Journal of Engineering and Applied Sciences 13 (16): 6777-6786, 2018
ISSN: 1816-949X

Optimized Image Retrieval Using HSV Color Space, Local Edge Binary Patterns and Zernike Moments

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Abstract: This study presents a new approach for image retrieval in extracting and integrating the color, texture and shape features. The proposed descriptor converts the RGB color image into HSV color space. HSV color space is used in this approach make use of color, intensity and brightness of the color image. From the Hue (H) and Saturation (S) color features are extracted and from value color space texture features are extracted. To extract the texture features from the value component Local Maximum Edge Binary Patterns are applied (LMEBP). Apply Zernike moments on gray scale image to extract the shape features. To extract the feature vector all the histograms are concatenated three experiments have been carried out in demonstrating the worth of our approach. The presented method is tested on two databases, Corel-10k and MIT-Vistex. The retrieval performance has shown a significant improvement in terms of precision and recall as compared with Center-Symmetric Local Binary Pattern (CS-LBP) Local Edge Pattern for Segmentation (LEPSEG) and Local Edge Pattern for Image Retrieval (LEPINV) and other existing transform techniques in image retrieval system.

Key words: Local features, local edge binary pattern, Zernike moments, HSV color space, Corel-10k database, Mit-Vistex database, histogram

INTRODUCTION

Image retrieval has become active research area, since, 1990. Generally, image retrieval system is based on two techniques. First is based on annotation method. As manual image keyword is an annoying process it is very difficult to annotate all images for large databases. Furthermore, due to the multiple contents of the image and multiple subjectivities of human discrimination it is also difficult to make the same annotation to the same image for different users according to their perception. To overcome these difficulties, Content-Based Image Retrieval (CBIR) attempts to mechanize the process of annotating images in the database. The CBIR uses the visual contents of an image like color, shape, texture, spatial layout etc., to represent and index the image in the database. The image features can further classify into general features which contain color texture and shape. The feature extraction plays animportant role in CBIR whose efficiency depends on the methods adopted by methods used for extracting the features. The comprehensive and extensive literature survey is presented on CBIR (Datta *et al*., 2008; Rui *et al*., 1999; Smeulders *et al*., 2000; Liu *et al*., 2007).

Color and texture analysis has been attracting a great deal of attention due to its potential value in computer vision and pattern recognition. The use of combined color texture in texture feature extraction has given successful results in color texture analysis. Texture feature is based on the local intensity of an image. Therefore, neighborhood and statistical features are exposedfor texture pattern. The color feature represents the distribution of intensity in different color channels, so that, color histogram, color correlogram color coherence vector, etc., used to propose as color feature descriptors. Palm (2004) used the correlation between textures of different color channels calculated and applied for content-based image retrieval system. Ahmadian and Mostafa (2003) used wavelet transform for texture classification. Do and Vetterli (2002) proposed Discrete Wavelet Transform (DWT) based texture feature extraction using generalized Gaussian density and Kullback-Leibler distance. However, DWT can extract the features only in three directions. Therefore, rotated wavelet filters (Kokare *et al*., 2007) Gabor transform (Manjunath and Ma, 1996) a combination of dual-tree complex wavelet filters (Kokare *et al*., 2005) and Dual Tree Rotated Complex Wavelet Filters (DT-RCWF) (Kokare *et al*., 2006) had proposed to extract the more directional features which are not present in DWT.

The concept of coloris one of the important features in the field of CBIR if it is maintained semantically impact

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and perceptually tilting way. In addition, a color structure in visual scenery changes in size, orientation and resolution. Swain *et al.* (1992) proposed color histogram for image retrieval and it is very simple to implement. By Pass *et al.* (1997) color coherence vector, color distribution feature, cumulative histograms were discussed to extract the color feature for image retrieval. Murala *et al.* (2009) proposed a standard wavelet transform and Gabor wavelet transform was combined with a color histogram to extract both color and texture features for image retrieval.

Now, a brief review of the related literature available, targeted for development of our algorithm is given here. The Local Binary Pattern (LBP) features are designed to describe the texture features of an image. Ojala *et al.* (1996) proposed the LBP for rotational invariant texture features. Ahonen *et al.* (2006) and Zhao and Pietikainenm (2007) used the LBP operator for the analysis and recognition of facial features. Huang *et al.* (2004) proposed the extended LBP for shape localization. Li and Staunton (2008) proposed the combination of LBP and Gabor filter for texture segmentation. Zhang *et al.* (2010) proposed Local Derivative Pattern (LDP) for face recognition. Takala *et al.* introduced the block based texture feature which uses the LBP texture feature as a source for image description. The combination of Center Symmetric-Local Binary Pattern (CS-LBP) which is a modified version of LBP and Scale Invariant Feature Transform (SIFT) for texture feature extraction. Yao and Chen (2003) introduced two types of local edge pattern histograms: LEPSEG for image segmentation and the other is LEPINV for image retrieval. Few more feature extraction methods are available by Liao *et al.* (2009). By Ipparthi *et al.* multi-joint histogram is proposed for texture feature extraction for image retrieval. Murala *et al.* (2013) proposed a new approach for object tracking and image retrieval is local extrema patterns and a joint histogram of color and LEP.

Shape of an object in the image is another important feature for image retrieval. Shape representation should be invariant, robust and easy to derive and match. In relating such meaningful shape representation, moment descriptors are the common and widely used methods. The well-known orthogonal moments include Zernike moments. Khotanzad and Hong (1990) introduced a two-dimensional orthogonal moments, i.e., Zernike moments which are invariant to image translation, orientation and size. It is observed that the magnitude of Zernike moment would not change for any rotation and scaling of an image. Due to these properties of Zernike moment it outperforms than many other shape descriptors such as geometric, Li *et al.* (2009). Sucharitha *et al.* (2017) introduced, the lower order Zernike moments for efficient shape descriptors.

Recent methods on spatial patterns LEBP and significance of color feature motivated us to propose a new feature vector for image indexing and retrieval. The primary contribution of the work is briefed as follows: At first proposed method converts the RGB color image into HSV color space. Construct the histograms for Hue and Saturation in different quantization levels. Extracts the LEBP features on value color space and construct the histogram. Concatenate all three histograms and construct the feature vector which includes the color and texture features for better image retrieval.

Color and texture descriptors

Color space: Generally, images are of 3 types, 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 used RGB images which has three 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 0-360° and each degree occupies different colors. The brightness of an image represented by saturation ranges from 0-1, astheintensity of color increases it goes from low to high. Value, also, ranges from 0-1. Many researchers proved that individual RGB components are not usually recommended and HSV color model more appropriate than RGB Model. In the proposed method RGB image converted into HSV color space.

Local binary patterns: At first the LBP introduced by Ojala *et al.* (1996) for rotation invariant texture classification. Some of the precise features like discriminative power and simplicity made LBP renowned in many research directions. Due to its performance, observed in many research areas like such as face recognition and analysis, object tracking, texture classification, fingerprint identification and image retrieval. Given a grayscale image, I of size mxn pixels and I(g) denotes gray level of the gth pixel in the image I. A pixel at the center becomes the threshold to derive the local binary pattern in a small 3×3 array of spatial structure. Mathematical expression for LBP is as given in Eq. 1 and 2:

5	1	2
4	4	6
9	7	3

3×3 pattern

1	0	0
1		1
1	1	0

Binary pattern

8	4	2
16		1
32	64	128

Weights

	121	

LBP value

Fig. 1: Calculation of LBP for a 3×3 pattern

$$LBP_{P,R} = \sum_{i=1}^{P} 2^{(i-1)} f\left(g^p - g^c\right) \quad (1)$$

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

where, g^c is gray value of center pixel, g^p is gray value of circularly symmetric neighborhood, P represents No. of neighbors and R is length of the neighborhood.

After deriving the LBP structure for the whole image, a histogram is built to represent the image as per the Eq. 3 and 4:

$$Hi_{LBP} = \sum_{i=1}^{m} n \sum_{j=1} H_1\left(LBP(i,j), n \in \left[0, 2^P - 1\right]\right. \quad (3)$$

$$H_1(u,v) = \begin{cases} 1, & u = v \\ 0, & \text{else} \end{cases} \quad (4)$$

where the size of an image is mxn. Figure 1 shows an example of calculating the LBP pattern for a 3×3 matrix. The histogram of these patterns includes information on the distribution of edges in an image.

Center-Symmetric Local Binary Pattern (CS-LBP): Instead of comparing each pixel with the center pixel (Heikkila *et al*., 2006) proposed a new approach CS-LBP where the center-symmetric pair of pixels are compared as shown in Eq. 5:

$$CS_{LBPP,R} = \sum_{p=1}^{P} 2(p-1) X f\left(1\left(g_p - g_p + \left(\frac{P}{2}\right)\right)\right) \quad (5)$$

A histogram will be constructed to the whole image, after calculating CS-LBP pattern for each pixel (x, y).

Local Maximum Edge Binary Patterns (LMEBP): Local binary patterns relate the center pixel and reference neighborhood pixels by comparing intensity values. The local edge binary patterns are proposed by Subramanyam *et al.* (2012) and this is a continuation of LBP in such a way that it extracts the information based on the distribution of edges in the image. LMEBP capture the edge information between the center pixel and its eight neighbors. It does't consider any magnitude of edges. For a center pixel I_C and corresponding eight neighbor pixels I_i, LMEBP calculated as follows:

$$I_m(d_i) = I_m(I_i) - I_m(I_c) i = 1, 2, 3, ..., 8 \quad (6)$$

$$i_s = Sort\left(max\left(|I_m(d_1)|, |I_m(d_2)| I_m(d_8)|\right)\right) \quad (7)$$

where max (I)calculates the maximum value in an array I. Sort is the function where it sorts the array in descending order irrespective of the magnitude of I:

$$I^n(d_c) = f\left(I_m(d_c)\right) \quad (8)$$

where f(x) is defined if the edge is positive assign 1 for this center pixel otherwise 0:

$$f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & \text{else} \end{cases} \quad (9)$$

LMEBP defined as:

$$LMEBP(I(d_c)) = \left\{I^n(d_c), I^n(d_1), I^n(d_2), ..., I^n(d_8)\right\} \quad (10)$$

After calculation of LMEBP, the whole image represented by constructing a histogram based on:

$$H_{LMEBP}(j) = \sum_{k=1}^{m} \sum_{l=1}^{n} f_2(LMEBP(k,l)); j \in [0255] \quad (11)$$

where image size is mxn.

Steps involved in LMEBP algorithm:

- Consider a 5×5 matrix of a given image as shown in Fig. 2a
- Consider a 3×3 window in the above matrix which contains 8 neighbors and 1 center pixels
- Calculate the local differences in between center pixel to it's neighbors as shown in Fig. 2b
- Sort the differences in descending order irrespective of their signs
- Assign '0' and '1' to the differences according to sign as shown in Fig. 2c
- Change the center pixel by rotating the 3×3 pattern, such that each pixel in the pattern becomes center pixel at once
- Repeat the step 3-6 until 9 patterns get generated
- Calculate the eight edges using all patterns as shown in Fig. 2d

(a)

3	1	4	6	7
4	$16_{(4)}$	$8_{(3)}$	$2_{(2)}$	5
5	$8_{(5)}$	$9_{(0)}$	$14_{(1)}$	2
6	$1_{(6)}$	$10_{(7)}$	$7_{(8)}$	3
10	5	9	2	4

(b)

7(i3)	-1(i6)	-7(i2)
-1(i7)		5(i4)
-8(i1)	1(i8)	-2(i5)

(c)

i1	i2	i3	i4	i5	i6	i7	i8
-8	-7	7	5	-2	-1	-1	1
0	0	1	1	0	0	0	1

(d)

	0	1	2	3	4	5	6	7	8	LMEBP	EDGES
i1	0	0	1	1	0	1	0	0	1	105	1st Edge
i2	0	0	1	0	0	0	0	0	0	64	2nd Edge
i3	1	0	1	0	0	0	0	0	0	320	3rd Edge
i4	1	0	1	1	0	0	0	1	0	354	4th Edge
i5	0	0	1	0	0	0	0	0	0	64	5th Edge
i6	0	0	1	0	0	1	0	0	1	73	6th Edge
i7	0	0	1	1	0	1	0	0	1	105	7th Edge
i8	1	0	1	1	0	1	0	0	1	361	8th Edge

Fig. 2a-d): Execution procedure of LMEBP algorithm

Zernike moments: Zernike moments constitute a set of orthogonal basis functions mapped into a unit circle. The orthogonal property of ZM's suits better for shape recognition schemes. This property shows that the influence of each moment is independent and unique. Due to this property, the redundancy has been reduced as minimum as compared to the geometric moments. Mathematically, Zernike basis function is defined with an order n and repetition m over C = {(n, m)| 0 = n = 8, |m| = n, |n-m| = even}:

$$Z_{nm} = \frac{n=1}{\pi}\int_{0}^{2\pi}\int_{0}^{1} f(\rho,\theta)V_{nm}(\rho,\theta)d\rho d\theta \tag{12}$$

Where:

$$V_{nm}(\rho,\theta) = R_{nm}(\rho).{*}e^{-jm\theta} \tag{13}$$

And:

$$R_{nm}(\rho) = \sum_{k=0}^{\frac{n-|m|}{2}} (-1)^k \frac{(n-k)!}{k!\left(\left(\frac{n+|m|}{2}\right)-k\right)!\left(\left(\frac{n+|m|}{2}\right)-k\right)!}\rho^{n-2k} \tag{14}$$

where n is a positive integer representing the order of the radial polynomial and m is no.of repetitions. Where f(x, y) is a function of an image with the size of N×N. For digital images, the integrals in Eq. 12 are replaced by summations:

$$Z_{nm} = \frac{n+1}{\pi}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y).{*}V_{nm}(\rho,\theta) \tag{15}$$

The transformed distance • and the phase angle • at a pixel (x, y) are designed in such way to insert the image into the unit disk. The equations are:

$$\rho = \frac{\sqrt{(2x\text{-}N+1)^2+(2x\text{-}N+1)^2}}{N} \tag{16}$$

$$\theta = \tan^{-1}\left(\frac{2y\text{-}N\text{-}1}{N+1\text{-}2x}\right) \tag{17}$$

To map the digital image into the circle, first the image must convert into a square image, i.e., N×N where N must be an even number.

MATERIALS AND METHODS

In the present method, more information from the image has been tried to extract with the help of earlier explained methods. A new image retrieval method proposed here using color texture and shape information of images. As per earlier explanation, color and texture are both prominent features of an image. In the proposed method at first, the color image converted into HSV color space. Hue corresponds to color information where each angle corresponds to different colors. In this approach, two different quantization of hue component, i.e.,

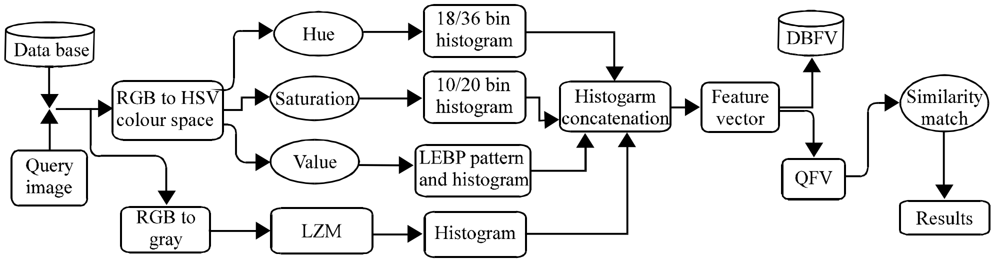

Fig. 3: Proposed system flowchart

18/36 bins have been used and the performance of the proposed work observed. The performance of the various quantization levels depends on the distribution of the colors in the image. The two quantization levels divide all colors into different sections, so that, bestcolor information can be extracted. Saturation is quantized into 10/20 bins for reasonable information extraction. The histogram is constructed for both hue and saturation for the best combination. The value component is almost close to the grayscale component of the color (RGB) image, consequently, value component is used to extract the texture information. The local information of each pixel can be extracted using edge binary patterns. It gives eight edge values for each pixel as shown in LMEBP map in Fig. 2. For each edge one histogram is constructed, so that, for the value space eight histograms are constructed and concatenated. In the next step, lower order zernike moments of order 5 applied on gray scale image. Where the gray scale image came from RGB conversion. The lower order Zernike moments have less complexity and low sensitive to the noise. The performance of the system may weaken if the order is the not chosen properly in higher order Zernike moments. The lower order Zernike moments calculated using Eq. 13-17. The Zernike moments for the order of n = 5 has shown in Table 1 with 21 moments.

At last, all the histograms from three local features are concatenated to construct the feature vector as shown in Fig. 3. To reduce the size of feature vector the database images are reduced to the size of 128×128 before converting the image into HSV and gray scale model. The length of the feature vector depends on the quantization number of Hue and Saturation. The lengths of feature vectors of various methods including the proposed method shown in Table 2 and 3.

Table 1: Lower order Zernike moments for the order n = 5

Order	Zernike moments	No.of moments
0	$Z_{0,0}$	1
1	$Z_{1,1}$, $Z_{1,-1}$	2
2	$Z_{2,0}$, $Z_{2,2}$, $Z_{2,-2}$	3
3	$Z_{3,1}$, $Z_{3,-1}$, $Z_{3,3}$, $Z_{3,-3}$	4
4	$Z_{4,0}$, $Z_{4,2}$, $Z_{4,-2}$, $Z_{4,4}$, $Z_{4,-4}$	5
5	$Z_{5,1}$, $Z_{5,-1}$, $Z_{5,3}$, $Z_{5,-3}$, $Z_{5,5}$, $Z_{5,-5}$	6

Table 2: Results for Corel-10k and MIT-Vistex in precision (for n = 10) and recall (for n = 100)

	Corel-10 k		MIT-Vistex	
Methods	ARP	ARR	ARP	ARR
Wavelet+Color	42.38	19.11	36.7	85.10
CS-LBP+Color	45.18	20.53	38.3	88.10
LEP+Color	46.45	19.84	41.8	88.60
LEPINV+Color	43.41	21.60	40.2	87.15
LEPSEG+Color	42.66	22.40	41.2	87.50
PM	65.12	26.90	44.5	94.20

Table 3: Feature vector length for a given query image using several methods

Methods	Feature vector length
Wavelet+Color	24+192 = 216
CS-LBP+Color	16+24 = 40
LEP+Color	16×8×8×8 = 8192
LEPINV+Color	72+24 = 96
LEPSEG+Color	512+24 = 536
LMEBP	8×511= 4088
PM(H_{18}-S_{10}-V)	18+10+8×511+21 = 4137
PM(H_{18}-S_{20}-V)	18+20+8×511+21 = 4147
PM(H_{36}-S_{10}-V)	36+10+8×511+21 = 4155
PM(H_{36}-S_{20}-V)	36+20+8×511+21 = 4165

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

$$\text{d1 distance}: d(q,b) = \sum_{(i=1)}^{flen} \left|(f_b(i)-f_q(i))/(1+f_b(i)+f_q(i))\right| \tag{18}$$

$$\text{Canberra distance}: d(q,b) = \sum_{(i=1)}^{flen} \left|(f_b(i)-f_{(q(i))}/(f_b(i)+f_q(i)\right| \tag{19}$$

$$\text{Manhattan distance}: d(q,b) = \sum_{i=1}^{flen} | f_{\alpha(i)} \tag{20}$$

Where:
q = The query image
b = The database image.

Proposed system framework for image retrieval: Figure 3 demonstrates the proposed image retrieval system framework:

- Convert the RGB image into HSV color space
- Convert the RGB image into gray scale image
- Construct the histograms for Hue and Saturation in the quantized bins (i.e., 18/36 for Hue, 10/20 for Saturation)
- Calculate the local edge binary patterns for value
- Calculate the lower order Zernike moments (n = 5) for gray scale image and construct the histogram
- Construct feature vector by concatenating all the histograms
- Compare the query image with database images using Eq. 18
- Retrieve the images based on the best matches

Advantages of proposed method: The proposed methodcollects all local features information. Whereas existing methods collects only either texture or texture color information for image retrieval. The RGB color space contains only gray level information whereas HSV color space contains three different information. Hence, it is clear to say that HSV outperforms than the RGB for feature extraction. As compared to the other shape feature descriptors Zernike moments are orthogonal. The scaling and rotational properties of Zernike moments make flexible in extracting the shape feature.

RESULTS AND DISCUSSION

In image retrieval, various databases are used for various purposes, some of these include Corel database, MIT color database, Brodtz texture database etc. Corel dataset (1, 5 and 10 k) is the famous and frequently used database to verify the retrieval results. Corel dataset available in three different sizes, i.e., 1, 5 and 10 k. The MIT-Color dataset used for color and texture feature analysis and Brodtz dataset used for texture analysis. In this study, to verify the retrieval performance of the proposed method Corel-10 k and MIT-Color databases are used. Existing algorithms connected to the color and texture are compared with the proposed work and renowned precision, recall measures are calculated for all database images and all methods. In every experiment, each image as a query image and retrieval performance is analyzed. The retrieval results of the proposed work measured in terms of precision, recall. Average Retrieval Rate (ARR) and Average Retrieval Precision (ARP) as given in Eq. 21-25 (Liao *et al*., 2009). Table1 gives the ARP and ARR for Corel-10K and MIT-Vistex for various algorithms. The precision defined for a query image $I_q$is:

$$P(Q_i, n) = \frac{1}{n}\sum_{k=1}^{|DB|} \Psi\big(f(I_k), f(I_q)\big) \big|Rank(I_k, I_q)\big| \le n \tag{21}$$

where, ‘n’ is the number of top image matches, f (x) is the category of ‘x’, returns the rank of image I_k for the query image I_q from the database |DB|:

$$\Psi\big(f(I_k), f(I_q)\big) = \begin{cases} 1 & f(I_k) = f(I_q) \\ 0 & \text{Otherwise} \end{cases} \tag{22}$$

Similarly, recall defined as:

$$R(I_q, n) = \frac{1}{N}\sum_{k=1}^{|DB|} \Psi\big(f(I_k), f(I_q)\big) \big|Rank(I_k, I_q)\big| \le n \tag{23}$$

where is the number of relevant images in the database. The Average Retrieval Rate (ARR) and Average Rretrieval Precision (ARP) are calculated using Eq. 24 and 25:

$$ARR = \frac{1}{|DB|}\sum_{k=1}^{|DB|} R(I_k, n)\,|_{n \le NR} \tag{24}$$

And:

$$ARR = \frac{1}{|DB|}\sum_{k=1}^{|DB|} P(I_k, n) \tag{25}$$

where |DB| total number of images in the database. Precision and recall are strong and individual. Including all these one more measures has been added that is F-measure. F-measure is defined as a relation between precision and recall. It is defined as shown in Eq. 26:

$$F_{measure} = \frac{2XARPXARR}{ARP+ARR} \tag{26}$$

To measure the capability of the proposed method, experiments have been done on two databases where the first one is Corel-10 k and second one MIT-Color database.

Database 1: The Corel-10k database consists of 10,000 images of 100 categories, each category has 100 images. It is bigger and adaptable than Corel-1 k and 5 k. It involves images of animals, e.g., fox, tiger, deer, etc., human, natural scenes, ships, food, buses, etc., army, ocean, cats, airplanes, etc. For this, database retrieval performance of the proposed research is calculated in terms of precision, recall, ARP, ARR and F-measure.

The performance of the proposed method compared with state-of-art techniques, Wavelet, CS_LBP, LEP, LEPINV and LEPSEG methods along with color histograms for each method. From Fig. 4a, b represents the category wise retrieval performance in terms of precision and recall curves for each query image from each category. Figure 4c, d characterize Average Rate Precision (ARP) and Average Rate Retrieval (ARR). Owing the shape features in the feature vector, the precision of shape oriented image categories have shown a significant improvement example categories 17, 18, 37, 42, 54, etc. It is clearly representing the considerable improvement in the average precision around 8.65% as compared to Wavelet+Color, 6.5% compared with CS_LBP+Color, 5.7% compared with LEP+Color, 5.85% compared with LEPINV+Color and 3.4% compared with the LEPSEG+Color histogram. Figure 4e showing the relation between top matched images to F-measure where F-measure is calculated from Eq. 22 and Table 2 indicates the presented method outperforms other existing methods.

Database 2: MIT-Vistex database is consists of a lot of colored texture images. This database consists of 40 different colored texture images and each in size of 512×512. For image retrieval, these images are divided into 16 blocks where each block size is 128×128, therefore, 640 (40×16) image database has been created. The samples of this database shown in Fig. 5. From Fig. 6 a, b the retrieval performance of the proposed method compared with the state-of-art approaches. It has been proved that the proposed descriptor has shown significant improvement in terms of precision around 7.8% as compared with Wavelet+Color, 6.2% compared with CS_LBP+Color, 4.3% compared with LEPINV+Color, 3.3% compared with LEPSEG+Color, 2.7% compared with LEP+Color. From Fig. 6c graph representing the top matched images vs. respective precision and recall relations F-measure. The similarity measurement d1 distance is used for all the experiment calculations.

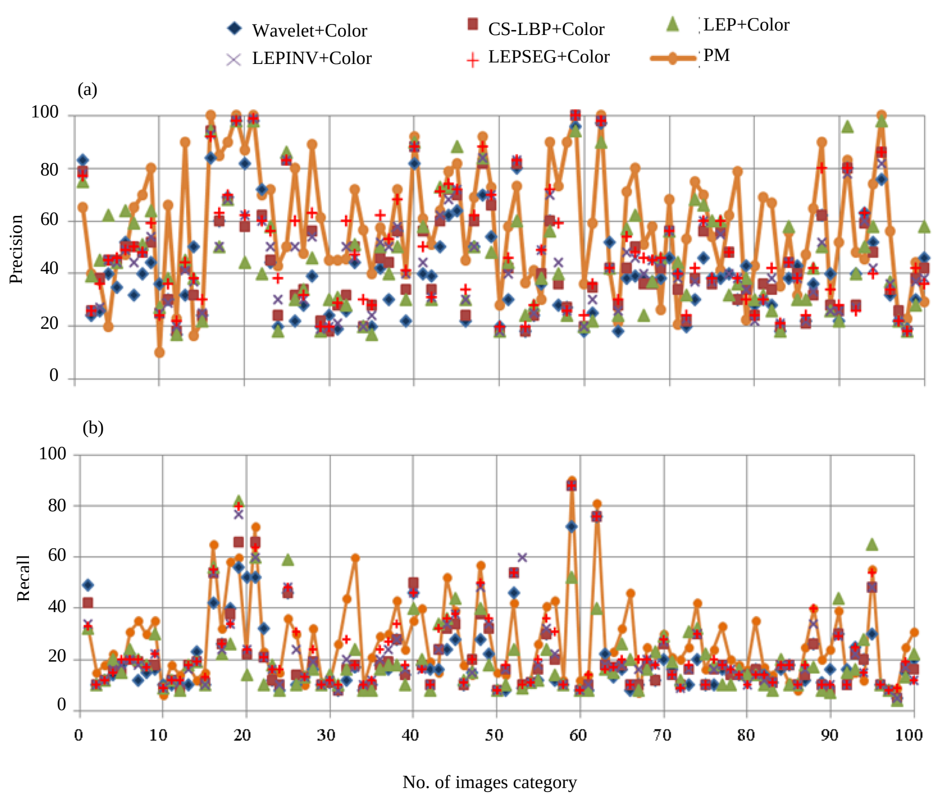

Fig. 4: Continue

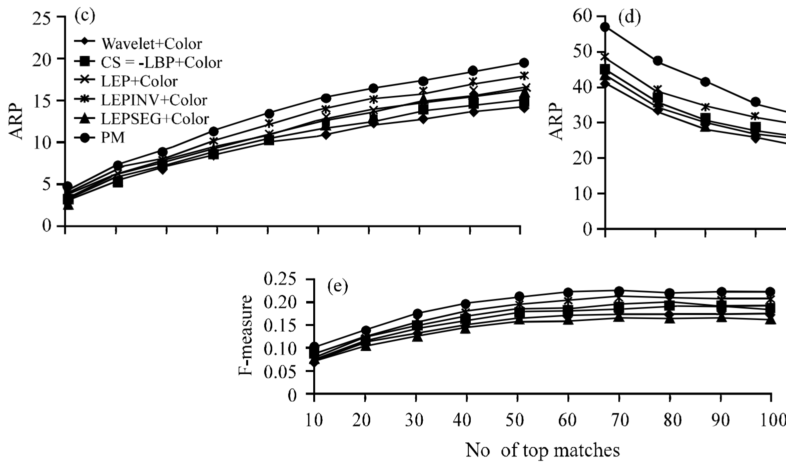

Fig. 4: Corel-10 k database: a) Precision and image category number; b) Recall and image category; c) ARP and images retrieved; d) ARR and images retrieved and e) F-measure vs. top matched images

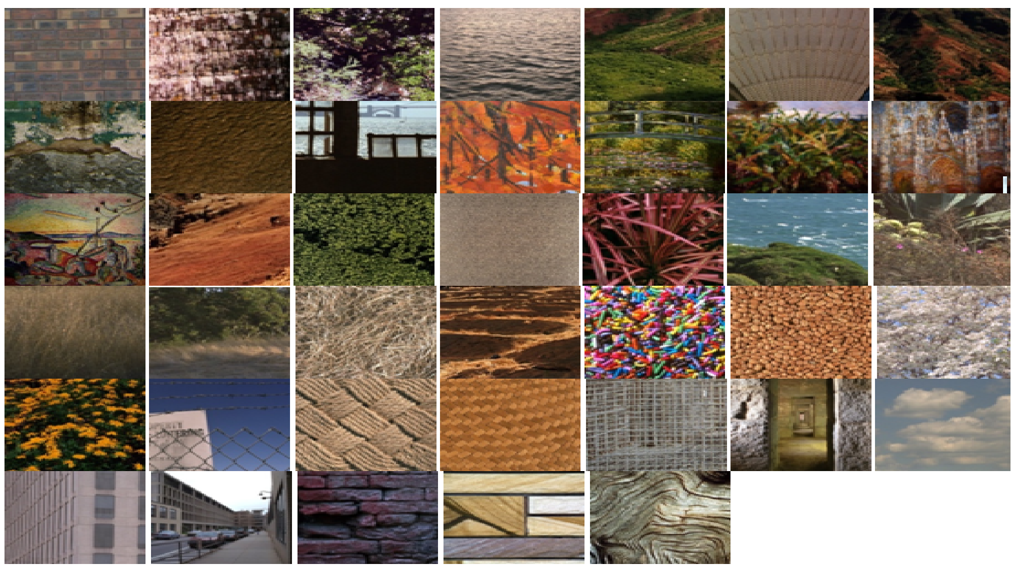

Fig. 5: Samples from MIT-Vistex database

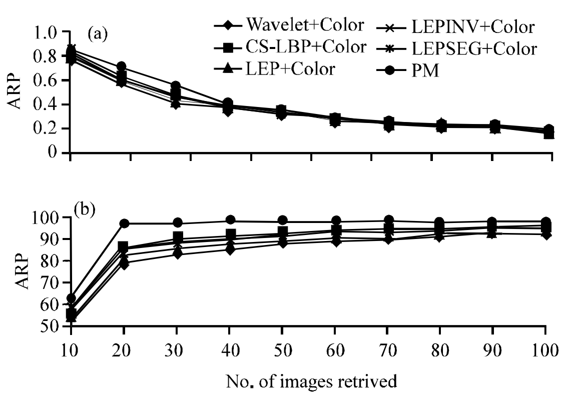

Fig. 6: Continue

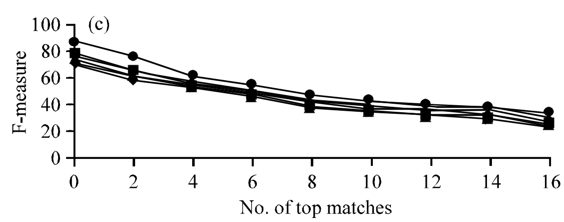

Fig. 6: MIT-Vistex database: a) ARP and images retrieved; b) ARR and images retrieved and c) F-measure vs. Top matched images

CONCLUSION

An optimized image retrieval has been proposed for image retrieval. Here, all local features color, texture and shape features extracted for the efficient image retrieval. Here colored image converted into HSV color space. Hue and saturation in various quantization levels used to extract the color features. It utilizes LMEBP for texture feature extraction on value color space. It extracts the texture information in calculating the eight maximum edges for each pixel. Each magnitude is calculated by the local difference between the center pixel and its eight neighbors. Lower order Zernike moments are extracted to represent the shape features of an image.

RECOMMENDATIONS

Further, the features of Hue, Saturation, LMEBP on value component and Zernike moments of gray scale image are integrated. The effectiveness of the proposed is tested by conducting experiments for image retrieval on different image database there by observed that significant improvement in terms of their respective evolution measures.

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