoted its first-order derivatives along 0º, 45º, 90º and 135º directions as $I^1_{\alpha,d}$, where α =0º,45º,90º and 135º, and *d* is the distance between the given point and its neighboring point. For example, in Fig. 2 the distance between the center point and its four directional neighbors is 1, i.e. *d* = 1 in four directions. Let $Z_{i,j}$ be a point in *I*, then the 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 the four directional derivatives to output a binary code in the given direction:

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

The DBC is defined as:

$$DBC(I(g_c))\big|_{\alpha} = \left\{ I^1_{\alpha,d}(g_c), I^1_{\alpha,d}(g_1); I^1_{\alpha,d}(g_2); \ldots\ldots\ldots I^1_{\alpha,d}(g_8) \right\} \quad (5)$$

Fig. 2 illustrates the DBC calculation in 0º direction.

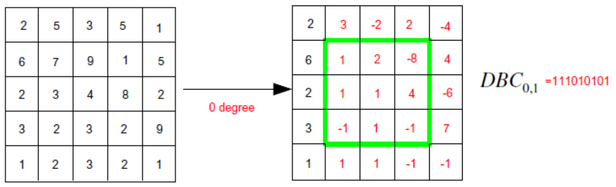


Fig. 2: An example of DBC calculation in 0º direction

From Eq. (5), it is clear that the DBC contains 9 binary bits. Hence the feature vector length is 512. To solve this feature vector length problem, we coded the DBC by excluding the center pixel edge value as shown in Eq. (6).

$$DBC(I(g_c))\big|_{\alpha} = \left\{ I^1_{\alpha,d}(g_1); I^1_{\alpha,d}(g_2); \ldots\ldots\ldots I^1_{\alpha,d}(g_8) \right\} \quad (6)$$

The uniform pattern refers to the uniform appearance pattern which has limited discontinuities in the circular binary presentation. In this paper, the pattern which has less than or equal to two discontinuities in the circular binary presentation is considered as the uniform pattern and remaining patterns considered as non-uniform patterns.

Fig. 3 shows all uniform patters for *P=8*. The distinct values for given query image is $P(P-1)+3$ by using uniform patterns. But these features are not rotational invariant.

The rotational invariant patterns $(DBC_{P,R}^{riu2})$ can be constructed by adding all eight patterns in the each row of Fig. 3 as shown in Fig. 4. The distinct values for a given query image is $P+2$ by using rotational invariant patterns $(DBC_{P,R}^{riu2})$.

After DBC calculation, the co-occurrence matrix is constructed in 0º, 45º and 90º directions for feature vector generation. The brief description of the co-occurrence matrix calculation is given in the next sub-section.

A. Gaussian Filter Bank

The 1-D Gaussian function is defined by

$$g(t,\sigma)=\frac{1}{\sqrt{2\pi\sigma}}e^{-t^2/2\sigma^2} \qquad (7)$$

where the parameter σ denotes the Gaussian half-width. Fig. 5 displays this Gaussian function and its 1st and 2nd derivatives for σ = 1.

The Fourier transform of the Gaussian function is also a Gaussian:

$$G(\omega,\sigma)=\int_{-\infty}^{\infty} dt\, e^{-i\omega t} g(t,\sigma)=e^{-\omega^2\sigma^2/2} \qquad (8)$$

Fig. 6 displays this Fourier transform and those of the 1st and 2nd Gaussian derivatives for σ = 1. Eq. (8) imply that convolution of a signal with a Gaussian is equivalent to low-pass filtering of that signal.

The 2-D circular Gaussian function is defined as:

$$g(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{-(x^2+y^2)/2\sigma^2} \qquad (9)$$

The Gaussian images of a given image are calculated as follows:

$$L(x,y,\sigma)=g(x,y,\sigma)*I(x,y) \qquad (10)$$

where σ is different scales and (*) indicates the convolution operator.

B. Gaussian Filter Bank

In this paper, co-occurrence matrix is used to represent the traversal of adjacent pattern difference in a DBC image.

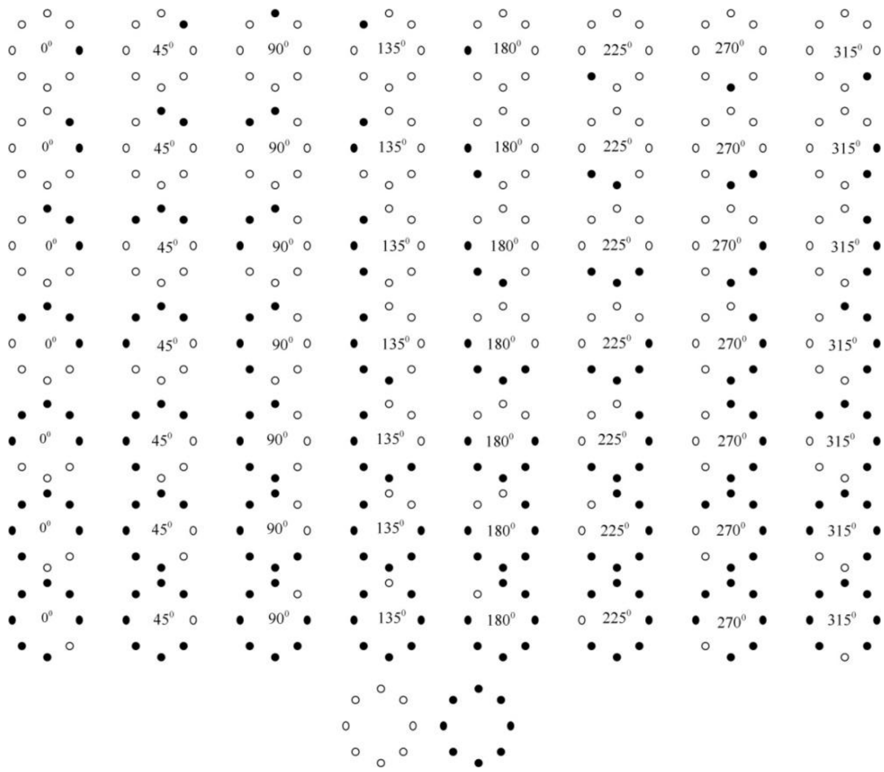


Fig. 3: Uniform patters when P=8. The black and white dots represent the bit values of 1 and 0 in the DBC operator

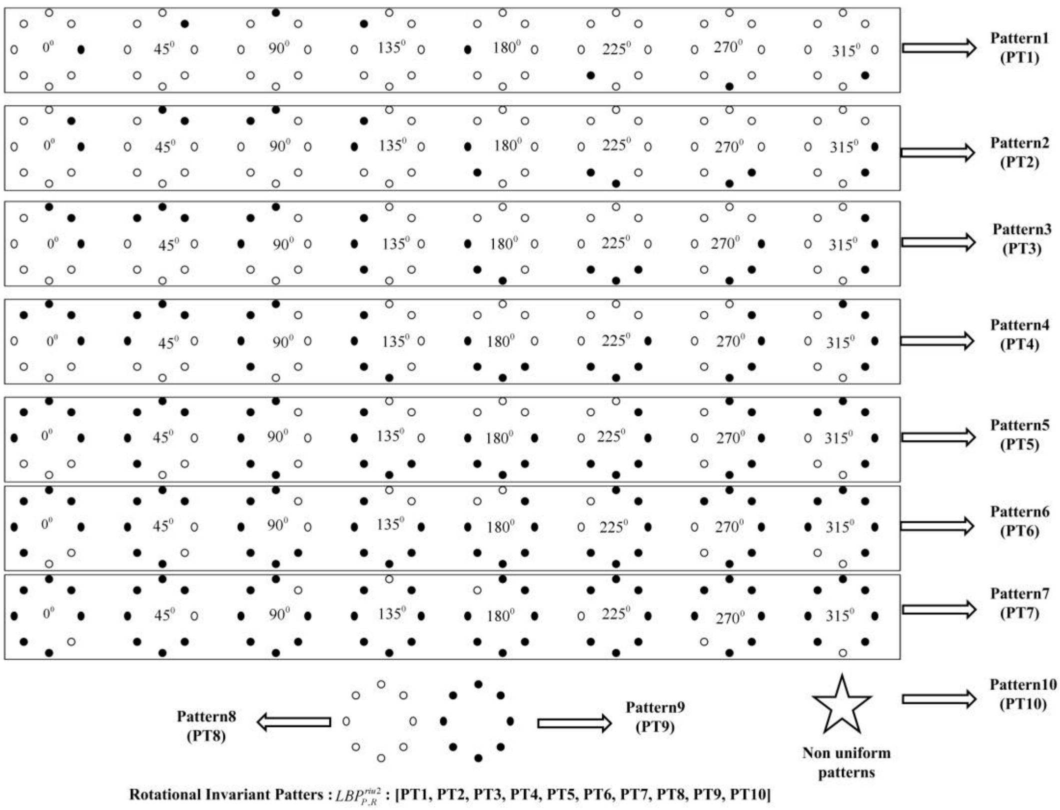


Fig. 4: Rotational variant DBC patterns are converted into rotational invariant DBC patterns

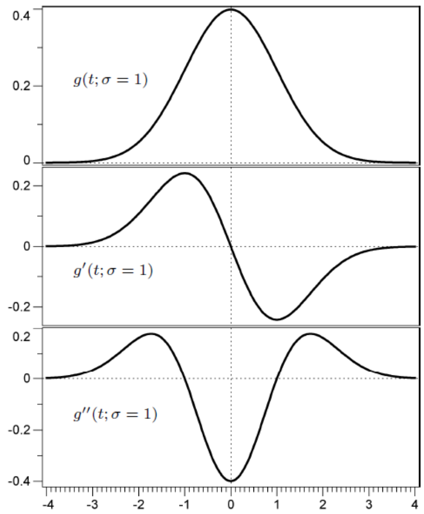


Fig. 5: The Gaussian function $g(t,\sigma=1)$ and its derivatives.

The co-occurrence matrix calculates the distribution within the two-dimensional pattern matrix $P_i[N_x, N_y]$. That is, it takes into account the probability of the co-occurrence between the two DBC pattern respectively corresponding to (*x, y*) and it's adjacent (*x* + *dx*, *y* + *dy*). This probability is then the attribute of image pattern variation used in this paper. The coordinate that distances from (x, y) on the x axis in dx and on y axis in *dy*, then the total number of co-occurring pattern pairs (*u, v*) (where *u*=0, 1, . . ., 6 and *v*= 0, 1, . . ., 6) is determined by Eq. (11).

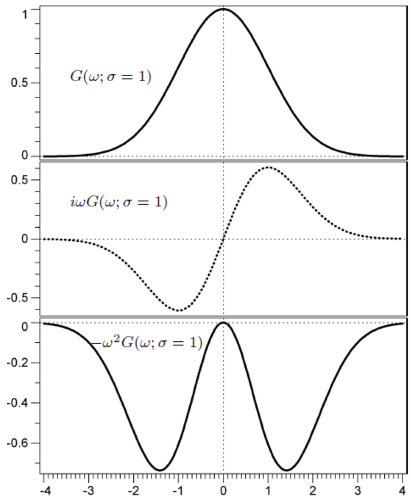


Fig. 6: The Fourier transforms of the Gaussian function $g(t,\sigma=1)$ and its 1st and 2nd derivatives. The Fourier transform of the Gaussian 1st derivative $g'(t,\sigma)$ is purely imaginary, as indicated here by the dashed curve.

$$M_i(u,v) = M_i(u,v|dx,dy) = M_i(P_i[x,y], P_i[x+dx, y+dy]) \quad (11)$$

where $P_i[x, y]$ = u, $P_i[x + dx, y + dy] = v$, $1 \le i \le 4$, $1 \le x \le N_x$, $1 \le y \le N_y$, $1 \le x + dx \le N_x$, and $1 \le y + dy \le N_y$.

IV.PROPOSED SYSTEM FRAMEWORK

In this paper, we proposed the new technique by calculating the co-occurrence matrix on rotational invariant DBC subimages. Finally, feature vector is constructed by concatenating the features collected using three directional co-occurrence matrix on four directional DBC.

Algorithm:

Input: Image; Output: Retrieval results.

1. Load the input image.
2. Convert RGB image to HSV.
3. Quantize the HSV spaces.
4. Construct the histograms.
5. Convert RGB image into a grayscale image.
6. Apply the Gaussain filter on the rayscale image and get te multi-resolution images
7. Perform the first-order derivative in 0º, 45º, 90º and 135º directions.
8. Calculate the DBC and make them into rotational invariant.
9. Calculate the co-occurrence matrix.
10. Form the feature vector by concatenating all co-occurrence matrixes (step 8) and color histigrams (step 4).
11. Calculate the best matches using Eq. (1.3).
12. Retrieve the number of top matches.

A. Similarity Measurement

In the presented work *four* types of similarity distance metric ares used as shown below:

Manhattan or L_1 or city-block Distance

This distance function is computationally less expensive than Euclidean distance because only the absolute differences in each feature are considered. This distance is sometimes called the city block distance or L_1 distance and defined as

$$D(Q,T)=\sum_i \left| f_i(Q)-f_j(T)\right| \qquad (12)$$

Euclidean or L_2 Distance

For p=2 in the equation (1.1) give the Euclidean distance and defined as:

$$D(Q,T)=\left(\sum_i \left| f_i(Q)-f_j(T)\right|^2\right)^{1/2} \qquad (13)$$

The most expensive operation is the computation of square root.

D_1 Distance

$$D(Q,T)=\sum_{i=1}^{Lg}\left|\frac{f_{T,i}-f_{Q,i}}{1+f_{T,i}+f_{Q,i}}\right| \quad (14)$$

Canberra Distance

$$D(Q,T)=\sum_{i=1}^{Lg}\frac{\left|f_{T,i}-f_{Q,i}\right|}{\left|f_{T,i}+f_{Q,i}\right|} \quad (15)$$

where *Q* is query image, *Lg* is feature vector length, *T* is image in database; $f_{I,i}$ is i^{th} feature of image *I* in the database, $f_{Q,i}$ is i^{th} feature of query image *Q.*

*V.*EXPERIMENTAL RESULTS AND DISCUSSIONS

For the work reported in this chapter, retrieval tests are conducted on corel-1K database, MITVisTex database and results are presented in the following subsections.

The performance of the proposed method is measured in terms of average retrieval precision (ARP) and average retrieval rate by following equations.

$$Precision(P)=\frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Images\ Retrieved}\times 100 \quad (16)$$

$$Group\ Precision(GP)=\frac{1}{N_1}\sum_{i=1}^{N_1}P \quad (17)$$

$$Average\ Retrieval\ Precision(ARR)=\frac{1}{\Gamma_1}\sum_{j=1}^{\Gamma_1}GP \quad (18)$$

$$Recall(R)=\frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ relevant\ images} \quad (19)$$

$$Group\ Recall(GR)=\frac{1}{N_1}\sum_{i=1}^{N_1}R \quad (20)$$

$$Average\ Retrieval\ Rate(ARR)=\frac{1}{\Gamma_1}\sum_{j=1}^{\Gamma_1}GR \quad (21)$$

where N_1 is number of relevant images and Γ_1 is number of groups.

A. Corel-1K Database

Corel database [35] consists of large number of images of various contents ranging from animals to outdoor sports to natural images. These images have been pre-classified into different categories each of size 100 by domain professionals. Some researchers think that Corel database meets all the requirements to evaluate an image retrieval system, due its large size and heterogeneous content. We have collected 1000 images to form database Corel–1K. These images are collected from 10 different domains namely *Africans, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, mountains* and *food*. Each category has N_G (100) images with resolution of either 256×384 or 384×256. The performance of the proposed method is measured in terms of ARP and ARR.

Table 1 and 2 summarizes the retrieval results of the proposed method (Multi_DBC Co-occurrence +Color Hist) with CC,DBC and other previously available methods in terms of average retrieval precision and recall respectively.

Table.1.Results of various techniques in terms of precision (%) Corel-1Kdatabase

Category	Precision (*n*=20)			
	CC	DBC	DBC Co-occurrence +Color Hist	Multi_DBC Co-occurrence +Color Hist
Africans	80.4	58.9	70.8	72.1
Beaches	41.25	56.3	53.8	55.1
Buildings	55.65	61.4	74.8	76.1
Buses	76.7	96.5	98.6	99.9
Dinosaurs	99	98.6	98.2	99.5
Elephants	56.2	43.7	52.7	54.0
Flowers	92.9	90.8	92.1	93.4
Horses	76.5	70.6	83.5	84.8
Mountains	33.7	38.6	37.3	38.6
Food	70.6	73.5	87.2	88.5
Total	**68.2**	**68.9**	**74.9**	**76.2**

n–No. top matches considered

Table.2. Results of various techniques in terms of recall (%) Corel-1Kdatabase

Category			Recall (*n*=100)	
	CC	DBC	DBC Co-occurrence +Color Hist	Multi_DBC Co-occurrence +Color Hist
Africans	46.2	33.5	41.9	43.2
Beaches	25.2	36.1	37.9	39.2
Buildings	35.0	35.6	42.1	43.4
Buses	60.9	64.1	72.6	73.9
Dinosaurs	89.5	84.0	89.1	90.4
Elephants	34.1	29.7	33.5	34.8
Flowers	77.6	70.6	73.8	75.1
Horses	36.1	37.7	49.5	50.8
Mountains	21.0	23.3	25.0	26.3
Food	39.2	50.2	56.2	57.5

Total	**46.5**	**46.5**	**52.2**	**53.5**

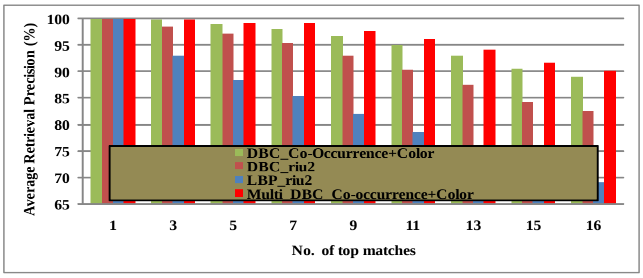
n–No. top matches considered

From Table 1 and Table 2, it is clear that the proposed method showing better performance compared to DBC and other previously available methods in terms of average retrieval precision and recall on Corel-1K natural database.

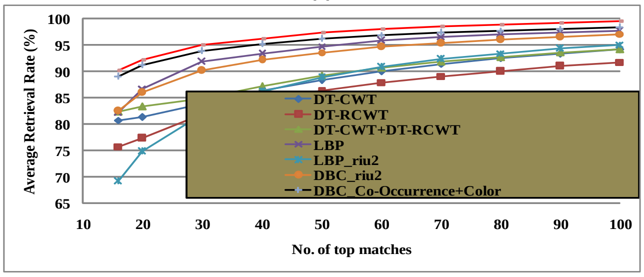
B. MIT VisTex Database

The MIT VisTex database is used in our experiment which consists of 40 different textures [36]. The size of each texture is 512×512. Each 512×512 image is divided into sixteen 128×128 non-overlapping sub-images, thus creating a database of 640 (40×16) images. The performance of the proposed method is measured in terms of average retrieval rate (ARR) is given by Eq. (22).

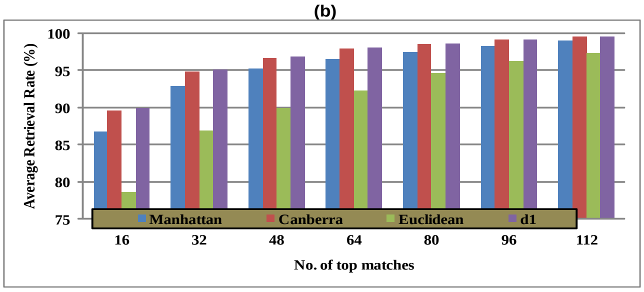
$$ARR = \frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Relevant\ Images\ in\ Database} \times 100 \quad (22)$$



(a)



(b)



(c)

Figure 7: Comparison of proposed method with LBP, DBC and other exiting transform domain methods in terms of: (a) average retrieval precision, (b) average retrieval rate and (c) performance of proposed method using various distance measures on MIT VisTex database.

Table 3: Performance of various methods in terms of ARP on MIT VisTex database.

	1	3	5	7	9	11	13	15	16
LBP_riu2	100	93.0	88.3	85.3	82.0	78.5	74.9	71.0	69.1
DBC_riu2	100	98.4	97.0	95.2	93.0	90.3	87.4	84.3	82.5
DBC_Co-Occurrence+Color	100	99.7	98.9	97.9	96.5	95.0	93.0	90.5	89.0
Multi_DBC_Co-occurrence+Color	**100**	**99.8**	**99.2**	**99.0**	**97.7**	**96.1**	**94.1**	**91.7**	**90.1**

Table 4: Performance of various methods in terms of ARR on MIT VisTex database.

	16	20	30	40	50	60	70	80	90	100
DT-CWT	80.7	81.3	83.8	86.3	88.4	90.0	91.4	92.5	93.3	94.1
DT-RCWT	75.7	77.3	81.9	84.5	86.4	87.9	89.1	90.0	91.0	91.7
DT-CWT+DT-RCWT	82.3	83.3	84.9	87.2	89.2	90.6	91.8	92.7	93.5	94.2
LBP	82.2	86.7	91.9	93.3	94.8	95.9	96.6	97.0	97.4	97.6
LBP_riu2	69.1	74.8	81.8	86.2	88.8	90.8	92.3	93.4	94.4	95.1
DBC_riu2	82.5	86.0	90.1	92.2	93.6	94.6	95.3	96.0	96.5	97.0
DBC_Co-Occurrence+Color	89.0	91.1	93.8	95.1	96.2	96.9	97.3	97.7	98.1	98.4
Multi_DBC_Co-occurrence+Color	**90.1**	**92.3**	**95.0**	**96.3**	**97.3**	**98.0**	**98.5**	**98.8**	**99.2**	**99.5**

Table 5: Performance of the proposed method with various distance measures in terms of ARR on MIT VisTex database.

	16	32	48	64	80	96	112
Manhattan	86.80	92.92	95.24	96.61	97.54	98.33	98.99
Canberra	89.57	94.95	96.74	97.95	98.56	99.18	99.58
Euclidean	78.68	86.85	89.95	92.28	94.71	96.32	97.43
d_1	89.93	95.09	96.89	98.04	98.67	99.19	99.60

This database is used to compare the performance of the proposed method (Multi-Resolution_DBC_Co-Occurrence+color hist.) with LBP and DBC. Fig. 7 (a) & Table 3 illustrate the retrieval results of proposed method and other existing methods in terms of average retrieval precision. From Table 3 & Fig. 7(a), it is evident that the proposed method is outperforming the other existing methods

Table 4 & Fig. 7(b), illustrates the comparison between proposed method and other existing methods in terms of average retrieval rate on MIT VisTex database. From Table 4, it is clear that the proposed method outperforms the other existing spatial and transforms domain methods. The results of the proposed method are also compared with the different distance measures as shown in Table 5. From Table 5, it is found that the d1 distance is outperforming the other distances.

VI.CONCLUSIONS

A new image indexing and retrieval algorithm is proposed in this paper by calculating the co-occurrence matrix on multi-resolution DBC suimages where multi-resolution texture images are computed using Gaussian filter for collection of DBCs from these particular textures. The experiments have been carried out on Corel-1K and MIT VisTex databases for proving the worth of our algorithm. The results after being investigated show a significant improvement in terms of their evaluation measures as compared to CC, LBP, DBC and other transform domain features.

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