Content-Based Image Retrieval using Enhanced Local Tetra Pattern

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Abstract

The content-based image retrieval system pays attention to color, texture, pattern, shape, faces, etc. In this paper the pattern is taken as the key feature for image retrieval. The standard Local Binary Pattern (LBP) and Local Ternary Pattern (LTP) encode the relationship between the referenced pixel and its surrounding neighbors by computing gray-level difference. The Local Derivative Pattern (LDP) encodes the relationship between the (n-1) order derivatives of the center pixel and its neighbors separately. Local Tetra Pattern (LTrP) represents the image by the directional information. It determines the relationship in terms of the intensity and directional information between the referenced pixels and their neighbors. As the directions used are only four, the image is encoded using only four distinct values. In this paper, eight directions are used for increasing the effectiveness of image retrieval. The Enhanced LTrP (ELTrP) takes in to account the horizontal, vertical and the diagonal pixels for derivative calculation thereby improving the effectiveness of the image retrieval. The effectiveness of the image retrieval is measured in terms of Average Retrieval Rate (ARR). The ARR with the proposed ELTrP is increased up to 12% when compared with the existing patterns used for image retrieval.
1 INTRODUCTION

A. Motivation
In recent years, there has been a massive increase of digital libraries due to the ease of availability of web/digital cameras, portable devices and mobile phones equipped with cameras. This makes the task of database management as tedious. Thus there is a need for automatic database management, one of which is content based image retrieval (CBIR).

The primary step in CBIR is to extract the features of the images. The features may be color, texture, shape, faces, etc. A detailed study on CBIR is presented in [1] [4]. Of all the features, texture has been used extensively as they extract the prominent features. This is being introduced by Moghaddam et al. using wavelet correlogram [5], [6]. Also, it is shown that the performance can be further improved by optimizing the quantization thresholds [7] for CBIR application.

Texture based image retrieval is widely used in manufacturing industries as it is suited for product identification. Other researches in CBIR include discrete wavelet transform (DWT) for texture classification [8] by Ahmadian et al., by using generalized Gaussian density with KullbackLeibler distance for texture image retrieval [9]. Since, the DWT is limited to three directions (horizontal, vertical, and diagonal), transforms such as Gabor transform (GT) [10], and rotated wavelet filters [11] are introduced. Other transforms for texture image retrieval include dual-tree complex wavelet filters (DT-CWFs), DT rotated CWFs [12], and rotational invariant complex wavelet filters [13].

B. Related Works
The local binary pattern (LBP) is a texture based feature extraction method for texture classification and retrieval. This is proposed by Ojala et al. [14]. The rotational invariant version for texture classification is introduced in [15], [16]. Other extensions of LBP are presented in [17] [23].
The local derivative pattern (LDP) is proposed by Zhang et al. for face recognition. They considered the LBP as non-directional [24]. Lei et al. [25] introduced a two phase mechanism. First the image is decomposed using multi-scale and multi-orientation Gabor filters. Later the LBP analysis is used to encode the relationship between neighboring pixels. LBP and Haar wavelet combined technique is proposed by Su et al. for graphic retrieval [26]. The other areas in which LBP has been used include texture segmentation [27], background modeling and detection [28], shape localization [29], interest region description [30], and biomedical image retrieval [31].

The limitations of the LBP and the LDP have led to the development of the local ternary pattern (LTP) [32]. The LBP, the LDP, and the LTP extract the information which is coded using only two directions. A four direction pattern called local tetra patterns (LTrPs) is introduced by Murala et al. [33]. It is evident that the efficiency of image retrieval can be improved by increasing the direction of the pattern, i.e., by differentiating the edges in the image in more than four directions. This observation has motivated us to propose the eight direction code, referred to as enhanced local tetra pattern (ELTrP) for CBIR.

2 LOCAL PATTERNS

A. Local Binary Pattern (LBP)

LBP [14] is a two valued code (0 or 1). For any image , with as the gray value of the center pixel and as the gray value of the neighboring pixels, the LBP is computed as

\[ LBP = \sum_{p=1}^{P} 2^{(p-1)} x_{f_1(g_p - g_c)} \]  

Where,

- is the number of neighbors,
- is a function defined by,

\[ f_1(x) = \begin{cases} 
1, & \text{if } x \geq 0 \\
0, & \text{else} 
\end{cases} \]  

Detailed discussions on LBP are available in [14].
B. Local Ternary Pattern (LTP) LTP [32] is a three valued code (-1, 0 or +1). For any image , with as the gray value of the center pixel and as the gray value of the neighboring pixels, the LTP is computed as

\[ LTP = \sum_{p=1}^{P} 2^{(p-1)} f_2(g_p, g_c, r) \]  

(3)

Where,

- \( P \) is the number of neighbors,
- \( r \) is the range,
- \( f_2 \) is a function defined by,

\[ f_2(g_p, g_c, th) = \begin{cases} +1, & g_p \geq g_c + r \\ 0, & |g_p - g_c| \leq r \\ -1, & g_p \geq g_c - r \end{cases} \]  

(4)

Detailed discussions on LTP are available in [32].

C. Local Derivative Pattern (LDP) The LDP is proposed by Zhang et al [24]. As the LBP is I-order non-directional pattern, it is extended to higher orders called the LDP. For any image , with as the gray value of the center pixel and as the gray value of the neighboring pixels, the LDP is computed as

\[ LDP^{n}_{\alpha}(g_c) = \sum_{p=1}^{P} 2^{(p-1)} f_2(I^{(n-1)}_{\alpha}(g_c), I^{(n-1)}_{\alpha}(g_p)) \]  

(5)

Where,

- \( P \) : is the number of neighbors,
- \( \alpha \) is the order of derivative,
- \( \alpha = 0^0, 45^0, 90^0 \& 13 \) is the direction,
- \( f_2(x) \) is a function defined by

\[ f_2(x, y) = \begin{cases} 1, & if \ x, y \leq 0 \\ 0, & else \end{cases} \]  

(6)

Detailed discussions on LDP are available in [24].

D. Local Tetra Pattern (LTrP) The LTrP is proposed by Murala et al. [33]. For any image , with as the gray value of the center pixel and as the gray value of the neighboring pixels, the I-order
derivatives along horizontal and vertical directions are given by

\[ I_{100}^1(g_c) = I(g_h) - I(g_v) \]  
(7)

\[ I_{900}^1(g_c) = I(g_v) - I(g_c) \]  
(8)

Where, represent the gray value of horizontal direction pixels, represent the gray value of vertical direction pixels.

The direction of center pixel is denoted by \( I^1_{Dir} \) and is calculated as

\[
\begin{align*}
    f_2(g_p, g_c, th) &= \begin{cases} 
        1, & I_{100}^1(g_c) \geq 0 \text{ and } I_{900}^1(g_c) \geq 0 \\
        2, & I_{100}^1(g_c) < 0 \text{ and } I_{900}^1(g_c) \geq 0 \\
        3, & I_{100}^1(g_c) < 0 \text{ and } I_{900}^1(g_c) < 0 \\
        4, & I_{100}^1(g_c) \geq 0 \text{ and } I_{900}^1(g_c) < 0
    \end{cases}
\end{align*}
\]  
(9)

The II-order LTrP is defined as

\[
LTrP^2(g_c) = \{ f_2(I_{Dir}^1(g_c), I_{Dir}^1(g_v)), \ldots, \ldots, f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_2)) \}_{p=2}
\]  
(10)

Where, \( f_3(x) \) is a function defined by,

\[
f_3(x, y) = \begin{cases} 
    0, & \text{if } x = y \\
    y, & \text{else}
\end{cases}
\]  
(11)

More details with illustrated examples are available in [33].

3 PROPOSED PATTERN

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

If, \( \& \) denote the horizontal, vertical and diagonal neighborhoods of respectively, then the I-order derivatives at can be written as
\[ I_{\text{Dir}} = \begin{cases} 
1, & I_{100}(gc) \geq 0 \text{ and } I_{190}(gc) \geq 0 \text{ and } I_{145}(gc) \geq 0 \\
2, & I_{100}(gc) \geq 0 \text{ and } I_{190}(gc) \geq 0 \text{ and } I_{145}(gc) < 0 \\
3, & I_{100}(gc) < 0 \text{ and } I_{190}(gc) \geq 0 \text{ and } I_{145}(gc) \geq 0 \\
4, & I_{100}(gc) < 0 \text{ and } I_{190}(gc) \geq 0 \text{ and } I_{145}(gc) < 0 \\
5, & I_{100}(gc) < 0 \text{ and } I_{190}(gc) < 0 \text{ and } I_{145}(gc) \geq 0 \\
6, & I_{100}(gc) < 0 \text{ and } I_{190}(gc) < 0 \text{ and } I_{145}(gc) < 0 \\
7, & I_{100}(gc) \geq 0 \text{ and } I_{190}(gc) < 0 \text{ and } I_{145}(gc) \geq 0 \\
8, & I_{100}(gc) \geq 0 \text{ and } I_{190}(gc) < 0 \text{ and } I_{145}(gc) < 0 \\
\end{cases} \] (15)

The direction of center pixel is denoted by \( I_{\text{Dir}} \) and is calculated as

The II-order LTrp is defined as

\[ \text{LTrP}^2(gc) = \{ f_2(I_{\text{Dir}}(gc), I_{\text{Dir}}(g_1)), \ldots, f_3(I_{\text{Dir}}(gc), I_{\text{Dir}}(g_2)) \} \] where

\[ f_3(x, y) = \begin{cases} 
0, & \text{if } x = y \\
y, & \text{else} 
\end{cases} \] (17)

Figure 1 shows an example for calculating the direction of the center pixel. In the illustrated example the direction of center pixel is 4. If the direction of the neighborhood 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 neighborhood. From Figure 2, for the first neighborhood 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 neighborhood pixel itself which is 3 in this case. Similarly for the neighborhood 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 neighborhood 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 $I_{bp}$ obtained using equation (15) is 1, then the pattern is segregated into seven patterns for directions 2, 3, 8 as

$$ELTrP_{Direction=2,3,...8} = \sum_{p=1}^{p} 2^{p-1} x f_{4}(LTrP^{2}(g_c))$$  \hspace{1cm} (18)

Where,

$$f_{4}(X)|_{Direction=0} = \begin{cases} 1, & \text{if } x = \Phi \\ 0, & \text{else} \end{cases}$$  \hspace{1cm} (19)

Equation (18) is repeated for the remaining seven directions resulting in 56 binary patterns.

![Figure 1: Direction of center pixel. Green color shaded represents the center pixel.](image)

The grouping is done based on directions. For direction 1 the pattern is grouped based on the remaining direction from 2 to 8. The first pattern is obtained by keeping 1 where the ELTrP value is 2 and 0 for other values, i.e., 0 0 0 0 0 0 0. Similarly, the second pattern is obtained by keeping 1 where tetra pattern value is 3 and 0 for other values, i.e., 1 0 0 0 0 0 0. Similarly the remaining
pattern are 0 0 0 0 0 0, 0 0 0 0 1 0 0, 0 1 0 0 0 1, 0 0 0 0 1 0 0, 0 1 0 1 0 0 0.

In the same way, tetra patterns for center pixels having directions 2 to 8 are computed. Thus for eight ELTrPs, 56 binary patterns are obtained.

The 57th binary pattern is obtained from the magnitude of the first-order derivatives. Using the 1-order derivative in horizontal and vertical directions of the center pixel, the magnitude is calculated as shown in figure 3.

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, vertical and diagonal 1-order derivatives (equations (12) to (14)) as

$$M_1(g_p) = \sqrt{(I_{100}(g_c))^2 + (I_{190}(g_c))^2 + (I_{145}(g_c))^2}$$  \hspace{1cm} (20)\]

Figure 2: Calculation of ELTrP. Green color shaded represents the center pixel; red color shaded represents the neighborhood pixels.
The Magnitude Pattern MP of I-order derivatives is defined as

\[ MP = \sum_{p=1}^{p} 2^{p-1} x f_1 (M_1(g_p) - M_1(g_c)) \bigg|_{p=2} \]  

(21)

In the similar manner, the magnitudes of the neighborhood pixels are calculated. For the first neighborhood 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 neighborhood pixels resulting in 0 0 0 1 0 0 1 1. This is illustrated in Figure 4.

Figure 3: Magnitude of center pixel.
Figure 4: Calculation of Magnitude Pattern. Green color shaded represents the center pixel; red color shaded represents the neighborhood pixels.

The 56 pattern (8 x 7) 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.

B. Advantages of ELTrP

• The ELTrP is able to encode the images with eight distinct values which results in detailed extraction of the image.

• The ELTrP encodes the relationship between the centre pixel and its neighbours based on directions.

• The ELTrP encodes the relationship based on the direction of the centre pixel and its neighbours, which are calculated by
combining derivatives of the directions

Figure 5: Flowchart of proposed image retrieval system.

C. Framework of ELTrP

Figure 5 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.

- Get the query image and convert it into grayscale
- Apply the first-order derivatives in horizontal, vertical and diagonal axis
- Calculate the direction for every pixel
- Divide the patterns into eight parts based on the direction of the center pixel
• Calculate the enhanced tetra patterns
• Separate then into seven binary patterns (Total 56 = 8 x 7 patterns)
• Calculate the histogram for each of the 56 binary pattern (56 ELTrP)
• Calculate the magnitudes pattern
• Calculate the histogram for the magnitude pattern (1 MP)
• Combine the histograms (56 ELTrP + 1 MP)
• Construct the feature vector
• Compare the query image with the images in the database
• Retrieve the images based on the best matches

D. Feature Vector Generation

An image data base containing 1000 images are taken for analysis. They are grouped into 10 classes with 100 images in each class. The images are taken from COREL database [34].

The feature vector for each image is generated (as explained in algorithm) and stored as a data base table which is used for image matching and retrieval.

The class of images used includes dinos, drinks, buses, masks, trains, flowers, clouds, sunset, owls, and women. Following are the sample images from the database with one image per class.

Figure 6: Sample images from database.
E. Average Retrieval Rate (ARR)

The efficiency of the image retrieval is measured in terms of Average Retrieval Rate (ARR). The process to find the ARR is as follows.

- A sample image from an image class is taken from the database
- The feature vector is calculated using the ELTrP
- The calculated vector is compared with the database for retrieval
- If the retrieved image belongs to the same category, then it is success else it is failure
- The above process is carried for all the images in a class and the success / failure is recorded
- The average of the success for a particular category is calculated which is called the Average Retrieval Rate (ARR)
- Similarly, the ARR for all class of images are calculated

The process is repeated using LTrP & LTP which is used for comparison.

4 SIMULATION RESULTS

The efficiency of the image retrieval is measured in terms of Average Retrieval Rate (ARR).

Comparison between the proposed algorithm (ELTrP) and the existing algorithms (LTrP & LTP) has been made to show the effectiveness of the proposed algorithm. The following table shows the ARR of ELTrP, LTrP & LTP for different image classes. It is clear from the table that the proposed algorithm (ELTrP) gives better result than LTrP & LTP for all image classes.
<table>
<thead>
<tr>
<th>Image Classes</th>
<th>Algorithm Used</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ELTrP</td>
</tr>
<tr>
<td>Dinos</td>
<td>69</td>
</tr>
<tr>
<td>Drinks</td>
<td>35</td>
</tr>
<tr>
<td>Buses</td>
<td>70</td>
</tr>
<tr>
<td>Masks</td>
<td>43</td>
</tr>
<tr>
<td>Trains</td>
<td>45</td>
</tr>
<tr>
<td>Clouds</td>
<td>40</td>
</tr>
<tr>
<td>Sunset</td>
<td>35</td>
</tr>
<tr>
<td>Flowers</td>
<td>31</td>
</tr>
<tr>
<td>Owls</td>
<td>32</td>
</tr>
<tr>
<td>Women</td>
<td>54</td>
</tr>
</tbody>
</table>

From Figure 7, it is evident that the ARR of ELTrP (Green Line) is high when compared to ARR of LTrP & LTP. By using ELTrP, the ARR is increased up to 12% with database mentioned.

![Figure 7: ARR Comparison Graph for LTP, LTrP and ELTrP](image)

5 CONCLUSION

In this paper a novel approach referred as ELTrPs for CBIR has been have presented. The ELTrP encodes the images based on the
direction of pixels that are calculated by horizontal, vertical and diagonal derivatives. The magnitude of the binary pattern is collected using magnitudes of derivatives. The effectiveness of the proposed approach has also been analyzed by comparing the performance of the proposed method with LTP and LTrP on gray scale. The ARR has improved up to 12% as compared with the LTP and LTrP with the database mentioned. In future the algorithm can be tested for more image classes and it can be implemented with suitable hardware.

References


[34] https://sites.google.com/site/dctresearch/Home/content-based-image-retrieval.