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LOCAL QUANTIZED EDGE BINARY PATTERNS FOR COLOUR TEXTURE IMAGE RETRIEVAL

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ABSTRACT

A new image retrieval technique has been proposed in this paper namely local quantized edge binary patterns using HSV color space. To make use of color, intensity and brightness of image HSV color space is used. Local quantized patterns are used to define the local information in all possible directions i.e $0^0, 45^0, 90^0$ and 135^0. Local edge binary patterns extract the maximum edge information from the quantized patterns in all directions in an image. Performance is compared with local binary pattern(LBP), Centre symmetric local binary pattern(CS_LBP) with color feature, local edge patterns for segmentation (LEPSEG) with color feature and wavelet transform with color feature and another existing method by conducting three experiments on standard databases Corel-10k, MIT-Vistex and Color Brodatz texture. After results investigation, a significant improvement in terms of their evaluation measures as compared with existing methods on respective databases.

Keywords: *Content Based Image Retrieval, Local Binary Patterns, HSV Color Space, Local Quantized Pattern, Edge Binary Patterns, Histograms, Feature Vector.*

1. INTRODUCTION

Now a days it is observed that, the multimedia libraries expanded radically in the internet due to high quality cameras, scanners etc. Handling of these massive digital libraries are extremely annoying rather impractical task. On the other hand, there exist two major difficulties, especially when the size of image collections is vast. To defeat these difficulties, content based image retrieval (CBIR) was proposed. In CBIR, the feature extraction is a important step and the success of a CBIR system depends typically on the method of feature extraction from raw images. Hence, there is a great need of some expert technique viz content based image retrieval (CBIR).

1.1 Background: The CBIR utilizes the low level features of an image such as color, shape, texture, spatial layouts and faces etc, in order to represent and index the image. However, complete and extensive literature survey in [1-4]. Among all these local features texture classification is an active research topic in the fields of medical, object based image coding, image retrieval and many more. Various algorithms have been proposed for texture analysis.Chellepaet.al[5] used the Gaussian Markov Random fields (GMRF) to model texture pattern based on statistical relationship between adjacent pixel intensity values. Ahmaddinet.al[6] used the Wavelet transmission (WT) for texture classification. Moghahaddam et.al [7] introduces a new algorithm called Wavelet correlogram (WC). Kokare et.al [8,9] proposed rotated and complex rotated wavelet filters to be used for CBIR. Subramanyamet.al[10] proposed correlogram algorithm for image retrieval using wavelet and rotated wavelet. The idea of color histogram was proposed by Swain et.al[11] for image matching and distance measure by histograms. Strickeret.al[12] introduced two new methods for color indexing, in that first gives the complete color distribution and second holds only major features. Compositions of color and texture features are used as a dominant descriptor for image retrieval. Wavelet and Gabor wavelet transform [13] combined with color histogram for color and texture based image retrieval. Further, Lin.et.al [14] introduced color co-occurrence matrix (CCM), color histogram for K-mean and (CHKM) and difference between pixels of scan patterns (DBPSP). Instead of RGB, HSV color space is used for color representation and this method is applied for image retrieval [15]. S.Jeonget.al[16] used Gaussian mixer vector quantization for better quantization of color histogram for image retrieval.

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In addition to the previous ones, the statistical local image feature extraction proved to be very efficient in recent years. Ojala et.al [17,18] introduced local binary pattern(LBP) to extract the local information of each pixel using eight neighbouring pixels. LBP was modified for rotational invariant texture classification [19]. LBP used for many signal and image processing applications eg, Face recognition[20], texture classification[21,22], object tracking[23]etc. Heikkilaet.al[24], proposed the modified LBP as center symmetric local binary pattern (CS_LBP) which computes the difference in only four directions. Some other extensions in LBP were introduced for better feature extraction like completed LBP[25], Dominant LBP [26], local edge patterns for segmentation and rotation invariant image retrieval (LEPSEG& LEPINV) [27]. Tan.et.al[28] proposed another approach for local feature extraction for face recognition was local ternary pattern (LTP). That computes the center pixel and its eight neighbouring pixels with a threshold interval, and assigns a ternary pattern. Zhang et.al[29] proposed a higher order local binary pattern called local derivative pattern (LDP) for face recognition. Hussainet.al[30,31] proposed the local quantized patterns for visual recognition. It inherits the flexibility and robustness compare to the traditional local pattern features. It can handle significantly larger patterns than previous local patterns. Subramanyamet.al[32] introduced a new approach based on edge distribution called local maximum edge binary pattern (LMEBP). In [33-36] local tetra patterns (LTrP), directional binary wavelet patterns (DBWP), local mesh patterns and local ternary co-occurrence patterns discussed for CBIR and biomedical image retrieval.Muralaet.al[37] proposed a new texture feature descriptor called local extrema patterns, where it collects the texture information in all possible directions of a pixel. Vermaet.al[38] proposed color texture feature descriptor called local extrema co-occurrence pattern.

The concepts of LQP and LMEBP have motivated us to propose the local quantized edge binary patterns(LQEBP) for image retrieval application. The main contributions of this algorithm are summarized as follows. a)The LQEBP features are extracted for database images as well as for query image in contrast of LBP. b) The combination of LQEBP and color features is proposed. c) The performance of the method is experienced for image retrieval on various color texture databases.

The organization of the paper is as follows.

In section1 literature survey, which includes motivation and main contribution of proposed work, section2 involves the introduction of color space and various texture descriptors LBP and LMEBP. In section3 proposed method, similarity measurements and framework of proposed method. Section 4 gives experimental results and discussions on two different databases. As a final point, the conclusion is achieved in section5.

2.LOCAL PATTERNS

2.1 Color Space: In nature, there are 3 types of images, Binary images, Grayscale images and Color images. Binary images contain only two intensity levels for black and white pixels. Grayscale images have a range of intensities in one specific band. The last color images have multiple bands and each band includes a range of intensity. In general color images use RGB color bands called red, green and blue. Hence it is called RGB color space. These three bands contain information about red, green and blue of an image. The other color space called HSV stands hue, saturation, and value.

Hue is directly related to color and hue is defined as an angle. Saturation represents the lightness and brightness of color segment, and value shows the intensity of color component. Hue gives an angle information from 0^0 to 360^0, and each degree occupies different colours. The brightness of an image represented by saturation ranges from 0 to 1, as theintensity of color increases it goes from low to high. Value also ranges from 0 to 1. Many researches proved that individual RGB components are not usually recommended and HSV color model is more appropriate than RGB model. In the proposed method RGB image converted into HSV color space.

2.2. Local Binary Pattern (LBP)

The concept of LBP introduced by Ojala.et.al[17] for feature classification from neighbourhood pixels. It succeeded in many research areas like face recognition, image retrieval etc, due to its performance and speed. For a center pixel in 3x3 pattern, LBP value is calculated by comparing its gray scale value with its neighbours as

$$LBP_{P,R} = \sum_{k=0}^{P-1} f(I(P_n - P_C)) \quad (1)$$

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

Where P stands for no.of neighbours and R stands radius of neighbourhood.

2.3. Local Quantized Pattern (LQP)

LQP proposed by Hussainet.al[30] for visual recognition. It is a generalized form of local patterns that uses large local neighbourhoods and deeper quantization with domain-adaptive vector quantization.

It collects all possible geometric features $0^0, 45^0, 90^0$ *and* 135^0 i.e horizontal(H), vertical(V), diagonal(D) and anti-diagonal(A) strips of pixels. Figure2 illustrates geometric structure for the LQP operator.

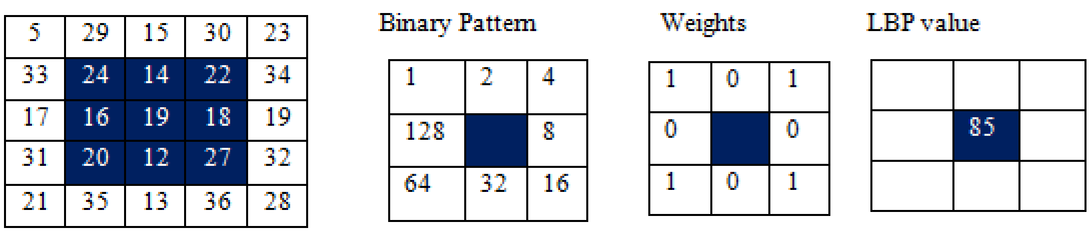

Fig1: Calculation of LBP

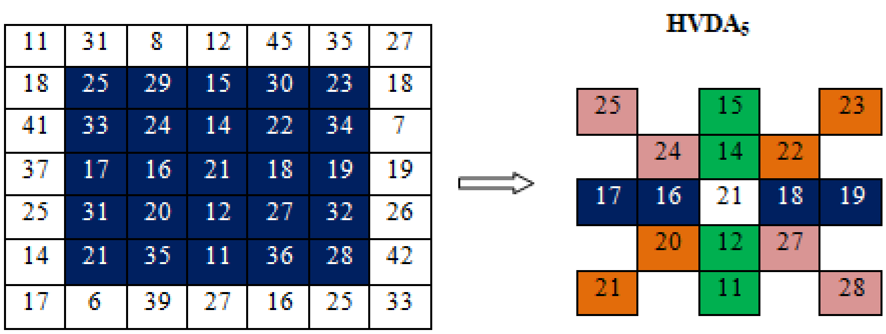

Fig 2: Structure of Local Quantized Pattern LQP

2.4. Local Maximum Edge Binary Patterns (LMEBP)

Subrahmanyamet.al[32] proposed this method for a given image.The first maximum edge is obtained by the magnitude of local difference between the center pixel and it's all neighbors. After calculation of differences all the values are arranged in descending order using only magnitudes as shown in Figure 3. Similarly, the remaining seven patterns are calculated to attain first maximum edge. The total eight maximum edges are evaluated using nine binary values.

3. PROPOSED FEATURE DESCRIPTOR

3.1. Local Quantized Edge Binary Pattern (LQEBP)

The concepts of LBP,LQP and LMEBP motivate us to propose local quantized edge binary patterns for image retrieval system. The LQEBP extracts the extreme edge information from an image in all possible directions using quantized patterns. The first maximum edge is obtained by the magnitude of local difference between the center pixel and its sixteen neighbors in $\pm 0^0, \pm 45^0, \pm 90^0$ *and* $\pm 135^0$ for radius equal to 1 and 2 as shown in Figure 4.

$$I_{P1R1}^{\cdot}(g_i) = I(g_c) - I(g_i)$$

$$\forall\, i = 1,2,\ldots\ldots P_1 \quad where\ P_1 = 8;\ R_1 = 1 \tag{3}$$

$$I_{P2R2}^{\cdot\cdot}(g_j) = I(g_c) - I(g_j)$$

$$\forall\, j = odd\ of\ P_2 \quad where\ \ P_2 = 16;\ R_2 = 2 \tag{4}$$

sort the values in descending order

$$i_1 = sort(Max(|I_{P1R1}^{\cdot}(1)|, |I_{P1R1}^{\cdot}(2)|, \ldots$$

$$|I_{P1R1}^{\cdot}(8)|, |I_{P2R2}^{\cdot\cdot}(1)|, |I_{P2R2}^{\cdot\cdot}(3)|, |I_{P2R2}^{\cdot\cdot}(5)|, \ldots$$

$$|I_{P2R2}^{\cdot\cdot}(15)|)) \tag{5}$$

If the value is greater than or equal to 0, assign '1' otherwise '0'.

$$I_{new}(g_c) = f(\ddot{I}(g_{i_1})) \quad (6)$$

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \quad (7)$$

LQEBP defined as

$$LQEBP(I(g)) = \{I_{new}(g1), I_{new}(g2), I_{new}(g3), I_{new}(g4), I_{new}(g_c), .. I_{new}(g5), \ldots \ldots I_{new}(g8)\} (8)$$

Now, the entire image converted to LQEBP image having the values from 0 to 511. After calculation the given image represented by building a histogram supported by Eq.(9).

$$H_{LQEBP} = \sum_{j=1}^{M} \sum_{k=1}^{N} f(LQEBP(j,k), l); \; l \in [0,511 \quad (9)$$

25	29	15	30	23
33	24(0)	14(1)	22(2)	34
17	16(3)	21(4)	18(5)	19
31	20(6)	12(7)	27(8)	32
21	35	11	36	28

-1(h)	-5(f)	9(c)
-9(b)		10(a)
7(e)	8(d)	3(g)

a	b	c	d	e	f	g	h
10	-9	9	8	7	-5	3	-1
1	0	1	1	1	0	1	0

	0	1	2	3	4	5	6	7	8	LMEBP	
a	1	0	0	0	1	0	0	0	1	273	1st
b	0	0	0	0	1	0	0	0	1	17	2nd
c	1	0	1	0	0	0	1	0	0	324	3rd
d	1	0	1	0	1	1	1	0	1	349	4th
e	1	0	1	0	0	0	1	0	1	325	5th
f	0	0	1	1	1	1	1	0	1	125	6th
g	1	0	0	1	0	0	0	0	0	288	7th
h	0	0	1	0	1	0	0	1	0	82	8th

Fig 3: LMEBP calculation

3.2. Analysis of proposed method

The LQEBP eight patters are highlighted with reference pixels as shown in Figure 4. For the first pattern Figure 4(a), the local differences between center pixel to its sixteen neighbours calculated using Eq.3&4. The difference pixel values "13,16,-21,-1,-5,9,-17,-9,10,2,7,8,3,-1,4,-3" are arranged in descending order with respect to magnitudes "-21,-17,16,13,10,-9,9,8,7,-5,4,-3,3,2,-1,-1" as shown in Figure 4(j). These sixteen edges are converted into binary pattern (0 0 1 1 1 01 1 1 0 1 0 1 1 0 0) based on their signs, similar procedure take on for all eight neighbours. Finally, the center to eighth LQEBP patterns (total in nine) performed as shown in Table 1. Total sixteen edges are calculated for a 3x3 pattern. Figure 5represent the flowchart of the proposed method and algorithm for the same is given below.

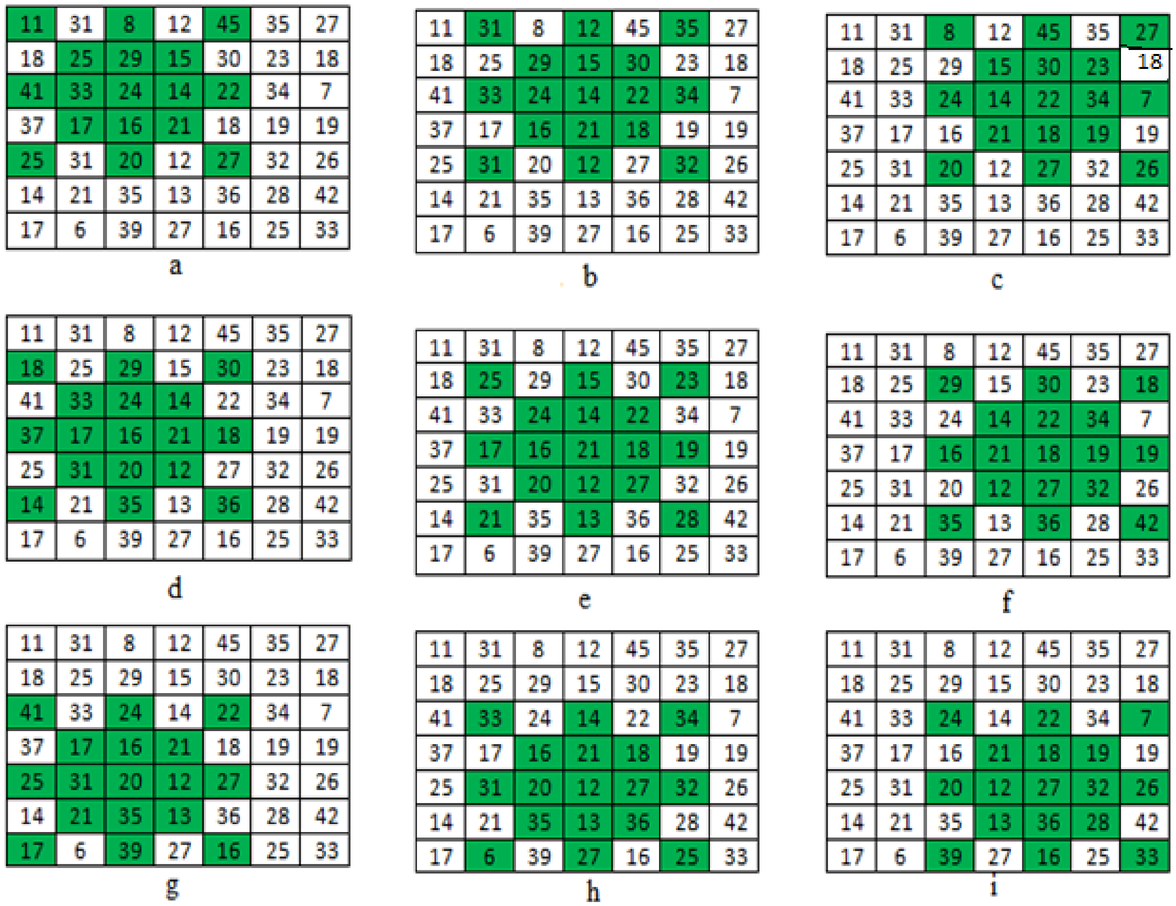

Fig 4: Example Of Obtaining LQEBP For The Matrix 3x3

Table 1: Calculation Of LQEBP For A Given 3x3 Matrix

	a	b	c	d	e	f	g	h	i	LQEBP
1	0	0	0	0	1	0	0	0	1	17
2	0	0	1	0	1	0	0	0	1	81
3	1	0	1	0	0	0	0	0	1	321
4	1	0	0	0	1	0	0	0	0	272
5	1	0	0	0	0	0	1	0	1	261
6	0	0	1	0	1	0	0	0	0	80
7	1	0	1	0	1	0	1	0	1	341
8	1	0	0	0	0	0	0	0	1	257
9	1	0	0	0	1	1	0	0	1	281
10	0	0	0	0	0	0	1	0	0	4
11	1	0	1	1	1	1	1	0	1	381
12	0	0	1	0	0	0	1	0	0	68
13	1	0	0	0	1	1	1	1	1	287
14	1	1	1	1	0	0	0	0	1	481
15	0	1	0	1	1	0	0	0	0	176
16	0	0	1	0	1	1	0	0	1	89

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3.3 Similarity measure and Query matching:

Feature extraction has to be calculated for all images including the query image, and a feature vector database has been constructed for the full database images. After completing the feature extraction process, similarity has to be performed for query image. In this paper three types of similarity distance measures are used as discussed below:

$$d1\ distance:\ d(q,b) = \sum_{i=1}^{flen} \left| \frac{f_b(i) - f_{q(i)}}{1 + f_b(i) + f_q(i)} \right| \quad (10)$$

$$Canberra\ distance: d(q,b) = \sum_{i=1}^{flen} \left| \frac{f_b(i) - f_{q(i)}}{f_b(i) + f_q(i)} \right| (11)$$

$$Manhattan\ distance: d(q,b) = \sum_{i=1}^{flen} |f_b(i) - f_{q(i)}|$$

(12)

Where q is the query image, b is the database image

3.4 Proposed system framework for image retrieval.

Figure 5 illustrates the proposed image retrieval system framework is specified below:

1. Load the image and convert it into HSV color space.
2. Construct the hue, saturation histograms separately.
3. Collect the HVDA5 structure for a given center pixel in the value space.
4. Compute the local differences in 0°, 45°, 90°, and 135° directions.
5. Calculate the 16-bit LQEBP pattern for center pixel and its eight neighbours.
6. Construct the histogram for all LQEBP patterns.
7. Construct the feature vector by concatenate all the histograms, i.e Hue, Saturation and Value.
8. Compare the query image with images in the database using Eq. (10).
9. Retrieve the images based on the best matches.

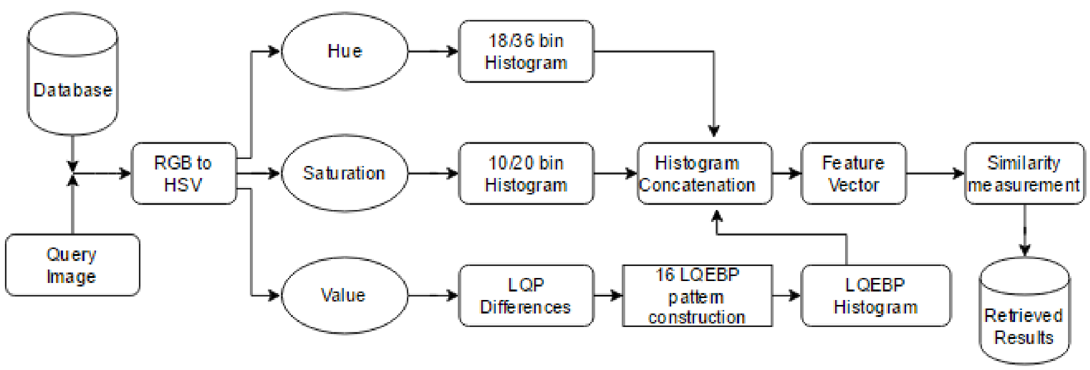

Fig 5: Block Diagram Of Proposed Method.

4.EXPERIMENTAL RESULTS:

The proposed method is evaluated on three standard databases followed by brief description about experimental conditions. Existing methods connected to color and texture have been compared with the proposed technique, and renowned measures precision, recall calculated for all databases for all methods [36]. Precision and recall are strong measures for image retrieval but they are individual. To relate these two measures, F-measure is defined. In every experiment, each image as a query image and retrieval performance is analyzed. Precision, recall, Average retrieval rate, and Average retrieval precision are calculated using Eq.(13)-Eq.(17).

The precision defined for a query image I_q is

$$\text{Precision } P(Q_i, n) = \frac{1}{n}\sum_{k=1}^{|DB|} \varphi\left(f(I_k), f(I_q)\right) \left|Rank(I_k, I_q) < n\right| \quad (13)$$

Where 'n' is the number of top image matches, $f(x)$ is the category of 'x',$Rank(I_k, I_q)$ returns the rank of image I_k for the query image I_q, from the database |DB|.

$$\varphi\left(f(I_k), f(I_q)\right) = \begin{cases} 1 & f(I_k) = f(I_q) \\ 0 & Otherwise \end{cases} \quad (14)$$

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Similarly, recall defined as

$$\text{Recall } R(I_q,n) = \frac{1}{N_R}\sum_{k=1}^{|DB|}\Psi\left(f(I_k),f(I_q)\right)\ |Rank(I_k,I_q)\le n| \quad (15)$$

Where, N_R is the number of relevant images in the database. The average retrieval rate(ARR) and average retrieval precision(ARP) are calculated using following equations.

$$Recall^{Avg} = \frac{1}{|DB|}\sum_{k=1}^{|DB|} R(I_k,n)|_{n\le N_R} \quad (16)$$

and

$$Precision^{Avg} = \frac{1}{|DB|}\sum_{k=1}^{|DB|} P(I_k,n) \quad (17)$$

Where, $|DB|$ total number of images in the database.

F-measure is defined as a relation between precision and recall[38]. It is defined as shown in Eq(18).

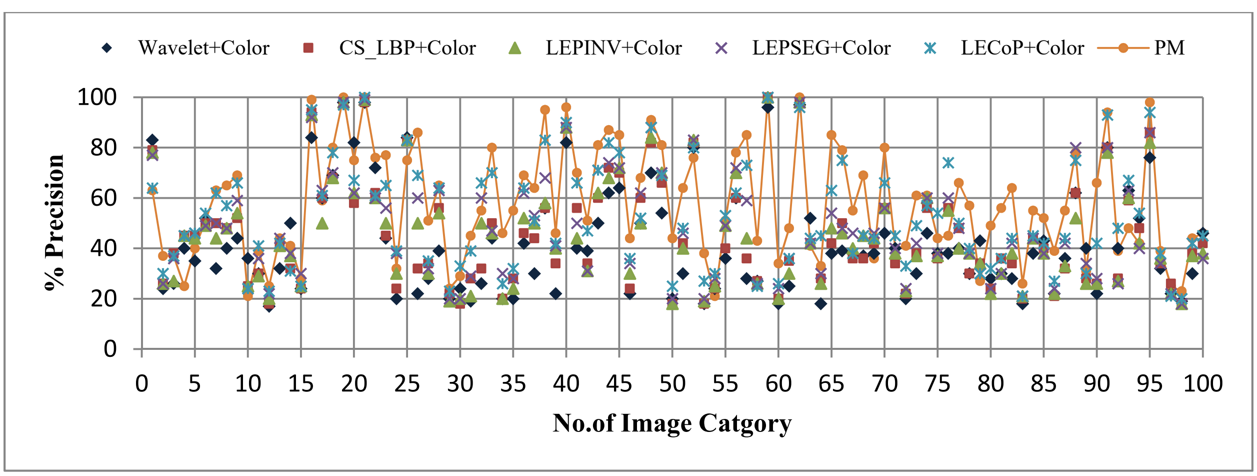
$$F\_measure = \frac{2X\ Avg.PXAvg.R}{Avg.P+Avg.R} \quad (18)$$

Table 2: Feature vector lengths for a given query image for several methods.

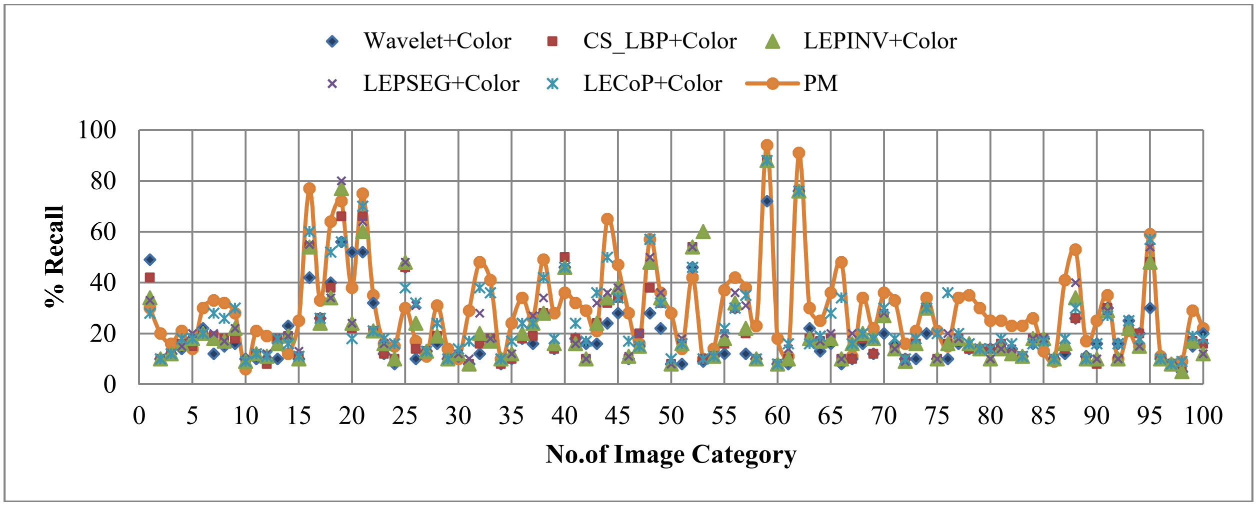
Method	Feature vector length
Wavelet+ Color	24+192=216
CS-LBP+ Color	16+24=40
LEPINV+ Color	72+24=96
LEPSEG+ Color	512+24=536
LMEBP	8X511=4088
PM(H_{18}-S_{10}-V)	18+10+16x511=8204
PM(H_{18}-S_{20}-V)	18+20+16x511=8214
PM(H_{36}-S_{10}-V)	36+10+16x511=8222
PM(H_{36}-S_{20}-V)	36+20+16x511=8232

To measure the capability of the proposed method, experiments have been done on two databases, where the first one is Corel-10k and second one MIT-Color database. The table 2 is giving the length of feature vectors for a query image including the proposed method and state of art techniques.

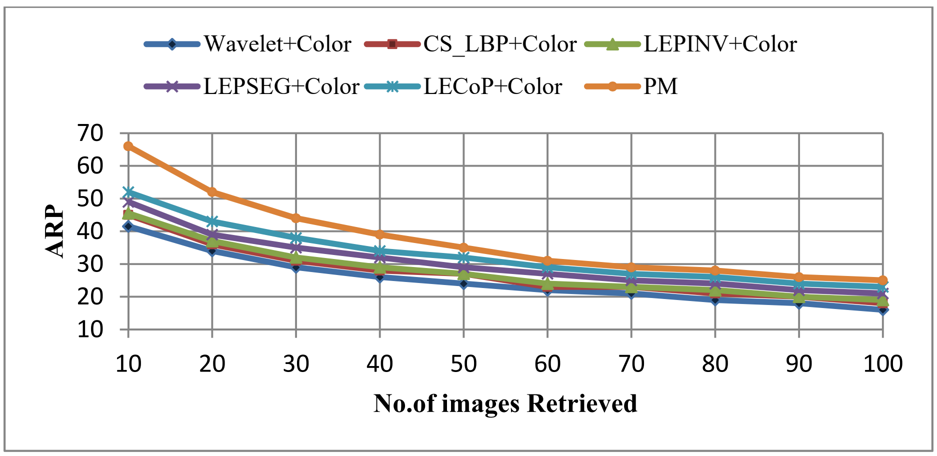
4.1 Database1: The Corel-10k[39] database is larger and adaptable than other Corel databases. It comprises of 10000 images of 100 categories, where each category has 100 images. It includes images of animals, e.g fox, tiger, deer etc., human, natural scenes, ships, food, buses etc., army, ocean, cats, airplanes etc. Size of images in the database is 85x128. Precision, recall, P^{Avg} , R^{Avg} and F-measure are calculated according to the Eq(13)-(18).A significant improvement has been observed as compared to the state-of-art techniques as shown in Fig(6). The image retrieval precision and recall are shown in Figs 6(a) and 6(b), similarly average retrieval precision, average retrieval recall and F-measure are shown in Figs 6(c)-6(e).



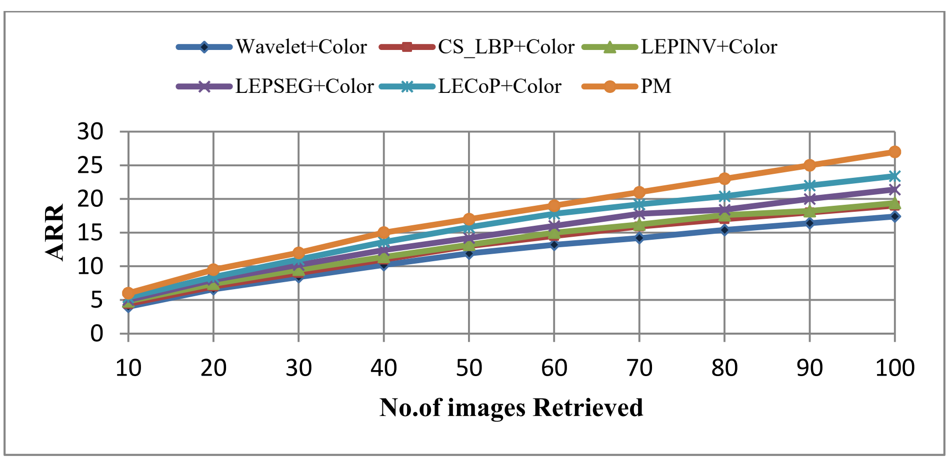
(a)


Wavelet+Color
CS_LBP+Color
LEPINV+Color
LEPSEG+Color
LECoP+Color
PM
% Recall
No.of Image Category

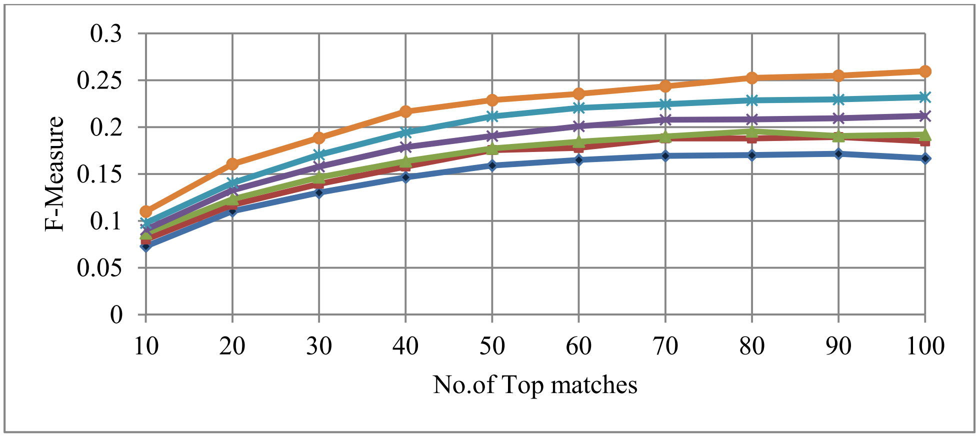
(b)


Wavelet+Color
CS_LBP+Color
LEPINV+Color
LEPSEG+Color
LECoP+Color
PM
ARP
No.of images Retrieved

(c)


Wavelet+Color
CS_LBP+Color
LEPINV+Color
LEPSEG+Color
LECoP+Color
PM
ARR
No.of images Retrieved

(d)



(e)

Figure6: Corel-10k Database:(A) Precision And Image Category Number (B)Recall And Image Category (C) ARP And Images Retrieved (D) ARR And Images Retrieved (E)F-Measure Vs Top Matched Images.

4.2 Database 2: MIT- Vistex database is used to evaluate our proposed method. Figure (7) shows an example where apiece image from each category of MIT-Vistex database [40].It comprises of 40 different colour texture images and each in size of 512x512. For image retrieval, these images are divided into 16 blocks where each block size is 128x128, therefore 640 (40x16) image database has been created. From Fig.8(a)&8(b) the retrieval performance of the proposed method compared with the state- of- art approaches in terms of ARP, ARR and F-measure in Fig.8(c). Table 3 shows the results of proposed method and previous methods on all colour and texture databases. It demonstrated that the proposed method showed a significant retrieval.

4.3 Database 3: Color Brodatz texture database[41] is used. It has 112 color and texture images of 640x640 size. Each image is divided into 25 sub images of size 128x128 like MIT-Vistex database. So, the total number of images in the database is 2800. It is comparatively bigger than MIT-Vistex database. Sample images from the database is shown in Fig.(9).The results are show in Fig (10). In Fig.10(a), the graph of precision with number of images retrieved for a group of 25, and in Fig.10(b) graph of recall with number of images retrieved from the whole database is shown. The results determined in graphs openly indicate that the proposed method is better than the existing local patterns.

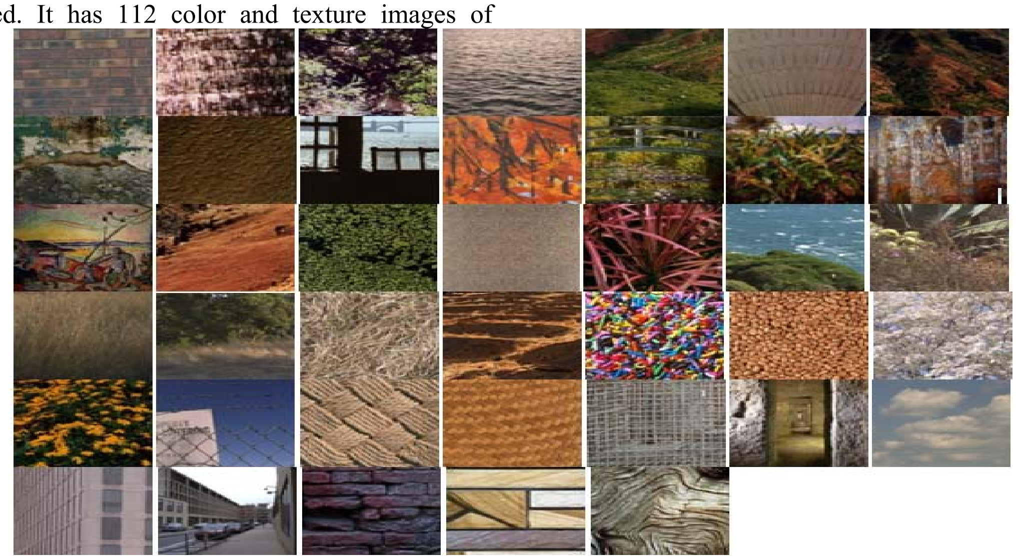


Figure 7: Sample images from MIT-Vistex Database.

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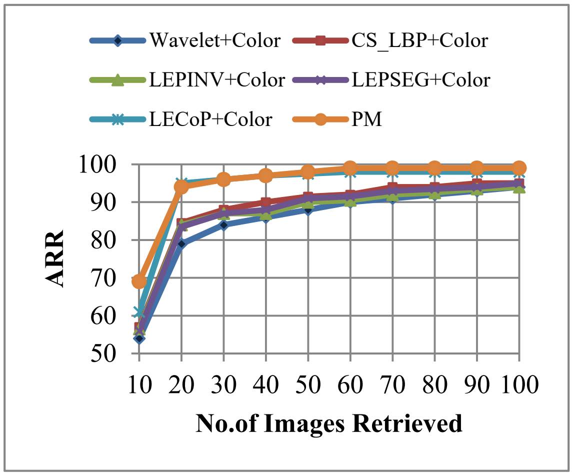
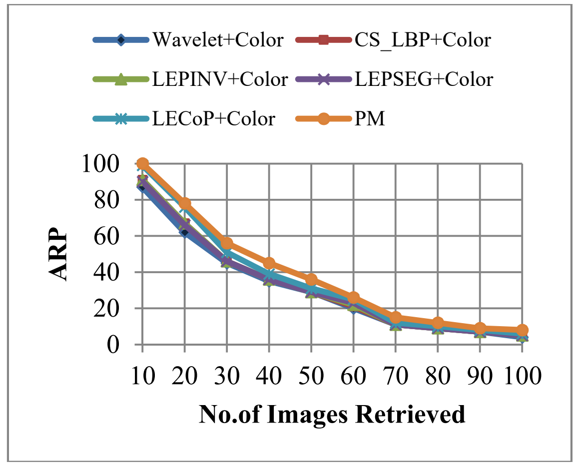
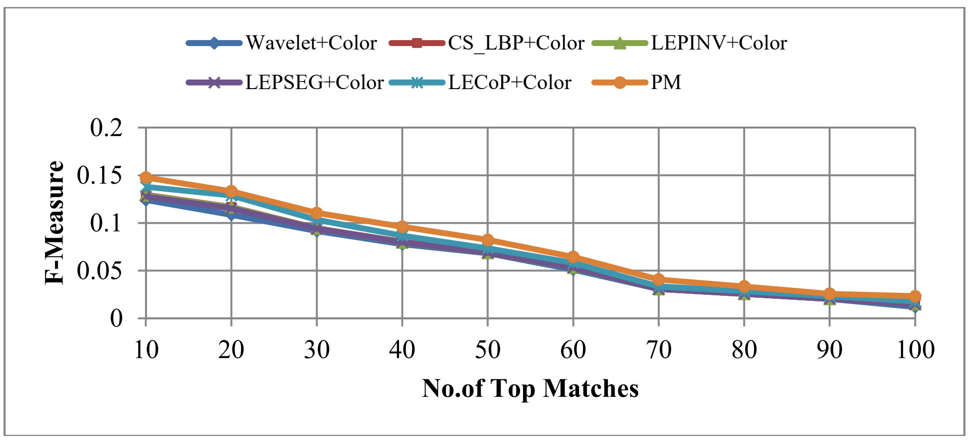


(a)



(b)



(c)

Figure 8: MIT-Vistex Database: (A) ARP And Images Retrieved (B) ARR And Images Retrieved (C)F-Measure Vs Top Matched Images.

Table 3: Results Of Previous Methods And The Proposed Method For The Following Databases.

	Corel-10K		MIT-Vistex		Color-Brodatz	
	ARP	ARR	ARP	ARR	ARP	ARR
Wavelet+ Colorhist	41.5	17.4	87	94	56	70.2
CS_LBP+ Colorhist	45	19	91	95	58	72
LEPINV+ Colorhist	45.5	19.4	91	94	59	74
LEPSEG+ Colorhist	49	21.4	90	95	65	80
LECoP+ Color	52	23.4	99	98	72	83.5
PM	67	27	100	99	76	86

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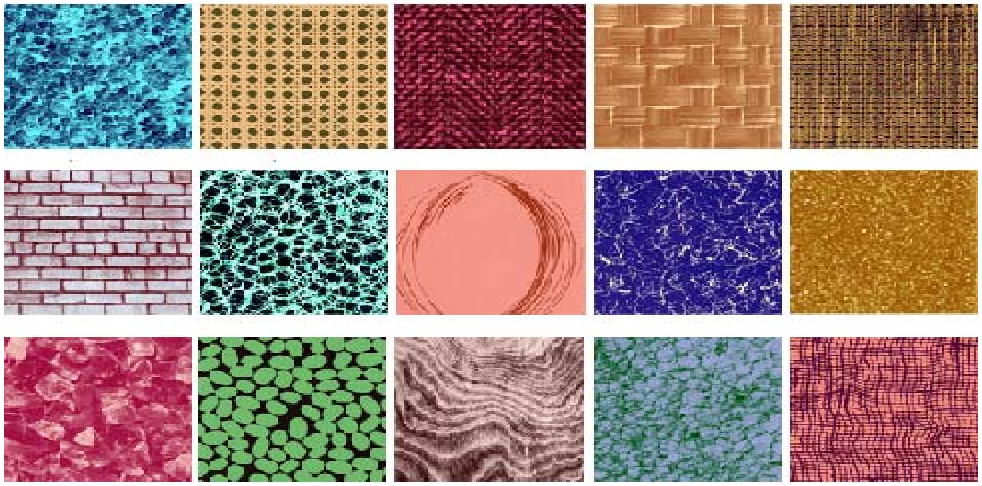
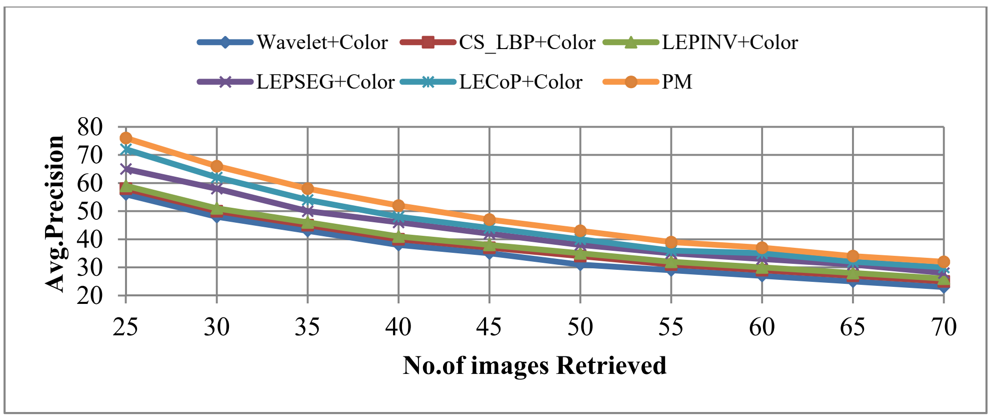
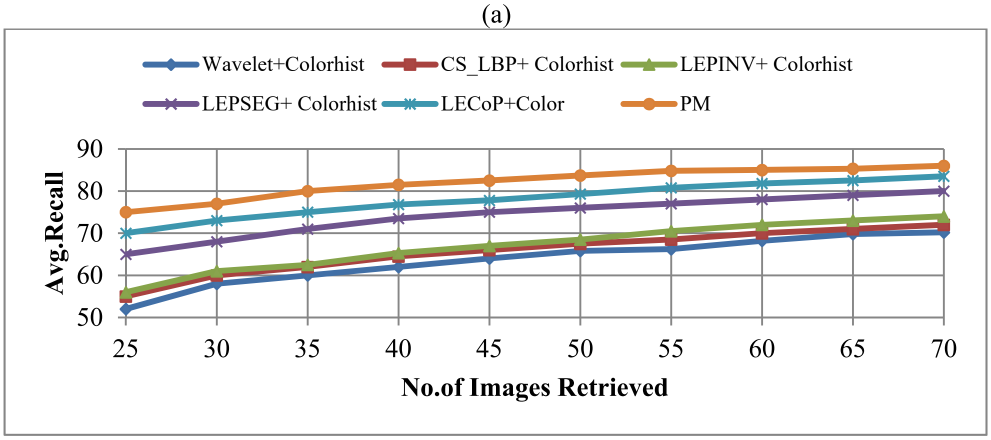


Figure 9: Sample Images From Colored-Brodatz Texture Database.



(a)



(b)

Figure 10: Avg. Precision And Avg. Recall Curves For Color Brodatz Texture Database.

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5. CONCLUSION & FUTURE WORK:

A new integrated color- texture feature descriptor is proposed for image retrieval. The color image converted into HSV color space. Hue and Saturation features extracted in various quantization levels. The LQEBP applied on value space to extract the texture features because the vale space is very near to gray scale image. It extracts the texture information in calculating the sixteen maximum edges in R=1 and R=2 for each pixel in all possible directions. Further, the combination of Hue, Saturation and LQEBP on value component gives integrated color and texture features. The effectiveness of the proposed method is tested by conducting experiments for image retrieval on different image database thereby observed that, significant improvement in terms of their respective evolution measures. The proposed method feature vector length is very high, if is compressed the feature extraction time get reduced. The extension of this paper may overcome these limitations.

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