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Content-Based Image Retrieval Using Extended Local Tetra Patterns

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Abstract: In this modern world, finding the desired image from huge databases has been a vital problem. Content Based Image Retrieval is an efficient method to do this. Many textures based CBIR methods have been proposed so far, for better and efficient image retrieval. We aim to give a better image retrieval method by extending the Local Tetra Patterns (LTrP) for CBIR using texture classification by using extended version of LTrP. These features give additional information about the color and rotational invariance. So an improvement in the efficiency of image retrieval using CBIR is expected.

Keywords— Local binary Patterns, Content Based Image Retrieval (CBIR), Local Ternary Patterns (LTP), Local Tetra Patterns (LTrP), Extended Local Tetra Pattern (ELTrP), Histogram Equalization

I. INTRODUCTION

The unstable development of advanced libraries because of Web cameras, computerized cameras, and cell phones furnished with such gadgets is making the database the board by human explanation an amazingly monotonous and awkward errand [1, 2]. Along these lines, there exists a requirement for building up a productive way to deal with look for the ideal pictures shape enormous databases. Content Based Image Retrieval (CBIR) is one of the received answers for the issue.[4, 5, 10]

Content Based Image Retrieval (CBIR) has turned into an imperative region for individuals to search and retrieve data. CBIR framework retrieves the similar images from the image database for the given question images, by matching the feature vector of questions image and images in the database [3]. The CBIR uses visual substance of a picture, for example, color shading, texture, shape, faces, spatial design, and so on., to speak to and list the picture database. These highlights can be additionally named general highlights, for example, shading, surface, and shape, and space explicit highlights, for example, human faces, fingerprints, and so on [6, 11, 12].

In today's time texture analysis has been one of the most significant are for research used in computer vision and pattern recognition [8]. Texture Analysis is broadly justified into texture classification and texture segmentation. Texture classification is used to determine to which of a finite number of physically defined classes a homogeneous texture region belongs. The Texture Classification is done by using Discrete Wavelet Transform (DWT), Be that as it may, the DWT can extract just three-directional (Horizontal, vertical, and slanting) information from a picture. To address this directional limitation, Gabor transform (GT) is proposed for texture image retrieval [15]. The idea of local descriptors is one of the strategies for statistical method for texture classification.

The rest of the paper is organized as follows. Section 2 presents a brief review of studies related to techniques of local patterns, whereas Section 3 explains the details of our proposed CBIR system descriptor ELTrP. Section 4 is the empirical section wherein experimental results and their comparative evaluations are reported. Finally, Section 5 concludes our work.

II. RELATED WORK

Some of the famous Local Descriptors shown given below, which have been proposed:

i. LBP-Local Binary Patterns
ii. LDP-Local Derivative Patterns
iii. LTP-Local Ternary Patterns
iv. LTrP-Local Tetra Patterns (LTrP)

These local descriptors utilize the neighboring pixel information to design the binary patterns, which can be further useful for image recovery. The Local Binary Patterns (LBP) [13] was the first kind of local pattern proposed for texture feature extraction. It became a great success in the field of texture classification and retrieval [9]. Various extensions of the LBP have been proposed which are proved to be a greater success than the normal LBP. The LBP operator on facial expression analysis and recognition is successfully reported by S. Banerji *et al.*[9]. Various extensions of Local Binary Patterns like the variance of LBP with global matching, Completed LBPs, joint distribution of local patterns with Gaussian mixture etc. have been proposed for rotational invariant texture classification. Zhang et al. accompanies Local Derivative Patterns (LDPs) [17], which is a famous technique for face recognition, where they examine the LBP as non-directional first-order local patterns, arrange from the 1^{st}-order derivatives and expanded a similar methodology for n^{th} order LDPs. This was the first local pattern descriptor which considered the derivatives for texture classification. The variants of the LBP and the LDP in the open literature can't enough manage the scope of appearance varieties that usually happen in unconstrained natural pictures because of brightening, present, outward appearance, maturing, halfway impediments, and so on. So as to address this issue, the LTP[14] has been presented for face acknowledgment under various lighting conditions. The LTP use the concept of thresholds for obtaining the information from the patterns. The LBP, LDP and LTP extricate the data dependent on the conveyance of edges, which are coded utilizing just two headings (positive or negative direction). This drawback motivated in the development of a new pattern descriptor called Local Tetra Patterns (LTrP) [16]. In LTrP, along with the magnitude and intensity of the neighboring pixels, also focuses on the connection between the direction of the central pixel and its neighboring pixels. The LTrP can encode images with four particular values as it can extricate more point-by-point data than LBP, LTP and LDP. The LBP and the LTP encode the connection between the gray intensities of the center pixel and its neighbors though the LTrP encodes the connection between the center pixel and its neighbors dependent on directions that are determined with the assistance of $(n-1)^{th}$-order derivatives. This meant that more information about the neighboring pixels resulted in a better texture classification and therefore a better CBIR. This is evident from the fact that in LBP, only the neighbors are considered in forming the patterns. In LDP, even their derivatives are considered while from LTP, two different LBPs can be drawn out, which in turn suggests that it is nearly twice as efficient as LBP. The LTrP is able to encode the images using four distinct values and the computational cost of it is less when compared to the other pattern descriptors. In the LTrP, the horizontal and vertical pixels of the neighbors have been used for derivative calculation. This resulted in a total of 13 Local Binary Patterns (LBPs) from a single LTrP. Therefore, it is 13 times more informative than the LBP. However, in all these patterns, only textural information has been used. The use of other features can improve the efficiency of CBIR.

III. METHODOLOGY

The ideas from the previous local pattern have been adopted to propose the Extended Local Tetra Pattern (ELTrP). For any image, with as the gray value of the center pixel and as the gray value of the neighbouring pixels, the I-order derivatives along $0°, 45°$ & $90°$ directions for any pixel are denoted as $I_\theta^1(g_p)|\theta = 0°, 45°, 90°$.

If $0°, 45°, 90°$ denote the horizontal, diagonal and vertical neighborhoods of respectively, then the I^{th}-order derivatives at can be written as Eqn.(1).

$$I_{0°}^1(g_c) = I(g_h) - I(g_c)$$
$$I_{45°}^1(g_c) = I(g_d) - I(g_c) \quad \ldots\ldots\ldots(1)$$
$$I_{90°}^1(g_c) = I(g_v) - I(g_c)$$

The direction of center pixel is denoted by $I_{Dir}^1(g_c)$, is calculated as Eqn. (2)

$$I_{Dir}^1(g_c) = \begin{cases} 1, if\ I_{0°}^1(g_c) \geq 0, I_{45°}^1(g_c) \geq 0, I_{90°}^1(g_c) \geq 0 \\ 2, if\ I_{0°}^1(g_c) \geq 0, I_{45°}^1(g_c) < 0, I_{90°}^1(g_c) \geq 0 \\ 3, if\ I_{0°}^1(g_c) < 0, I_{45°}^1(g_c) \geq 0, I_{90°}^1(g_c) \geq 0 \\ 4, if\ I_{0°}^1(g_c) < 0, I_{45°}^1(g_c) < 0, I_{90°}^1(g_c) \geq 0 \\ 5, if\ I_{0°}^1(g_c) < 0, I_{45°}^1(g_c) \geq 0, I_{90°}^1(g_c) < 0 \\ 6, if\ I_{0°}^1(g_c) < 0, I_{45°}^1(g_c) < 0, I_{90°}^1(g_c) < 0 \\ 7, if\ I_{0°}^1(g_c) \geq 0, I_{45°}^1(g_c) \geq 0, I_{90°}^1(g_c) < 0 \\ 8, if\ I_{0°}^1(g_c) \geq 0, I_{45°}^1(g_c) < 0, I_{90°}^1(g_c) < 0 \end{cases} \ldots(2)$$

The calculation of second-order patterns $ELTrP^2(gc)$ of the image are defined by Eqn.(3) as follows.

$$ELTrP^2(g_c) = \{f_1(I_{Dir}^1(g_c), I_{Dir}^1(g_{g1})), .. f_1(I_{Dir}^1(g_c), I_{Dir}^1(g_{g8}))\} \ldots\ldots (3)$$

Where, f_1 is defined by Eqn.(4)

$$f_1(x,y) = \begin{cases} 0, & if\ x = y \\ I_{Dir}^1(g_p), & otherwise \end{cases} \ldots\ldots\ldots\ldots(4)$$

Figure 1 shows an example for calculating the direction of the centre pixel. In the illustrated example, the direction of centre pixel is 4. If the direction of the neighbourhood pixel is 4 then the ELTrP is coded with 0. If the directions are different then the ELTrP is coded with the direction of the neighbourhood. From Figure 2, for the first neighbourhood pixel 4, the direction is 3 which is different from that of the direction of the center pixel and hence the ELTrP is coded with the direction of neighbourhood pixel itself which is 3 in this case. Similarly, for the neighbourhood pixel 5, the direction is 8 which is different from that of the direction of the center pixel and hence the ELTrP is coded with the direction of neighbourhood pixel itself which is 8 in this case. Similarly, the remaining bits of the ELTrP are coded resulting in 3 8 6 8 7 5 1 6.

After coding the ELTrP, it is separated it into seven binary patterns as follows. If the direction of the center pixel I_{Dir}^{1} obtained using Eqn. (2) is 1, then the pattern is segregated into seven patterns for directions 2, 3, ...8 as

$$ELTrP^{2}_{Dir=\emptyset} = \sum_{p=1}^{P} 2^{p-1} \times f_2(ELTrP^{2}(g_c))\ldots(5)$$

Where, f_2 is defined as

$$f_2(x) = \begin{cases} 1, & if\ ELTrP^{2}(g_c) = \emptyset \\ 0, & otherwise \end{cases} \ldots\ldots\ldots.(6)$$

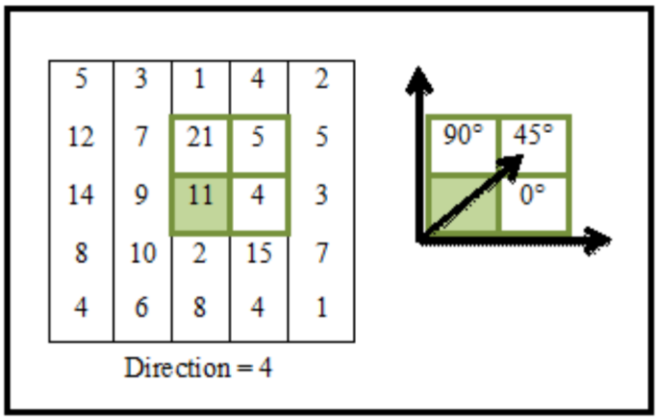


Fig-1: Direction of center pixel. Green color shaded represents the center pixel.

Eqn. (5) is repeated for the remaining seven directions resulting in 56 binary patterns. The gathering is done, as dependent on directions. For first direction, the pattern is assembled dependent on the rest of the directions from 2 to 8. The main example is gotten by putting 1 in-place of ELTrP esteem is 2, otherwise 0 for all other values, i.e., 0 0 0 0 0 0 0 0. So also, the 2nd pattern is gotten by purring 1 in place where tetra design esteem is 3, otherwise 0 for different numbers, i.e., 1 0 0 0 0 0 0 0. Likewise the rest of the example are 0 0 0 0 0 0 0 0, 0 0 0 0 0 1 0 0, 0 0 1 0 0 0 0 1, 0 0 0 0 1 0 0 0, 0 1 0 1 0 0 0 0.

In same fashion, tetra designs for central pixels having directions 2 to 8 are figured. In this way for eight ELTrPs, 56 paired of binaries values are acquired. The 57th pattern is gotten from the magnitude of the first-order derivatives. Using the I-order derivative in horizontal and vertical directions of the center pixel, the magnitude is calculated. In addition to the 56 binary patterns, an additional magnitude pattern is added to the feature vector. The magnitude pattern (is calculated using the magnitudes of horizontal, diagonal and vertical I-order derivatives using Eqn.(1) as Eqn.(7)

$$M_1(g_p) = \sqrt{(I^{1}_{0^\circ}(g_p))^2 + (I^{1}_{45^\circ}(g_p))^2 + (I^{1}_{90^\circ}(g_p))^2}\ldots(7)$$

The Magnitude Pattern MP of I-order derivatives is defined by Eqn.(8) and (9)

$$MP = \sum_{p=1}^{P} 2^{p-1} \times f_3(M_1(g_p) - M_1(g_c))\ldots\ldots(8)$$

Where, f_3 is define as

$$f_3(x,y) = \begin{cases} 1, & if\ x - y \geq 0 \\ 0, & otherwise \end{cases} \ldots\ldots\ldots.(9)$$

In the similar manner, the magnitudes of the neighbourhood pixels are calculated. For the first neighbourhood pixel 4, the magnitude is 1.73, which is less than the magnitude of the center pixel. Hence, the magnitude pattern is coded with 0. Similarly the magnitude pattern is coded based on other neighbourhood pixels resulting in 0 0 0 1 0 0 1 1. The 56 pattern (8x7) obtained by grouping the ELTrP, along with the magnitude pattern adds to a total of 57 patterns. The histogram of these 57 patterns constitutes the feature vector of the image.

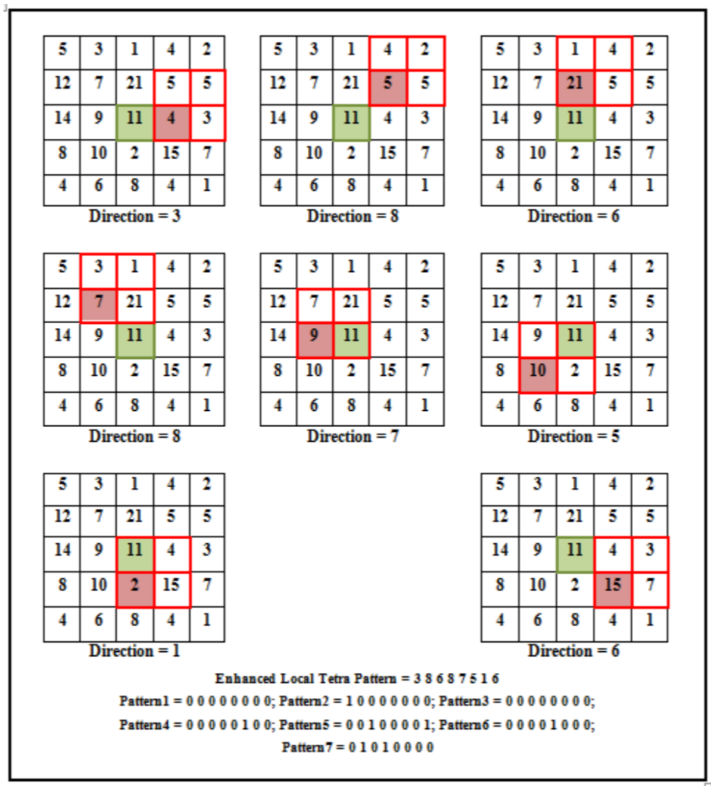


Fig-2: Calculation of ELTrP. Green color shaded represents the center pixel: red color shaded represents the neighbourhood pixels.

Framework of ELTrP

Figure 3 shows the flow chart of the proposed image retrieval algorithm using ELTrP. The algorithm for the proposed framework is as follows. The input is the query image and the output is the retrieval result. Figure 3.5 represent the flowchart of proposed image retrieval system

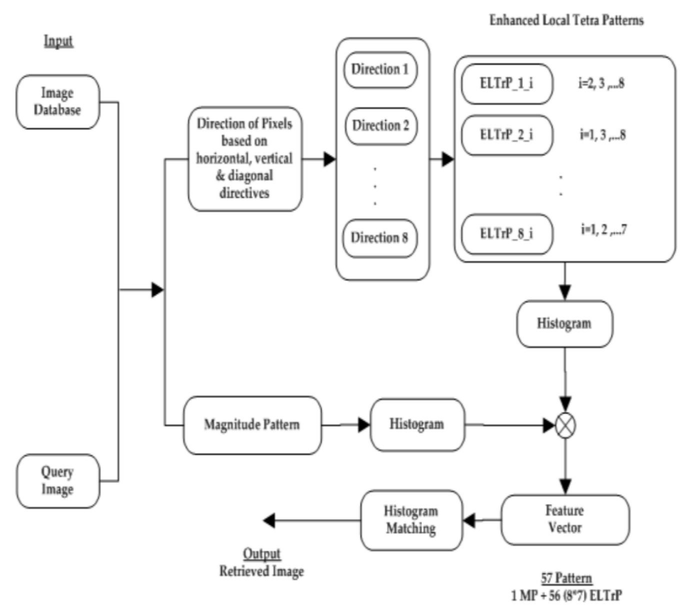


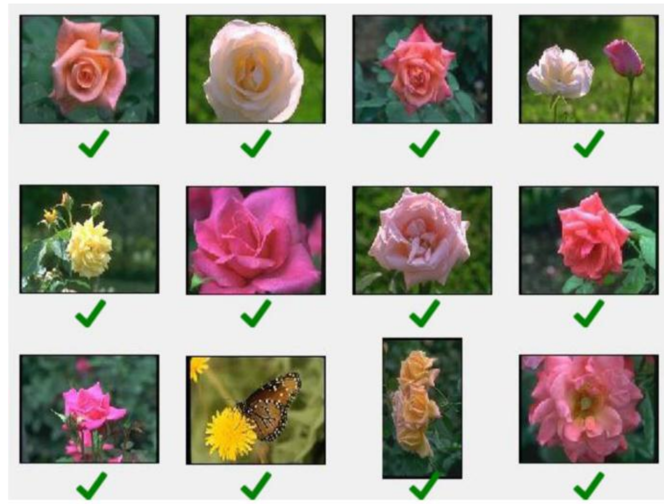
Fig-3. Flowchart of proposed image retrieval system.

Algorithm

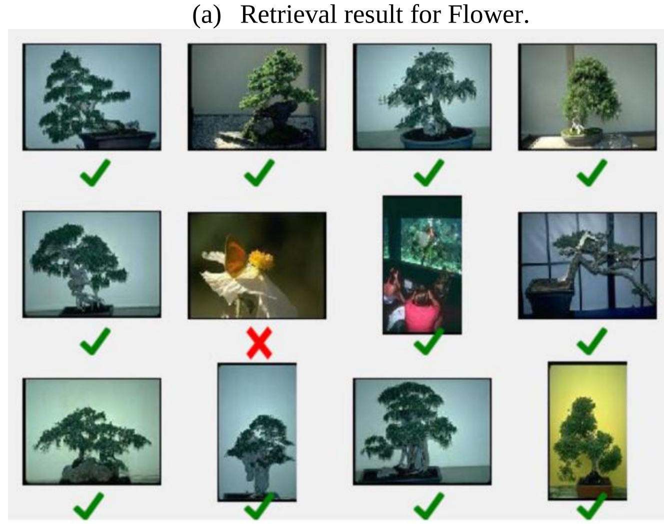
1. Start with query image and alter it into equivalent grayscale values image.
2. Calculate the horizontal, vertical and diagonal directional first order derivative.
3. Ascertain the direction of each pixel
4. Partition the binary patterns into eight sections dependent on the center pixel's directions and find the improved tetra patterns for query image.
5. Separate then into seven patterns of binary (Total 56 = 8x7 examples)
6. Figure out the histogram for each of the 56 pattern (56 ELTrP)
7. Ascertain the magnitude pattern
8. Ascertain the histogram for magnitude pattern (1 MP)
9. Consolidate the histograms (56 ELTrP + 1 MP) and construct the feature vector for query image.
10. Compare the inquiry image feature vector with the feature vectors of images in the database
11. Retrieve the images dependent on the best matches.

IV. RESULTS AND DISCUSSION

In this experiment, we used the Corel0k Image Database, which consists of total 31 types of images, each type having 100 of images. Some of the types are House, Beach, Heritage, Building, Heritage, Copter, Ocean, Lamb, Goat, Paris, London, Elephant, Tiger, Ocean, Dog, Buttery, Ape, Fighter Plane, Balloons, Sunset, Bird, Horse, Tree, Fireworks, and Flowers etc. We select randomly 4 type among this 100 types and then selected one images from each of the selected types. These images has used as query image and search results are given below:



(a) Retrieval result for Flower.

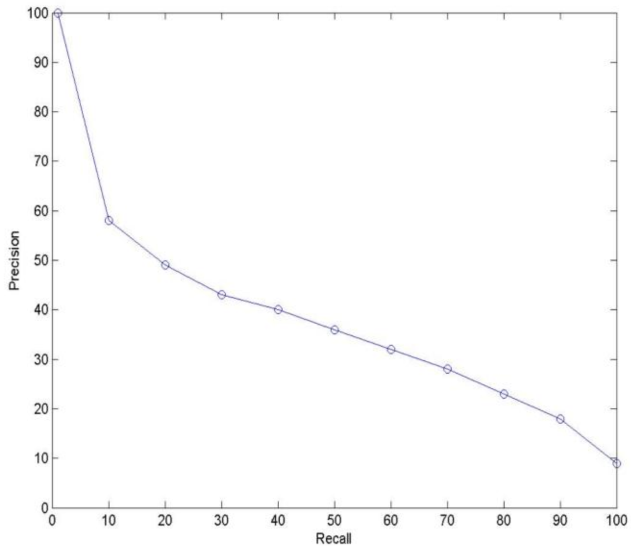


(b) Retrieval result for Bonshai.

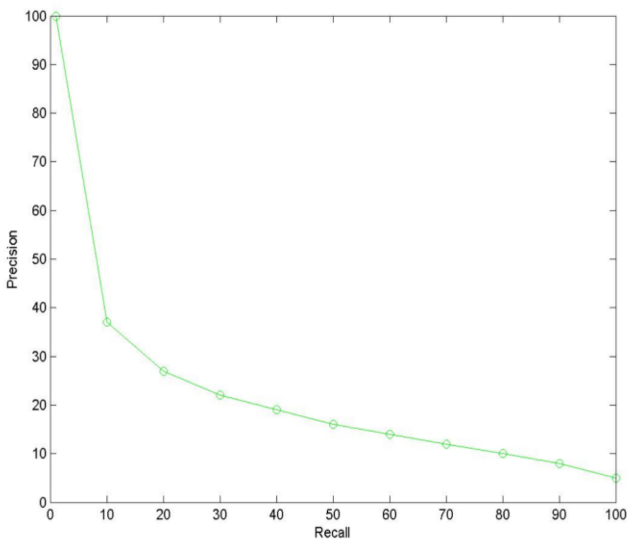
Fig-4: Retrieval results for random images

As we can see from the Figure 4(a), first 12 images for Flower as query image is retrieved correctly. On the other hand result for Bonshai, Figure 4(b), first five images are retrieved correctly and 6^{th} image is a wrong one and the later ones are retrieved correctly.

In the Figure 5, the precision vs recall curve for each of the image type shown above. Clearly, precision of type Flower is better than other types. It is because, all the images in this category have almost same background, mostly blurred green area, and so the images are retrieved correctly.



(a) For Flower



(b) For Bonshai.
Fig-5: Precision vs Recall curve

If we compare the results to each other category, which is a precision vs recall curve, it is shown that flowers give the best result whereas Bonshai give less result. As other images like sunset consist of shade, which responds less quickly to color gradient calculation, these images give a dissatisfactory result.

The results are considered to be better if average values of precision and recall are high. From Table 1, it can observed that the ELTrP feature vector length is very high which gives us the better results in term of precision and recall. From Table II, it outperform the LBP by 8.3%, LTP by 5.6%, LDP 8.4%, and LTrP by 2.6% on corel10k database.

Table 1 feature vector length of query inage using various methods

Method	Feature Vector Length
LBP	59
LTP	2 x 59
LDP	4 x 59
LTrP	13 x 59
ELTrP	57 x 59

Table 2 Average Retrival Rate (Arr) For the Classes of Corel10k Image Database

Method	ARR (%)
LBP	79.97
LTP	82.51
LDP	79.91
LTrP	85.30
ELTrP	88.27

V. CONCLUSION AND FUTURE SCOPE

In this paper, we proposed a feature using local patterns to retrieve image from a database. The feature is extracted using the idea of a texture based feature descriptor Extended Local Tetra Pattern (ELTrP), used to retrieve gray scale image. Local patterns for color image are more complex than gray scale image as each of its pixel have three values for three channel. We extended the idea of computing local patterns for color image as it was for gray scale image. We used the idea of Local Tetra Pattern (LTrP) for this purpose. ELTrP extract feature from gray scale image efficiently and ELTrP perform well. This method gives a satisfactory result.

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