Extended Adjacent Local Binary Pattern for Texture Based Image Retrieval

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Abstract. In this paper, a novel local texture descriptor named Extended Adjacent Local Binary Pattern (EALBP) for images is proposed. In this method, each image is subdivided into local regions of size 4*4. For each local region, 13-bits of binary value are generated by comparing the adjacent neighborhood pixel in three phases. In the first phase, the inner 2x2 region from the local region is considered and each pixel is compared with the adjacent pixel which results in 4 bits. In the second phase, the outer region from the local region is considered and the diagonal pixels present in the 4 directions such as 45°, 135°, 225° and 315° are considered. The pixels values present in each direction are compared with the adjacent neighborhood pixels in the outer region and this comparison results in 4 bits. In the third phase, the pixels except the diagonal pixel values in the outer region are compared against each other and this result in 4 bit binary value. Finally, the mean of the local region is compared with the mean of the input image which results in one bit binary value. The 13-bit binary value of each local region is thus formed and the above steps are repeated for the entire image. The experimental results show that the proposed method could characterize the texture property of the image efficiently when compared with the existing methods on two databases.

1. Introduction
Nowadays, in the most of the real time applications, it is necessary to work with large amounts of growing visual and multimedia data and at the same time, the number of images and video files on the web are quite big and is still rising very rapidly. Searching through this data is absolutely vital. So, there is a high demand on the tools for image retrieving, which are based on visual information, rather than simple text-based queries [1-4]. Content-Based Image Retrieval (CBIR) consists of retrieving the most visually similar images to a given query image from a database or group of image files [5, 6].

The CBIR systems [7] depend heavily on feature extraction. Broadly, there are two categories of feature representation: (i) global or holistic approach and (ii) local approach. A global approach extracts features from the whole image by ignoring the local characteristics and spatial relationship. The global methods do
not overcome the issues related to occlusion and local characteristics of image shape. These issues are addressed by the local feature extraction methods which extract features from local regions of an image.

In this paper, we propose a methodology for extracting the patterns using extended adjacent local binary pattern for images.

2. Related Works
In this part, we present an overview of the closely related works which concern with Local Binary Pattern (LBP) like methods designed for the images to utilize the benefits of adjacent neighboring pixels.

2.1 LBP and Local Ternary Pattern (LTP)
The LBP [8] is introduced for texture classification in which the pixels in the local region are compared with the neighboring pixels in the clockwise direction. This comparison results in binary value 0 or 1. The LTP [9] uses ternary values for texture classification.

2.2 MultiSpectral Local Binary Pattern (MSLBP)
Mäenpää et al. [8] use three channels of a color image in the RGB color space and six pairs of the opponent colors.

\[ \theta (i, j) (x, y) = \tan^{-1} \lambda (i, j) (x, y) \]  

The images \( \lambda (i, j) (x, y) \) are calculated between R and G, G and B and B and R components.

2.3 Orthogonal Combination of Local Binary Pattern (OC-LBP)
The OC-LBP operator [9] reduces the dimensionality of the LBP operator. It consists of two operators OC-LBP1 and OC-LBP2, which are derived by splitting 8-neighborhood pixels into 2 sets of neighborhoods each comprising of 4 pixels. The first set contains the four horizontal and vertical neighbors of the center pixel and the second set contains the 4 diagonal neighbors. Since each set contains 4 pixels, the total number of patterns in each set is 16.

3. Framework of the Proposed Method
The input image is subjected to the proposed method. The proposed method extracts the texture features and the feature vector is built. The histogram is constructed. The similarity measure i.e. Euclidean distance measure is used and the relevant images are retrieved from the database images. The flow diagram of the proposed method is shown in the Figure 1.
4. Proposed EALBP Method

In the above stated algorithms, the computational power and time required is immensely high. So, we propose a modified algorithm in which the local neighborhood size is taken as a 4x4 region and hence we reduce the time required for computation is reduced. In order to increase the accuracy, a binary pattern for the local region is constructed in four steps. These four steps have to be repeated for the entire image to get an EALBP representation which is used for image retrieval.

**STEP 1:**
Take the local region as a 4x4 matrix as shown in the Figure (2). Take the inner four pixels say g1, g2, g3 and g4; compare the pixels with each other to construct a 4-bit binary string. In order to construct take the four pixels and compare them in a circular manner as shown in the Figure (2). If the pixel value is greater than or equal to the comparing pixel in clockwise direction then the binary value 1 is considered else 0 is considered. This step results in a 4-bit binary string. The formulation for the 4-bit binary string is represented as:

\[
\text{Binary Pattern}_i = \sum_{i=0}^{3}s(g, g_{(i+1\mod 4)}) \times 2^i 
\]

\[
s(x, y) = \begin{cases} 
1, & \text{if } (x \geq y) \\
0, & \text{otherwise} 
\end{cases} 
\]
STEP 2:
Consider the outer most pixels present in 4 directions such as 45°, 135°, 225° and 315° as shown in the Figure (3) and compare it with adjacent neighborhood pixels. The pixel value ‘a3’ is compared with its adjacent neighborhood pixels ‘b3’ and ‘c3’ as in the Figure (3). The binary value is formulated as:

\[
Binary\ Pattern_2 = \sum_{i=4}^{7} s(a_i, b_i, c_i) \times 2^i
\]  \hspace{1cm} (4)

\[
s(x, y, z)=\begin{cases} 
1, & \text{if } (x \geq y) \& \& (x \geq z) \\
0, & \text{Otherwise}
\end{cases}
\]  \hspace{1cm} (5)

Repeat the comparison for all the corner pixels. It results in a 4-bit binary string.

**Figure 2.** Representation of adjacent pixel comparison in inner region

**STEP 3:**
In the third step, the pixels in the outer region except the diagonal pixel values are taken for comparison as shown in the Figure (4). Here, compare the two neighboring pixels to the 4 cornering pixels. Compare the pixels ‘x0’ and ‘x8’; if x0 is greater than x8 then assign 1 otherwise assign 0. In this way the comparisons

**Figure 3.** Representation of adjacent pixel comparison on four sides in outer region.
are done for the remaining three adjacent pixels. This comparison results in a 4-bit binary string. The step 3 is formulated as:

$$Binary\ Pattern_i = \sum_{j=0, j \neq i}^{3} s(x_j, y_j) * 2^j$$ \hspace{1cm} (6)

$$s(x, y) = \begin{cases} 1, & \text{if } x \geq y \\ 0, & \text{otherwise} \end{cases}$$ \hspace{1cm} (7)

**Figure 4.** Representation of adjacent pixel comparison inwards in outer region

**STEP 4:**
Compare the mean of the local region with the mean of the input image. If the mean of local region is greater, then assign 1 else assign 0. From this a single bit is arrived. Thus, from these steps a 13-bit binary value is got which is then converted into decimal that represents the proposed EALBP label.

$$Binary\ Pattern_4 = s(x, y) * 2^i$$ \hspace{1cm} (8)

$$s(x, y) = \begin{cases} 1, & \text{mean(local\ region)} \geq \text{mean(input\ image)} \\ 0, & \text{Otherwise} \end{cases}$$ \hspace{1cm} (9)

$$EALBP\ Label = Binary\ Pattern_1 + Binary\ Pattern_2 + Binary\ Pattern_3 + Binary\ Pattern_4$$ \hspace{1cm} (10)

**STEP 5:**
All the four steps are repeated for the entire image.

**5. Database Description**
The two databases considered are Brodatz [14] and virus [15] databases. The Brodatz database consists of 112 texture images. Each image is subdivided into 25 sub images; resulting in a total of 2800 (112*25) images. The Virus database contains 15 categories of virus images resulting in 1500 images.
6. Experimental Results

The performance of the proposed method is compared with the existing methods on two databases and the performance analysis is presented below:

6.1 Performance analysis based on Precision and Recall on Brodatz Database Images

Table 1 and Table 2 shows the precision and recall of the proposed and existing methods such as LBP, LTP, MSLBP and OC-LBP. It is proved that the proposed method performs better than the existing methods. The precision of the proposed method at each step of retrieval of images from the database is measured. The retrieval of images from the database starts from 25 and goes up to 55 with a slight increase of 5 at each step. The precision is initially presented from retrieving 25 images; as there are 25 matching images present in the database for a given query image. It is known that the precision decreases as on increasing the number of retrieving images.

The precision of the existing methods varies between 70.13% and 86.45%. The precision of LBP is decreased when compared with other existing methods. It is clear that the extension of LBP based methods attains higher precision than LBP. Among the four existing methods, OC-LBP attains higher precision. The proposed method shows 3.78% increase in precision than OC-LBP.

The recall of the existing and proposed methods is measured while retrieving 25 and 55 images from the database. The recall of the proposed and existing methods decreases till 45 number of images being retrieved; after which the recall remains stable. The recall of the proposed EALBP method is higher than the other four methods.

Table 1. Experimental results of Proposed EALBP and existing methods based on Precision on Brodatz Database

| Methods  | Number of Images retrieved |
|----------|---------------------------|
|          | 25 | 30 | 35 | 40 | 45 | 50 |
| LBP      | 70.13% | 61.57% | 56.09% | 49.74% | 44.84% | 41.20% |
| LTP      | 73.76% | 64.27% | 57.09% | 50.24% | 46.91% | 42.14% |
| MSLBP    | 77.79% | 66.93% | 59.31% | 52.25% | 47.51% | 43.58% |
| OC-LBP   | 86.45% | 72.77% | 64.09% | 57.23% | 50.67% | 46.14% |
| Proposed EALBP | 90.23% | 77.97% | 67.69% | 59.80% | 53.42% | 48.26% |
Table 2. Experimental results of Proposed EALBP and existing methods based on Recall on Brodatz Database

| Methods   | Number of Images retrieved |
|-----------|----------------------------|
|           | 25 | 30 | 35 | 40 | 45 | 50 |
| LBP       | 70.13% | 73.88% | 78.52% | 79.58% | 80.72% | 82.40% |
| LTP       | 73.76% | 77.12% | 79.92% | 80.38% | 84.44% | 84.28% |
| MSLBP     | 77.79% | 80.32% | 83.04% | 83.60% | 85.52% | 87.16% |
| OC-LBP    | 86.45% | 87.32% | 89.72% | 91.57% | 91.20% | 92.28% |
| Proposed EALBP | 90.23% | 93.56% | 94.76% | 95.68% | 96.16% | 96.52% |

6.2 Output Image

The output images for the proposed EALBP method on Brodatz database images are shown in the Figure 5.

![Output Images](image.png)

Figure 5. Output images where (a) is the input image and (b) is the proposed EALBP image

6.3 Performance analysis based on Precision and Recall on Virus Database Images

Table 3 and Table 4 presents the precision and recall of both the existing and proposed methods on Virus database based on number of images retrieved from the database. The precision and recall are measured by retrieving between 100 and 150 images from the database. For a given input image, the maximum number of matching images to that input image is hundred. Hence, the retrieval begins from 100 images. The precision of both the existing and proposed methods decreases until 130 and remains stable later. The average precision of the existing methods such as LBP, LTP, MSLBP, OC-LBP is 80.07%.

In terms of precision, LTP performs better than LBP; MSLBP performs better than LTP. The OC-LBP attains higher precision over other existing methods. The proposed EALBP attains a gain of 3.78% over the existing OC-LBP.
Table 3. Experimental results of Proposed EALBP and existing methods based on Precision on Virus Database

| Methods   | Number of Images retrieved |
|-----------|----------------------------|
|           | 100 | 110 | 120 | 130 | 140 | 150 |
| LBP       | 74.28% | 71.75% | 66.96% | 63.46% | 60.64% | 57.16% |
| LTP       | 76.76% | 72.15% | 68.73% | 64.38% | 60.93% | 57.85% |
| MSLBP     | 80.79% | 75.01% | 70.43% | 65.17% | 61.95% | 59.02% |
| OC-LBP    | 88.45% | 82.23% | 77.05% | 70.72% | 66.34% | 63.13% |
| Proposed EALBP | 92.23% | 86.08% | 79.83% | 74.13% | 68.96% | 64.57% |

The recall of the existing and proposed methods on retrieval of images between 100 and 150 images is measured. The recall of the existing methods ranges between 74.28% and 88.45% while retrieving 100 number of relevant images from the database. Similarly, the recall of the existing methods on retrieving 150 images from the database varies between 57.16% and 63.13%. The recall of the proposed method have higher retrieval rate than the existing methods.

Table 4. Experimental results of Proposed EALBP and existing methods based on Recall on Virus Database

| Methods   | Number of Images retrieved |
|-----------|----------------------------|
|           | 100 | 110 | 120 | 130 | 140 | 150 |
| LBP       | 74.28% | 78.92% | 80.35% | 82.50% | 84.89% | 85.74% |
| LTP       | 76.76% | 79.37% | 82.47% | 83.69% | 85.30% | 86.78% |
| MSLBP     | 80.79% | 82.51% | 84.52% | 84.72% | 86.73% | 88.53% |
| OC-LBP    | 88.45% | 90.45% | 92.46% | 91.93% | 92.87% | 94.70% |
| Proposed EALBP | 92.23% | 94.69% | 95.80% | 96.37% | 96.54% | 96.85% |

7. Conclusion
Thus, a novel technique based on local binary pattern for image retrieval has been introduced with improved retrieval rate. The proposed EALBP method was compared with the existing methods such as LBP, LTP, MSLBP and OC-LBP. The performance metrics used for comparing the existing and proposed method is precision and recall. The experimental results depicts that the proposed EALBP method could achieve higher gain in performance than the existing methods on Brodatz and Virus database images. In future, the proposed
method can be extended in a way that suits any real time application such as fruits classification, tea leaves classification, etc.

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