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Local Color Oppugnant Mesh Extrema Patterns: A New Feature Descriptor for Image Retrieval

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Abstract

Objectives: This paper presents a new feature extractor which we named as Local Color Oppugnant Mesh Extrema Patterns (LCOMeEP) for retrieval of images. **Methods/Statistical Analysis:** The suggested method gathers the color-texture statistics among the RGB (Red, Green and Blue) and gray scale of the given image. The color-texture statistics is extracted based on mesh extrema which assembles the relationship among the neighbors using extrema. **Findings:** The proposed method is diverse from the Directional Local Extrema Patterns (DLEP) collect the directional information which is based on local extrema in an image. Whereas the method presented in this paper, (LCOMeEP) gathers the mesh extremas amid the RgG (red, gray, green), GgB (green, gray, blue) and BgR (blue, gray, red) spaces. The enactment of the presented technique is amended by assimilating the LCOMeEPs with histograms of HSV (hue, saturation, value). The enactment of the research work is estimated by simulating on standard data sets, Corel-5K and Corel-10K in context of recall, precision, Average Retrieval Rate (ARR) and Average Retrieval Precision (ARP). **Application/Improvements:** The outcome after inspection illustrates a substantial enhancement as related to the contemporary features for image retrieval.

Keywords: Image Retrieval, Local Binary Patterns (LBP), Local Extrema Patterns, Local Oppugnant Patterns, Pattern Recognition, Texture

1. Introduction

Content Based Image Retrieval (CBIR) covers a approach to label contents within the image based on characteristics and retrieves images consequently. It determinations the elementary difficulties of text based image retrieval by spontaneous collection of low level charcteristics from the contents of image like color, texture, shape etc which we can seen from naked eyes. After feature collection the following step is the extent of resemblance amid different images depending on these characteristics. The outcome of CBIR system is considerably reliant on low level visual charactristics. The extensive existing literature on image retrieval systems is given in references¹⁻⁴.

Texture deals with the physiognomies of images with reverence to deviations in certain directions and scales⁵⁻⁷. It collects significant statistics about structural prearrangement of exteriors (like clouds, fabrics, bricks etc.) and their association to the neighboring location.

Typically texture statistics deliberate the behavior of collection of pixels rather than nature of single pixel. Natural images are the best examples of color and texturemedley. Even though greatest texture features work on gray space, but to optimize the enactment of features occasionally they can be realistic on color images. Numerous approaches are shadowed to extract texture features⁸.

Moghaddam et al.⁹ have anticipated the wavelet transform based correlogram for image retrieval application. Additionally, the enactment of wavelet correlogram is enhanced by using evolutionary genetic algorithm (GA)¹⁰. Birgale et al.¹¹ and Subrahmanyam et al.¹² coupled the color and texture properties for CBIR. Subrahmanyam et al. have recommended the correlogram algorithmtot retrieve images with help of 'wavelets' and 'rotated wavelets' (WC+RWC)¹³.

Ojala et al. have proposed the Local Binary Patterns (LBP) for the depiction of texture¹⁴. The rotation varient

LBP is transformed into rotational invarient for texture classification^{15,16}. For facial expression analysis and recognition, the LBP features are used in 17,18. Heikkila et al. presented the contextual demonstrating and detection with the help of LBP19. Huang et al. presented the widespread LBP for the localization of shape^{20, 21}. Li et al. used the mixture of Gabor filter and LBP for segmenting texture²². Zhang et al. recommended the 'Local Derivative Pattern' (LDP) for facial identification²³.

The LBP texture feature based on blocks is proposed for CBIR²⁴. A modified variety of famous LBP feature known as the 'Center-Symmetric Local Binary Pattern' (CS-LBP) is joined along with 'Scale Invariant Feature Transform' (SIFT) for ROI (Region Of Interest)description²⁵. Two kinds of Local Edge Patterns (LEP) histograms, LEPINV for image retrieval, and further LEPSEG for image segmentation were proposed by Yao et al.²⁶. The LEPSEG is sensitive to deviations in rotation and scale, on the opposing, the LEPINV is resilient to deviations in rotary motion and scale.

The existing LBP and the LDP are not able to satisfactorily handle the wide range of external discrepancies that usually occur in unrestricted normal images due to aging, lighting, facial appearance, pose, partial constrictions, etc. To resolve this problem, the 'Local Ternary Pattern' (LTP)27 was proposed for facial recognition indiverse lighting environment. Subrahmanyam et al. have presented the several features based on pattern, 'Local Maximum Edge Patterns' (LMEBP)²⁸, local tetra patterns (LTrP)²⁹ and Directional Local Extrema Patterns (DLEP)30 for natural/texture image retrieval and Directional Binary Wavelet Patterns (DBWP)31, Local Mesh Patterns (LMeP)32 and Local Ternary Co-occurance Patterns (LTCoP)³³ for medical image retrieval. An extension to the 'DLEP' characteristics by inserting the magnitude info of the confined gray values of an image is given in [34] by Reddy et al. "Local Oppugnant Color Texture Pattern" for image retrieval (LOCTP) is given in 35 by Jacob et al.

In collected work, current features accumulate the association among the pixels in the specific planes, red, gree, blue, gray, hue, saturation, etc or between the planes. But not contemplate the association among the more than two planes like (red, gray, green), (green, gray, blue), (blue, gray, red), etc. In this paper, we propose the relationship between the three planes using local mesh extrema features. The novel donations of this research can be summarized as follows. (a) A new feature method, named "local mesh extrema patterns" are proposed for feature extraction, (b) the proposed local mesh extrema patterns collect features form three planes of color image (RgG, GgB, BgR) which is named as Local Color Oppugnant Mesh Extrema Patterns (LCOMeEP) for image retrieval, (c) the enactment of the suggested scheme is enhanced by adding it with the 'HSV' color histogram. The evoluation of the suggested technique is done on benchmark 10000 image record.

The summary of the layout of the research paper is as follows: The short-lived assessment regarding image recovery and related work are summarized in section 1. The assessment of the current contemporary features for image retreival are given in section 2. The proposed scheme structure and doubt matching are desribed in Section 3. Experimental results and discussions are summarized in section 4. Depends opon proposed work, conclusions and future scope are made in section 5.

Local Patterns

2.1 Local Binary Patterns (LBP)

Originally, LBP is used for texture classification by Ojala et al. 14. Additionally, LBP is used for further applications like, image retreival, face recognition, palmprint recognition, etc. and got accomplishment due to its rapidity and enactment. The LBP is well-definedgrounded on the association among the middle pixel and its adjacentpixel in an image. The association which is collected among the middle pixel and its neighbors is based on the edge stuck between the neighbor and center pixel. that LBP bit is implicit as '1', If the neighbor pixel gray value is larger or equal than the center pixel, else it implicit as '0' illustrated in *in Eq,* (1) *and Eq.* (2).

$$LBP_{P,R} = \sum_{i=1}^{P} 2^{(i-1)} \times f_1(I(g_i) - I(g_c))$$
 (1)

$$f_1(x) = \begin{cases} 1 & x \ge 0 \\ 0 & else \end{cases}$$
 (2)

where, $I(g_c)$ signifies the grayscale value of the center pixel, $I(g_p)$ signifies the gray value of its neighbors, Pstands for the number of neighbors and R, the radius of the neighborhood.

After figuring the LBP pattern for each pixel (j, k), the entire image is characterized by constructing a histogram as shown in Eq. (3).

$$H_{LBP}(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_2(LBP(j,k),l); \ l \in [0,(2^P-1)]$$
 (3)

$$f_2(x,y) = \begin{cases} 1 & x = y \\ 0 & else \end{cases}$$
 (4)

where, the size of input image is $N_1 \times N_2$.

Figure 1 demonstrates the exampleshrewdness for the LBP for a given 3×3 pattern. The histograms of these patterns grasp the data on the distribution of edges in an image.

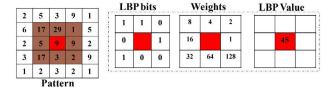


Figure 1. Calculation of LBP.

2.2 Block Based Local Binary Patterns (BLK-

LBP based on block was proposed by Takala et al.²⁴ for image retrieval. The block partition technique is a modestmethod that depend on sub-images arrangement with the three-dimensional possessions of images. This method can be utilized mutually with any other histogram descriptors analogous to LBP. The technique functions in the subsequent style: First of all the the model images are divided into rectangular blocks that are random in overlap and size. After dividing the next step is to compute the LBP disseminations for every block and than combine the sub-histograms representing the image histograms into a single vector.

2.3 Directional Local Extrema Patterns (DL-EP)

The "directional local extrema patterns" (DLEP)are introduced by Subrahmanyam et al.³⁰ for image retreival. DL-EP defines the spatial association among local texture by the help of the local extrema of middle gray pixel g_c .

In existing DLEP for a given test image the local extrema in 0 degree, 45 degree, 90 degree, and 135 degree directions are composed by calculating local variance between the center pixel and its neighbors as given:

$$I'(g_i) = I(g_c) - I(g_i); \quad i = 1, 2, \dots, 8$$
 (5)

The local extremas are obtained by Eq. (7).

$$\hat{I}_{\alpha}(g_c) = f_3(I'(g_j), I'(g_{j+4})); j = (1 + \alpha/45) \ \forall \alpha = 0^0, 45^0, 90^0, 135^0$$
(6)

$$f_3(I'(g_j), I'(g_{j+4})) = \begin{cases} 1 & I'(g_j) \times I'(g_{j+4}) \ge 0 \\ 0 & else \end{cases}$$
 (7)

The DLEP is defined ($\alpha=0^{\circ}$, 45°, 90°, and 135°) as follows:

$$DLEP(I(g_c))|_{\alpha} = \left\{ \hat{I}_{\alpha}(g_c); \hat{I}_{\alpha}(g_1); \hat{I}_{\alpha}(g_2); \dots \hat{I}_{\alpha}(g_8) \right\}$$
(8)

Finally, the given image is transformed to DLEP maps whose values ranging from 0 to 512.

After calculation of DLEP, the entire image is characterized by assembling a histogram which is mathematically given by Eq. (9) 30.

$$H_{DLEP|_{\alpha}}(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_2(DLEP(j,k)|_{\alpha}, l); \qquad l \in [0,511]$$
(9)

where, the dimension of input image is $N_1 \times N_2$. The more details about the DLEP is available in 30.

2.4 Local Color Oppugnant Mesh Extrema Patterns (LCOMeEPs)

In available literature, the assembly features are composed depends on the association among the middle pixel and its nearby neighbors on specific planes (LBP, LDP, etc.) or two oppugnantspaces like, Red-Green(Rg), Green-Blue (Gb), Blue-Red(Br), etc. The Local Color Texture Oppugnant Patterns (LCTOP)35 collect the association among the center pixel of one plane and the neighbors of the other plane with the same location of center pixel.

The operators LCTOP35 and DLEP30 are inspired us to plan a new feature extractor which is named as Local Colotoppugnant Mesh Extrema Patterns (LCOMeEP). The proposed scheme extracts the association among the three pixels which are composed from three unlike planes that means, it collects the association among the three planes. For gathering the association, we use the red (R), green (G), blue (B) and gray (b)sacel planes.

Let *I* is any given image, the RGB color channels and gray scale image are used for extracting the colour texture features of the given image. The LCOMeEP is mined depending on the local forward and backwordmesh differences between three oppugnant planes c_1 , c_2 and c_3 as follows.

The forward mesh differences between the planes are collected as:

$$I_{c_{1}c_{2}}^{1}(g_{i}) = I_{c_{1}}(g_{i+j}) - I_{c_{2}}(g_{i}); \forall \begin{cases} j = 1 + \mod((i + P), P) \\ c_{1}c_{2} = Rg, Gg, Bg \\ i = 1, 2, \dots, 8 \end{cases}$$
(10)

The forward mesh differences between the planes are collected as:

The local mesh extremas are calculated by Eq. (12).

$$\hat{I}_{c_1c_2c_3}(g_i) = f_3(I_{c_1c_2}^1(g_j), I_{c_3c_2}^2(g_j)); \forall c_1c_2c_3 = RgG, GgB, BgR$$
(12)

$$f_{3}(I_{c_{1}c_{2}}^{1}(g_{j}), I_{c_{3}c_{2}}^{2}(g_{j})) = \begin{cases} 1 & I_{c_{1}c_{2}}^{1}(g_{j}) \times I_{c_{3}c_{2}}^{2}(g_{j}) \ge 0\\ 0 & else \end{cases}$$
(13)

The LCOMeEP is defined as follows:

$$LCOMeEP(I_{c_1c_2c_3}(g_c))\Big|_{\alpha} = \left\{ \hat{I}_{c_1c_2c_3}(g_1), \hat{I}_{c_1c_2c_3}(g_2), \dots, \hat{I}_{c_1c_2c_3}(g_8) \right\}$$
(14)

The over-all possible LCOMeEP operators for a known image is presented mathematically as given.

$$\Gamma_{L} = \left\{ Pattern_{RgG}, Pattern_{GgB}, Pattern_{BgR} \right\}$$
 (15)

Finally, the test image is transformed to LCOMeEP maps with values stretching from 0 to 255. After computation of LCOMeEP, the entire map is denoted by building a histogram using Eq. (16).

$$\begin{split} &H_{\textit{LCOMeEP}(j,k)}(l) = \sum_{j=1}^{P_1} \sum_{i=1}^{P_2} f_2(\textit{LCOMeEP}(j,k))^{\textit{KMM}} & (16) \\ &, l); l \in [0,255]; \forall c_1c_2c_3 = \textit{RgG}, \textit{GgB}, \textit{BgR} \end{split}$$

Figure 2 illustrates the comprehensive demonstration of LCOMeEP for a given R, G, B and g planes. Let three pixels are selected for mesh extrema calculation. These three pixels are selected from three planes of R, G, B and g. For RgG structure, we selected the pixel values from R, g and G respectively. Similarly, GgB and BgR structures are selected for mesh extrema calculation. Lastly, the mesh extrema bits are encoded depending on the association between the middle pixel and its neighbor pixels as "0", "1" and "1" correspondingly as shown in Figure 2.

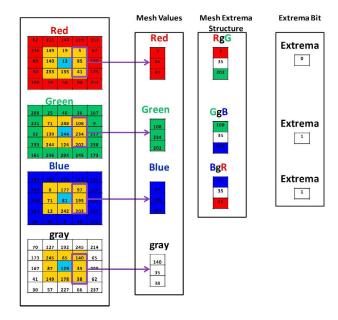


Figure 2. Sample calculation of LCOMeEP operator for RGB image.

3. Proposed Scheme Framework

3.1 Image Retrieval Scheme

In this work, we incorporate the theories of local extrema calculation and oppugnant planes relationship. The oppugnant planes which are used for mesh extrema calculation are RgG, GgB and BgR. The structure C_1gC_2 , characterizes the mesh extrema calculation among the pixels of C_1 , g and C_2 . Here, g is considered as center pixel and C_1 and C_2 are measured as neighbors. Further, the HSV color histograms are incorporated with the LCOMeEP for final feature vector compeers. Figure 3 illustrates the flowchart of the proposed research work and the algorithm for same is given as follows. Figure 4 illustrates the feature maps which are extracted using the proposed feature extraction method.

Algorithm:

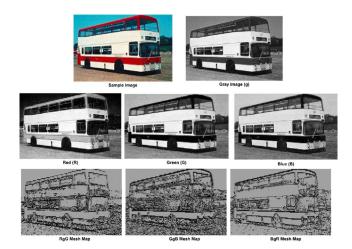
- Upload the color image and rehabilitated in to gray scale (g).
- For a given center pixel, collect the neighbors for *R*, G, B and g planes.
- Collect the three bits based on the structures, RgG, GgB, BgR.
- Calculate the local mesh extrema pattern bits for RgG, GgB, BgR.
- Compute the LCOMeEPs for RgG, GgB, BgR.
- Construct the histograms for RgG, GgB, BgR.
- Calculate the HSV histograms for H, S and V spaces of color image.
- Build the feature-vector by joining all histograms.
- Doubted image comparion with database using Eq.
- Image retrival depending on the finest matches.

3.2 Query _Matching

Feature descriptor for testing image Q is denoted as $f_{\mathcal{Q}} = (f_{\mathcal{Q}_1}, f_{\mathcal{Q}_2},f_{\mathcal{Q}_{l_g}})$ which we get after the feature collection. Same way, every image of the catalog is denoted with feature vector $f_{DB_j} = (f_{DB_{j1}}, f_{DB_{j2}}, \dots, f_{DB_{jLg}}); j = 1, 2, \dots, |DB|$. The purpose is to find n best similar images. This process is to select n best matched images by calculating the distance between catalog image. and testing image. Now to match the two images we have used x_i distance metric³⁰ computed by Eq. (17).

$$D(Q, DB) = \sum_{i=1}^{Lg} \left| \frac{f_{DB_{ji}} - f_{Q_i}}{1 + f_{DB_{ji}} + f_{Q_i}} \right|$$
(17)

where $f_{DB_{ii}}$ is i^{th} feature of i^{th} image in the database |DB|.



The LCOMeEP feature maps extracted from a sample image.

4. Simulation Results

The competence of the research work is verified by executing two observations on standard databases. The databases which are used for assessment are Core-5K and Core;l-10K.

We conducted two different experiments. In experiment #1we have used images from Corel database³⁶. The Corel database consist of number of images of a variety of contents stretching from outside sports to animals to normal images. These images in database are divided into diverse kinds each one containing 100 by area professionals. Some of the experts believe that Corel dataset contains whole the necessities to assess an image recovery method, because of its huge dimension and mixed data.

For every experiment we used every image of the dataset as the douted image. The scheme gathers ndataset images $X=(x_1, x_2, ..., x_n)$ with the smallest distance

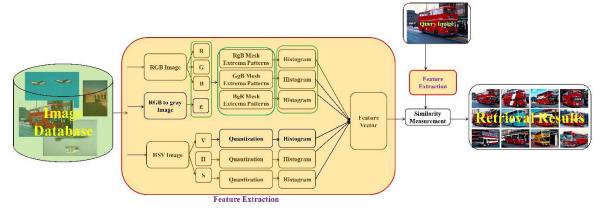


Figure 3. Proposed image retrieval system framework.

between similar image for each query. The smallest matching distance is calculated by using the formula given in equation. (16). In case the recovery image $x_i=1, 2, \ldots, n$ is from the same group as that of the doubted image then we can asses that the method has appropriately recognized the predictable image otherwise the method is unsucessful in finding the predictable image.

The evaluation of the outcomes of the presented scheme is done in context of average precision or 'average retrieval precision' (ARP) and average recall/ 'average retrieval rate; (ARR) as shown below:

For the identified image I_q , the precision is mathematically represented as

$$Precision: P(I_q) = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ images\ retrieved}$$

(18)

Average Retrieval Precision :
$$ARP = \frac{1}{|DB|} \sum_{i=1}^{|DB|} P(I_i)$$

(19)

$$Recall: R(I_q) = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ relevant\ images\ in\ the\ database}$$

(20)

Average Retreival Rate:
$$ARR = \frac{1}{|DB|} \sum_{i=1}^{|DB|} R(I_i)$$
 (21)

4.1 Corel-5K Dataset

The Corel-5K dataset comprises of 5000 natural images of 50 dissimilar classes. Every class is comprised of 100 images. The 50 classes covers a wide range and comprised of images presented in nature such as, peoples, plants,

beaches, buses, hills etc. The enactment of the suggested image retrieval method is calculated depending on 'precision', 'recall', 'ARP' and 'ARR'.

Table 1 contains the detail of the image retrieval outcomes of the existing and proposed method on Corel–5K and Corel–10K databases in context of average_ precision and re-call. The classwise enactment of the different techniques in terms of average_recall and average_precision are demonstrated in Figure 5 (a) and Figure 5 (b) respectively on Corel-5K database. Further, the enactment of the several methods are also assessed in context of ARP and ARR on Corel_5K database. The 'ARP' and 'ARR' results are illustared in Figure 6(a) and Figure 6(b) correspondingly.

Following observation are made from From Table 1, Figure 5 and Figure 6:

- The LCOMeEP shows28.8%, 20.2%, 26.6%, 16.0%, 18.1%, 12.9%, 7.3% and 5.3%improved resultsin comparision to CS-LBP, LEP_SEG, LEP_INV, BLK-LBP, LBP, DL_EP, MD_LEP and LOC_TP correspondingly, in terms of 'ARP' on Core_5K database.
- The LCOMeEP shows15.8%, 11.5%, 15.0%, 9.5%, 10.6%, 8.7%, 5.7%, and 3.7% healthier results in comparision to CS-LBP, LEP_SEG, LEP_INV, BLK-LBP, LBP, DL_EP, MD_LEP and LOC_TP correspondingly, in terms of 'ARR' on Core_5K database.

From Table 1, Figure 5, Figure 6 and other results mentioned ablove, it is evident that the proposed scheme shows an important development as compared to the state-of-the-art schemes in terms of their estimate procedures on Corel_5K database. Figure 7 depicts the inquiry retrieval performance of LCOMeEP on Corel-5K database.

Table 1. Results of different techniques in context recall and precision on Corel–5K and Corel–10K databases MDLEP: DLEP+MDLEP; BLK_LBP: Block based LBP, Proposed Method: LCOMeEP.

Database	Performance	Method								
		CS_LBP	LEPSEG	LEPINV	BLK_LBP	LBP	DLEP	MDLEP	LOCTP	LCOMeEP
Corel-5K	Precision (%)	32.9	41.5	35.1	45.7	43.6	48.8	54.4	56.4	61.7
	Recall (%)	14.0	18.3	14.8	20.3	19.2	21.1	24.1	26.1	29.8
Corel-10K	Precision (%)	26.4	34.0	28.9	38.1	37.6	40.0	45.4	47.3	52.3
	Recall (%)	10.1	13.8	11.2	15.3	14.9	15.7	18.4	20.3	22.4

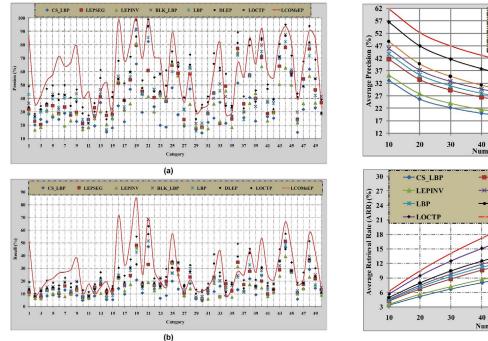


Figure 5. Evaluation of LCOMeEP with other contemporary techniques on Corel-5K. (a) Classwise wise performance in context of precision, (b) class wise wise performance in context of recall.

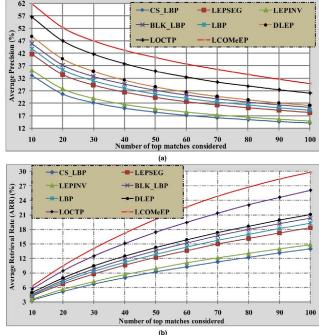


Figure 6. Comparison of various methods in terms of ARP and ARR on Corel-5K database.

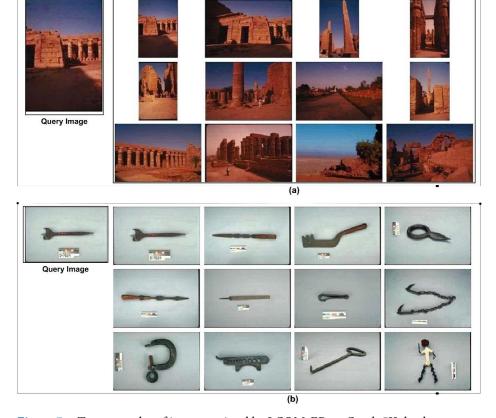


Figure 7. Two examples of image retrieval by LCOMeEP on Corel-5K database.

4.2 Corel 10K Database

The Corel_10K dataset comprises of 10000 natural images of 100 dissimilar categories. Every category comprises of 100 images. The efficiency and performance of the research work for image recovery is evaluated on the basis of ARP, precision (P), recall(R), ARR and recall.

The classwise performance of the different techniques in context of of APR and ARR are demonstrated in Figure 8 (a) and Figure 8 (b) respectively on Corel-10K database. Further, the results of a variety of schemes are also evaluated in conditions of ARP & ARR on Corel_10K dataset. The 'ARP' & 'ARR' results are illustared in Figure 9(a) and Figure 9(b) respectively. it is evident from Table 1, Figure 8 and Figure 9, that the method proposed in research work shows an important development as compared to the state-of-the-art methods in terms of their assessment measures on Corel_10K dataset. Figure 10 depicts the query retreival outcome of LCOMeEP on Corel 5K database.

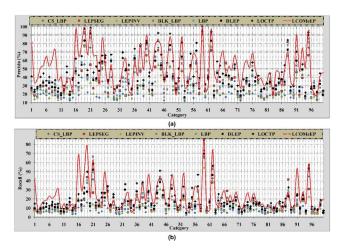


Figure 8. Comparison of LCOMeEP with other existing methods on Corel–10K. (a) Category wise performance in terms of precision, (b) category wise performance in terms of recall.

4.3 Merits of Suggested Technique over the Privious Technique

- The prevailing features ('LBP', 'LOCTP', etc) in related work gather the color-texture info from different color planes such as HSV,RgB, LaB, etc. On the other hand our operator (LCOMeEP) is acquired by calculating the texture sample over RgG, GgB, BgR planes.
- LCOMeEPgathers information form the the inter space joint color-texture for 'local color-texture'

- (LCT) feature which is not there in the other prevailing methods.
- The outcome of the suggested technique is proved on bench-mark normal image dataset in terms of 'average retrieval precision' (ARP) and 'average retrieval rate' (ARR).

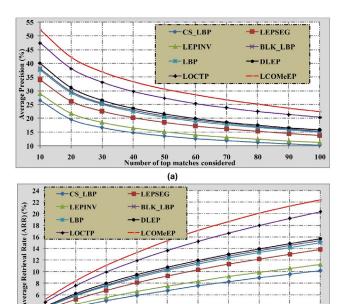


Figure 9. Comparison of various methods in terms of ARP and ARR on Corel-10K database.

(b)

5. Conclusions

A new feature retrival named as "local color oppugnant mesh extrema patterns" (LCOMeEP) for image recovery. The presented scheme (LCOMeEP) combines the mesh extremas among the RgG (red, gray, green), GgB (green, gray, blue) and BgR(blue, gray, red) spaces. The enactment of the suggested technique is enhanced by integrating the LCOMeEPs and H-S-V (hue-saturation-value) histograms. The performance of the proposed method is tested by conducting experiments on benchmark dataset, Corel_5K and Corel_10K in context of Recall (R) and Precision (P), 'average retrieval rate'(ARR) and 'average retrieval precision' (ARP). The outcome after examination depicts a significant enhancement as compaerd to the contemporary features for image retrieval.

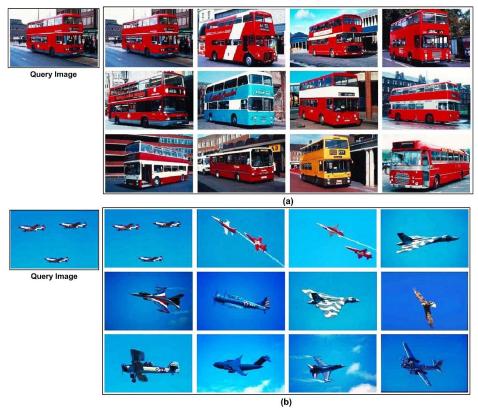


Figure 10. Two examples of image retrieval by LCOMeEP on Corel-10K database.

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