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# Novel Texture Feature for Content Based Image Retrieval

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***Abstract:***
Content-Based Image Retrieval (CBIR) is an image retrieval technique that fetches relevant pictures from a huge image database based on the content feature of a given query image. It has many applications such as satellite image indexing, development of recommendation system in many applications and medical image processing. Feature extraction, indexing and similar image retrieval are few major steps in the development of CBIR system for any applications. Extraction of relevant feature that effectively represents the image is a challenging task. Therefore, the performance of a CBIR system completely depends upon the ability of the feature sets used to represent the image contents. In addition the dimensionality of the feature set used also affect the retrieval performance in terms of response time. The objective of this work is to analyze the retrieval performance of few recently proposed texture features and propose a novel feature extraction technique that has better retrieval efficiency while addressing the issues of dimensionality. In this paper we implemented and analyze the retrieval performance of three recently proposed texture features and also proposed a novel method for texture feature extraction for the design of CBIR system. The evaluation is performed using five popular publicly available benchmark data sets with varied complexities. The data sets include real-life images, texture images, facial images, etc. Extensive experiments are performed to tune the parameter that affects the retrieval performance for each texture feature considered for evaluation. The performance of the proposed method is compared with other methods in terms of average precession and average recall percentage. The performance of the proposed method is found to be best among all irrespective of the dataset used.

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## 1. INTRODUCTION

An image is considered as an important piece of information. A picture makes communication easieras our brain can translate them much quicker than any kind of textual representation. In today's world due to advanced technology and availability of smart gadget, very large amount of images are deposited to the database every day, thus the demand for efficient retrieval techniques are proportionally

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increasing which can retrieve relevant information as well as can use less storage. Thus, with the immense availability of digital images, retrieving information from them becomes essential and is a genuine challenge. CBIR is an efficient way to retrieve images. Image retrieval is generally divided into two main groups: Context-based image retrieval and content-based image retrieval (CBIR). Context-based image retrieval is based on key-words, so its execution is a simple assignment. However, this system *has its* own disadvantages: first, manual annotation is expensive and second, certain images and scenes cannot be expressed in the form of word or sentences and it is language-dependent. To solve the issues in these traditional techniques; CBIR came into the picture by Kato in 1992. The most contrast between context-based and content-based methods is that in the traditional method, human interference is vital whereas, in CBIR, retrieval is done automatically considering image content such as image texture, color, and shape.In this work, a texture descriptor is proposed that proved to represent image better at the same time its dimension is also low as compared to the competing methods considered for comparison. Three widely used texture descriptors from literature are considered for performance comparison. This competing descriptor as well as the proposed descriptor are implemented and tested on five databases with varying complexity. The databases include fingerprint, real-life images, texture patterns (rotated and non-rotated), and a facial image database. Parameter used in each texture feature computation is varied to find out its optimal value. All methods are evaluated tuning the associated parameter to the optimal value obtained through extensive experimentation

## 2. LITERATURE REVIEW

CBIR is a searching technique where searching is performed using image features. Advanced data storage techniques lead to an increase in the size of the dataset. Since then the CBIR system has received importance to efficiently manage and extract similar images from the database by receiving image as an input. To build an efficient CBIR system a good visual descriptor is the key issue. An automatic machine-based object retrieval and classification system which is both discriminative and computationally efficient is a difficult task due to intra-class dissimilarity and inter-class likeness [1]. In the early CBIR system domain, global features of images were used for feature extraction like the color histogram of the entire image, detecting edges, texture in an image, etc [2]. Global features were computationally efficient technique but it is quite sensitive to image variation which leads to decrease discriminative ability. To overcome the problem of global feature extraction techniques, local feature extraction techniques came into the picture, where descriptors are implemented in a certain region of an image. Local Binary Pattern (LBP) was proposed by Ojala.et.al which extracts features based on the grayscale difference between the center pixel and its neighbors [3]. The LBP feature has been effectively applied to texture image classification and retrieval under the rotation invariant and multiresolution constraints [4]. To get better results, Liu et.al proposed modified LBP descriptors by adding color information feature (CIF) that extracts rich color content and texture information of an image [5]. It is used for facial image classification purposes [6]. It is also used in medical imaging, for analyzing pulmonary emphysema by Sorensen.et.al.[7]. Since the LBP descriptor is non-resistant to noise variations Local Ternary Pattern (LTP) was evolved to overcome the demerit we face due to LBP [8]. Next, the center pixel was compared with the center symmetric neighboring pixels and provided a good accuracy and was named as center symmetric local binary pattern (CSLBP) [9, 10]. Variation of CS-LBP is also performed know as CS-LGBP (Center-symmetric Local Gabor binary pattern) and a comparison study was performed on facial identification [11]. Many other variations of LBP were framed like completed local binary pattern (CLBP) [12], semi-uniform local binary pattern [13],

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multi structural local binary pattern (Ms-LBP), dominant local binary pattern [14]. Many image texture content feature extraction descriptors have been proposed and were implemented on the different database for different purposes like face detection[15, 16], texture classification[17], object identification, scene detection, gender identification, security purpose, medical imaging. No specific technique is said to be efficient enough which could classify and give the best result for all databases for all purposes. The objective of our work is to study the existing feature descriptors and propose a new feature descriptor that best represents the image and thereby improving the retrieval accuracy. The claim is established with extensive experimentation performed on five different datasets [18-21] with varying complexity and sufficient comparative study.

## 3. TEXTURE DESCRIPTORS

In addition to our proposed texture feature descriptor, we have considered four widely used texture descriptors to be applied on five different datasets for performance comparison. All the competing as well as the proposed feature descriptor are explained in following sub-sections.

### 3.1. **Local Binary Pattern:**

LBP is a texture feature descriptor. This operator is a simple and fast technique proposed by Ojala [17]. It works on a 3x3 neighborhood of an image which takes the difference between the neighbor pixel and central pixel and uses the decimal number to label central pixel. It is mathematically represented as:

$$LBPn,r(x_c,y_c) = \sum_{n=0}^{n-1} I(g_n - g_c) \times 2^n \qquad (1)$$

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

Where I is image name, $g_c$ is the value of the center pixel is, $g_n$ corresponds to the pixel values of the N neighbouring pixels located around the circle of radius R. It results in an eight-bit binary value, the LBP value of the central pixel is then calculated by multiplying the eight-bit binary value with weights given by powers of two, and finally, the summation of all multiplication result gives the LBP value.

### 3.2. **Local Ternary Pattern:**

LTP is a local texture feature extraction descriptor. It is an extension of the Local Binary Pattern proposed by Tan et al. [3]. Its sensitivity towards noise is less than LBP. It is a three-level quantization (-1,0,+1), LTP has proven to be a highly efficient texture features extraction technique for texture classification and retrieval having an angular resolution of 22.5° and they are resistant to lighting effects. LTP includes the formation of two windows, a positive window, and a negative window. It is encodes as:

$$LTPp,r = \sum_{p=0}^{p-1} s'(i_p - i_c)2^p$$

where s'(z, t) is the threshold function, t is a pre-defined threshold.

$$s'(z,t) = \begin{cases} 1 & \text{if } z > t, \\ 0 & \text{if } |z| < t, \\ -1 & \text{if } z \leq t. \end{cases} \qquad (3)$$

LTP code is split into a positive LBP code and a negative code as:

$$s'_p(z,t) = \begin{cases} 1 & \text{if } z \geq t, \\ 0 & \text{if } z < t \end{cases} \qquad (4)$$

$$s'_n(z,t) = \begin{cases} 1 & \text{if } z \leq t, \\ 0 & \text{if } z > -t \end{cases} \qquad (5)$$

From the above equation we can know that $s'_p$ is the positive window and $s'_n$ is the negative window. After getting the patterns from positive and negative window, convert into a decimal value as in case of LBP and the feature vector of an image is extracted by merging the feature of both the window of each

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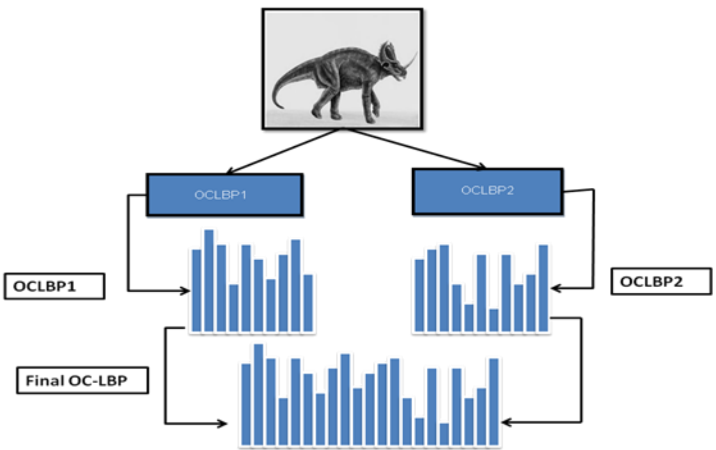
pixel. If the dimension of the LTP histogram will be $2^N$ for upper and $2^N$ for lower window, it forms the dimension of $(2^N + 2^N)$ after concatenation both of their histogram values and as the no. of neighbourhood will increase their dimension will increase respectively.

### 3.3. Orthogonal Combination -Local Binary Pattern (OC-LBP):

OC-LBP is a texture descriptor similar to LBP but with a resolution of 90°. LBP produces a 256-dimensional histogram which can be reduced by considering four neighboring pixels at a time. To not to decrease the discriminating power OC-LBP is computed by dividing a grayscale image into a 3x3 neighborhood into two non-overlapped orthogonal groups. In the first group, we consider vertical and horizontal neighboring pixels and in the second group, we consider both diagonal neighboring pixels. In each group, we compare center pixel value with its neighboring pixels. The center pixel represents a threshold value. After getting binary patterns from both the groups, generate the LBP histogram for both then concatenate them to use as image descriptor.




OC-LBP1=$I(g_0 - g_c) \times 2^0$

OC-LBP2= $I(g_1 - g_c) \times 2^0$

$I(g_2 - g_c) \times 2^1$ $\quad$ $I(g_3 - g_c) \times 2^1$

$I(g_4 - g_c) \times 2^2$ $\quad$ $I(g_5 - g_c) \times 2^2$

$I(g_6 - g_c) \times 2^3$ $I(g_7 - g_c) \times 2^3$

Final OC-LBP = [OC-LBP_1 OC-LBP_2]

Fig. 1. Description of OC-LBP

If the dimension of the LBP histogram is 2N, where N is 8. LTP histogram forms the dimension of $(2^N + 2^N)$ i.e. 512. Similarly, for OC-LBP the dimension is $(2^{N/2} + 2^{N/2})$ i.e 32 after concatenating both the histogram.

### 3.4. Proposed Method (Enhanced Orthogonal Combination of Local Binary Pattern)

In our proposed method, the region of interest for texture description is increased from 3x3 to 5x5, as a result, the fine angular resolution is achieved. The 5x5 window gives rise to six different windows, two windows for R=1 and the other four for R=2 (Outermost neighbor pixels of 5x5 window). Detail description of the proposed texture descriptor is given in Fig.2.

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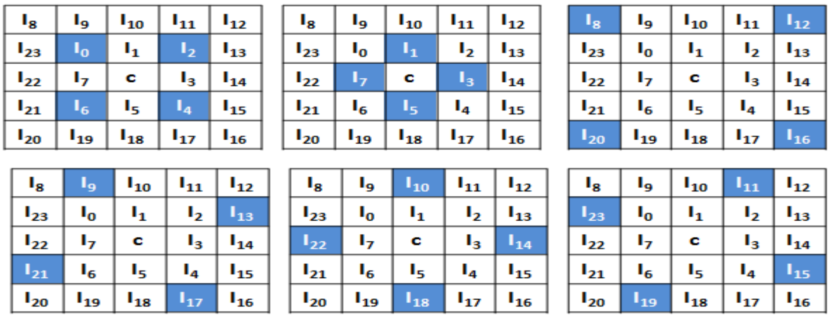

Fig. 2. Enhanced Orthogonal Combination of Local Binary Pattern

The proposed feature descriptor can be mathematically explained as below.

$$I_n = \begin{cases} 1 & x(n) > c \\ 0 & x(n) < c \end{cases}$$

$$L1 = \sum_{n=0,2,4,6} 2^{\frac{(n)}{2}} \times I_n \qquad (6)$$

$$L2 = \sum_{n=1,3,5,7} 2^{\frac{(n-1)}{2}} \times I_n \qquad (7)$$

$$L3 = \sum_{n=8,12,16,20} 2^{\frac{(n-8)}{4}} \times I_n$$

$$L4 = \sum_{n=9,13,17,21} 2^{\frac{(n-9)}{4}} \times I_n$$

$$L5 = \sum_{n=10,14,18,22} 2^{\frac{(n-10)}{4}} \times I_n \qquad (10)$$

$$L6 = \sum_{n=11,15,19,23} 2^{\frac{(n-11)}{4}} \times I_n \qquad (11)$$

Where n is neighbouring pixel and *C* is centre pixel.

C= [L1, L2, L3, L4, L5, L6]

By using this method we tried to incorporate content from pixels present in R=2, for better discrimination. We are also tackling the dimensionality problem. Our descriptor generates a feature dimension of size 6(2N/2), i.e. 96 which is much less than that of other feature descriptors.

## 4. EXPERIMENTAL SETUP

This section explains the different set of experiments carried out to evaluate the performance of the proposed texture descriptor.

### 4.1. Dataset Used

In our experiment we are using 5 publicly available databases which include fingerprint database, real life image database, texture database, facial image database etc. The detailed descriptions of all the databases used are as follows.

Database 1 (DB1): FVC2000-DB1 is a finger print database consist of 10 different classes, each class having eight finger print images taken by low-cost optical sensor. Each image of size 300x300. Total images in this database are 80 [18].

Database 2 (DB2): Coral-1k is a colour database by James Z. Wang. It consists of ten different classes, each class having hundred images. Each image of dimension 256x384 or 384x256.This database consists of real life images [19].

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Database 3 (DB3): Brodatz-Rotated-1465 database is a texture database from Brodatz album [40]. These consist of the thirteen classes of size 512x512 at seven different rotation angles ($0^{\circ}, 30^{\circ}, 60^{\circ}, 90^{\circ}, 120^{\circ}, 150^{\circ}, 200^{\circ}$). Each image was divided into non-overlapping sub-images of size 128x128, i.e. 16 sub-images are extracted from a single image forming a database of size 1456.

Database 4 (DB4): Brodatz-non-rotated-2675 database is a texture database from Brodatz album [20]which includes images of multiple patterns like sand, straw, clouds, bricks etc. having 107 different classes. Each image was divided into small non-overlapping images of size 128x128, which give rise to 25 sub-images.

Database 5 (DB5): FEI frontal image database by which includes facial images of size 360x260 of two-hundred different people of different age, two images with different expression of each person (one normal, another with a smile). Out of these 400 images, 200 images are of male and other 200 are of female [21].

### 4.2. Distance Metric

Distance measurement can be found using different distance measurement algorithm but we have used Euclidean distance in our experiment. Euclidean distance is simply the distance between two different points.

If p = ($p_1, p_2,..., p_n$) and q = ($q_1, q_2,..., q_n$) are two points in Euclidean $n$-space, then the distance (d) between p to q is:

$$d(p,q)=d(p,q)=\sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \quad (12)$$

### 4.3. Performance Measure

We have used all the datasets as mentioned in section 4.1 to evaluate the retrieval performance of texture descriptors such as LTP, LBP, OC-LBP operators in the application of the image retrieval system. The performance of a CBIR system is found by calculating precision and recall of a system and represented in a graphical form called a precision-recall graph. Here we found the precision-recall graph of LBP, LTP, OC-LBP using different bin to find the best among all and the difference can be observed in the bar graph.

$$Precision = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} \quad (13)$$

$$\text{Recall} = \frac{\text{Numberof relevant images retrieved}}{\text{Total number of images in a class}} \quad (14)$$

### 5. RESULTS AND DISCUSSION

The retrieval performances of LTP, LBP, OC-LBP are evaluated using five benchmark databases those are listed in section 4.1. In each case, the average performance is calculated retrieving 25% more than the number of images in a particular class. Euclidean distance is used to calculate the distance between images. Different experiments are performed by changing the bin size of the histogram of each profile (i.e. LTP, LBP, OC-LBP and the proposed method) to identify the optimal bin size. The average precision and recall are calculated for each operating point (number of top retrieval) and the precision vs. recall curve is drawn for each case.

Experiment 1: Effect of bin size on retrieval performance on FVC2000 database.

Experiment 2: Effect of bin size on retrieval performance on CORAL-1K database.

Experiment 3: Effect of bin size on retrieval performance on BRODATZ-ROTATED database

Experiment 4: Effect of bin size on retrieval performance for BRODATZ-NON-ROTATED database.

Experiment 5: Effect of bin size on retrieval performance for FEI database.

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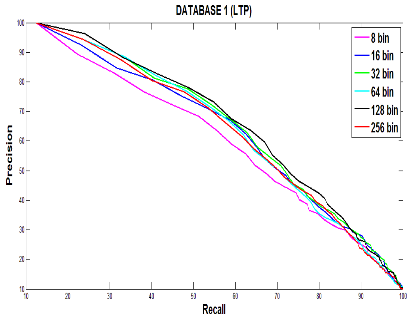


Fig. 3. Precision vs. recall Curve for LTP on DB1

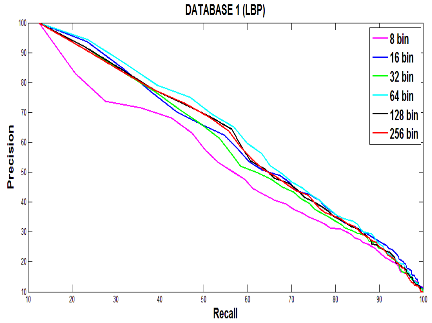


Fig. 4. Precision vs. recall Curve for LBP on DB1

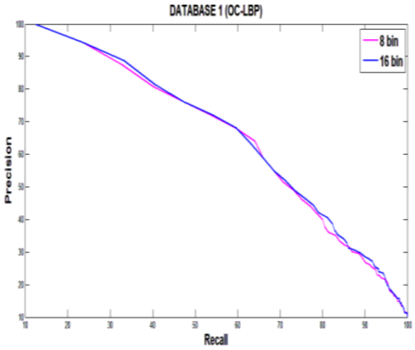


Fig. 5. Precision vs. recall Curve for OC-LBP on DB1

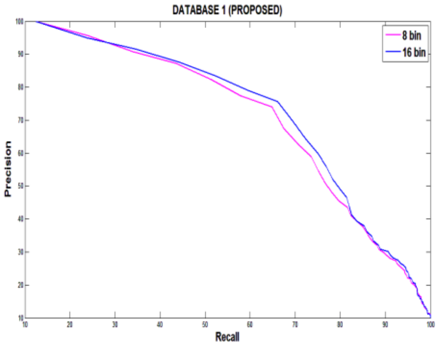


Fig. 6. Precision vs. recall Curve for Enhanced Orthogonal combination of Local Binary Pattern on DB1

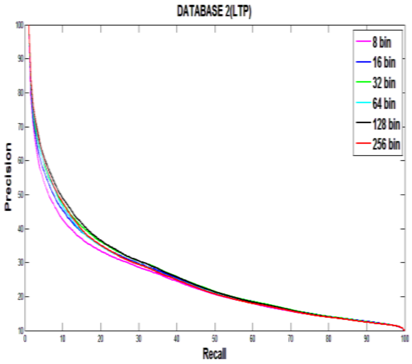


Fig. 7. Precision vs. recall Curve for LTP on DB2

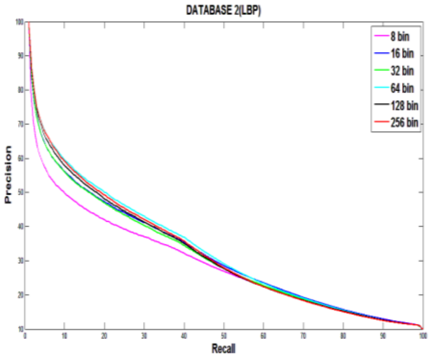


Fig. 8. Precision vs. recall Curve for LBP on DB2

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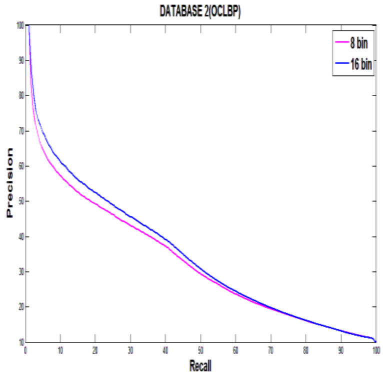


Fig. 9. Precision vs. recall Curve for OC-LBP on DB2

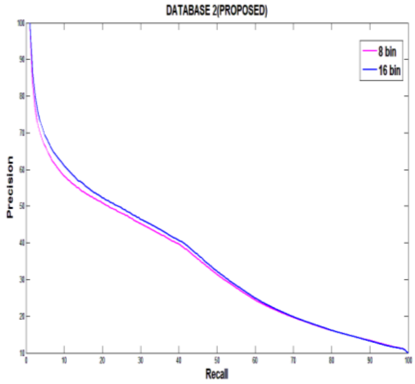


Fig. 10. Precision vs. recall Curve for Enhanced Orthogonal combination of Local Binary Pattern on DB2

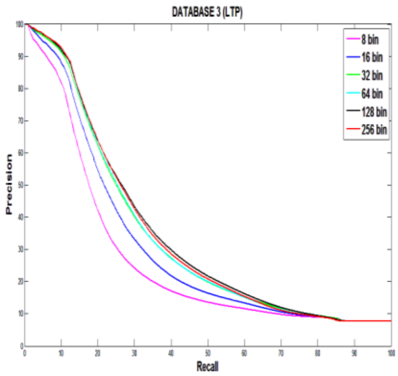


Fig. 11. Precision vs. recall Curve for LTP on DB3

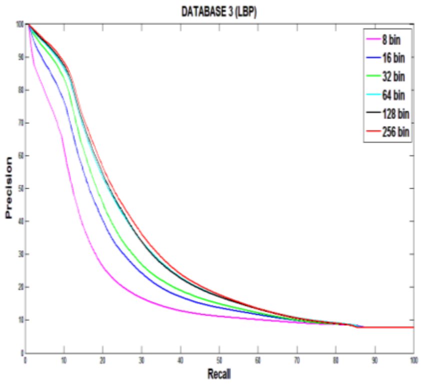


Fig. 12. Precision vs. recall Curve for LBP on DB3

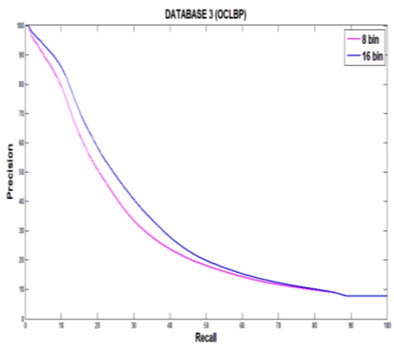


Fig. 13. Precision vs. recall Curve of OC-LBP on DB3

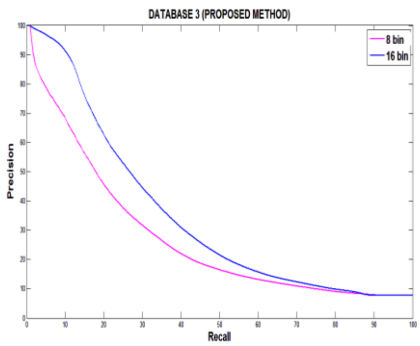


Fig. 14. Precision vs. recall Curve for Enhanced Orthogonal combination of Local Binary Pattern on DB3

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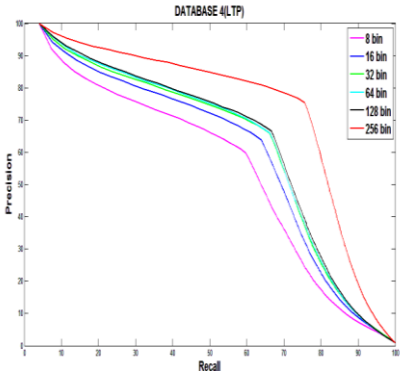


Fig. 15. Precision vs. recall Curve for LTP on DB4

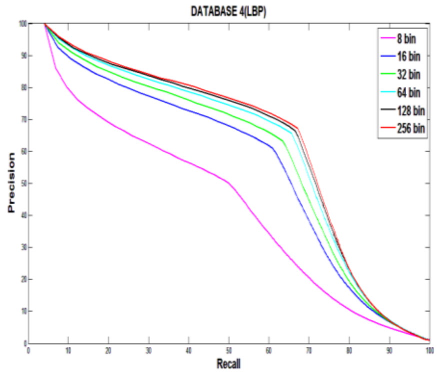


Fig. 16. Precision vs. recall Curve for LBP on DB4

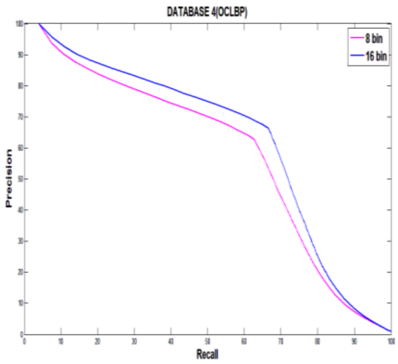


Fig. 17. Precision vs. recall Curve for OC-LBP on DB4

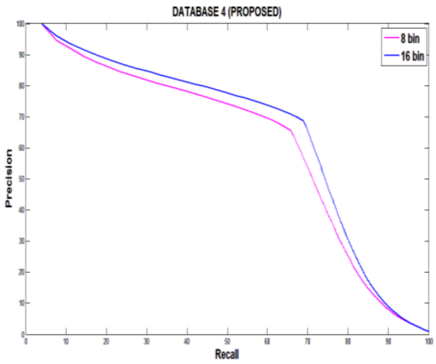


Fig. 18. Precision vs. recall Curve for Enhanced Orthogonal combination of Local Binary Pattern on DB4

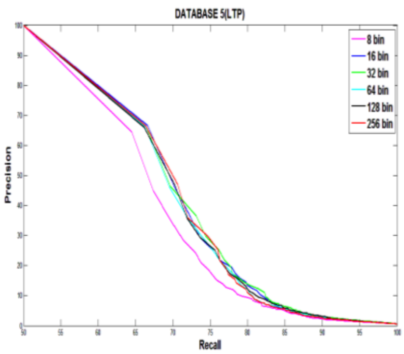


Fig. 19. Precision vs. recall Curve for LTP on DB5

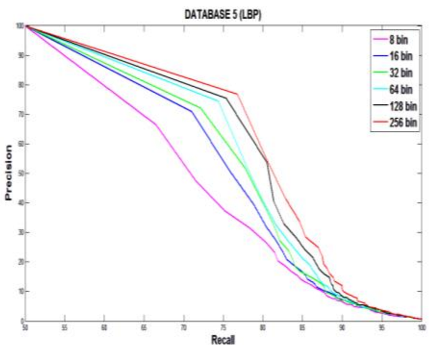


Fig. 20. Precision vs. recall Curve for LBP on DB5

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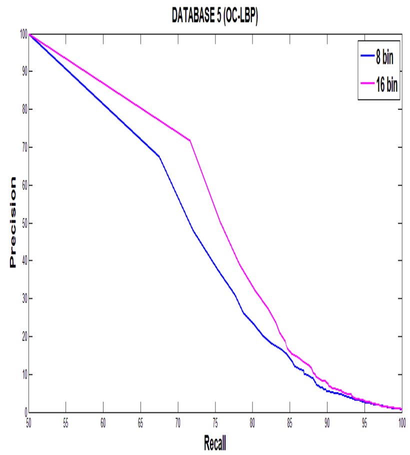


Fig. 21. Precision vs. recall Curve of OC-LBP on DB5

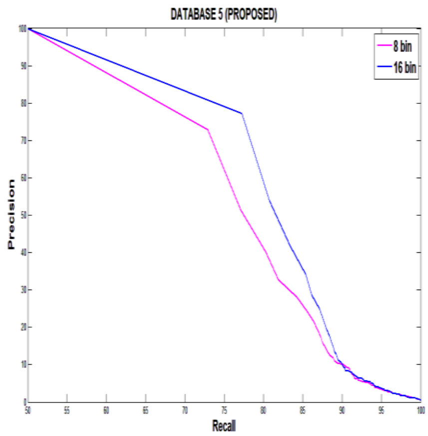


Fig. 22. Precision vs. recall Curve for Enhanced Orthogonal combination of Local Binary Pattern on DB5

Four methods applied on five different databases gives rise to twenty precision vs. recall curve. Fig. 3 through Fig. 22 shows the precision vs. recall curve for various methods applied on different datasets. For each method applied on a database, the bun size is varied and precision recall curve is obtained to find the optimal bin size for each method. In each of the Fig. 3 through Fig. 22, the bin size that results maximum area under the curve is the optimal bin size. For example, Fig. 3 presents the precision vs. recall graph for Local Ternary pattern applied on DB1 for varying bin size ranging from 8 to 256. Here, it is found that the area under the curve is maximum for bin size 128. Hence, in this case, the optimal bin size is considered to be the 128. Similar observations can be made from all other precision vs. recall graphs to conclude regarding the optimal bin size for each method.

Table 1. Average precision for each method at their optimal bin size

| Database | No. of classes | Texture descriptor | Optimal bin size | Average Recall |
|---|---|---|---|---|
| FVC2000 | 10 | LTP | 128 | 68.96 |
| | | LBP | 64 | 65.16 |
| | | OC-LBP | 8/16 | 68.59 |
| | | PROPOSED | 16 | 75.00 |
| Corel 1K | 10 | LTP | 32 | 35.24 |
| | | LBP | 256 | 42.31 |

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| | | | | |
|---|---|---|---|---|
| | | OC-LBP | 16 | 44.37 |
| | | PROPOSED | 16 | 45.41 |
| Brodatz rotated | 13 | LTP | 128 | 38.81 |
| | | LBP | 256 | 35.59 |
| | | OC-LBP | 16 | 37.86 |
| | | PROPOSED | 16 | 39.47 |
| Brodatz Non rotated | 107 | LTP | 256 | 69.99 |
| | | LBP | 256 | 70.25 |
| | | OC-LBP | 16 | 69.91 |
| | | PROPOSED | 16 | 72.07 |
| FEI | 200 | LTP | 256 | 70.62 |
| | | LBP | 256 | 80.62 |
| | | OC-LBP | 16 | 75.62 |
| | | PROPOSED | 16 | 80.75 |

Table 1 Shows the average precision obtained for all the methods at their optimal bin size. It is observed that the proposed descriptors wins over all other texture descriptors across all the databases used. A thorough investigation reveals that, optimal bin size is different for methods on different databases i.e. the optimal bin size is database specific. LBP is computationally efficient but has a high dimension and it is more sensitive towards the noise. LTP overcomes a drawback of LBP by reducing the sensitivity by its user-defined threshold value. However, computation of the threshold value is a difficult job as it varies from database to database. There is no automated technique to find the optimal threshold value which results best result. Another drawback of LTP observed is its dimension, which is twice the LBP (LBP of an upper window and LBP of a lower window). OC-LBP overcomes the dimensionality problem by reducing the dimensional size 8 times of LBP and 16 times of LTP. But its radius is limited to 1, i.e. it considers 8 neighboring pixels, whereas in our proposed work we are considering 5x5 window i.e. pixels at radius 1 and 2. This helps to extract more information about

neighboring pixels which in turn able to provide a better result. As we have considered 4 pixels at a time to extract a window (24 windows /4 i.e. 6 windows), as a result, it gives the feature of an image having dimension value 96, which solves the dimensionality problem to a greater extend, as well as provide better result than all the previously proposed techniques irrespective of database.

## 6. CONCLUSION

With the advent of digital media, managing huge amount of images generated every day becomes a challenging task. The information stored with these images created everyday (particularly in medical domain) can be exploited for gathering or inferring new information. Content based image retrieval is a technique that tries to retrieve images with similar contents against a given input image. The major challenge for the design of CBIR system is to handcraft the feature that can best describe the content of the images with high inter-class and low intra-class boundary in the feature space. The work presented in this paper is an effort to design a novel texture feature. A novel texture feature called Enhanced Orthogonal Combination of Local Binary Pattern (EOC-LBP) is proposed that achieves better retrieval performance as compared to other competing texture feature extraction methods. The feature vector proposed is low in dimension which makes the computation easy and practical for real life applications. The effectiveness of the proposed descriptor is evaluated on five popular publicly available benchmark databases with varied orientation and complexities. The proposed method is found to be efficient as compared to other competing methods across all the databases considered.

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