



ISSN(Online): 2320-9801  
ISSN (Print): 2320-9798

## International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: [www.ijircce.com](http://www.ijircce.com)

Vol. 5, Issue 1, January 2017

# Proposed Local Tetra Patterns – An Advanced Feature Descriptor for CBIR

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**ABSTRACT:** The rapid explosion of collection of an image over the Internet and the evolution of multimedia technology have been attracted significant research efforts. Also in generating tools for effective retrieval of visual data. Some difficulties faced by traditional text-based image retrieval brought the researchers to discover new solutions like CBIR to index visual information. CBIR uses the features and the contents of an image like color, edge, texture, etc. to represent and index the image. The quality of response is highly dependent on the two things, like choice of the method used to generate feature vectors as well as the similarity measurement for comparison of features. All research efforts are being made to evaluate the performance and accuracy of image retrieval systems by making changes to existing LTrP system.

**KEYWORDS:** Color, HSV, Content-Based Image Retrieval (CBIR), Local Tetra Patterns (LTrPs), Local Binary Pattern (LBP), Local Ternary Pattern (LTP).

### I. INTRODUCTION

Over the decade, the volume of digital image is increasing very exponentially because of many areas where digitized images are required like Multimedia, Hospitals, GIS, Crime Prevention, Pattern Recognition, Statistics and many more. Thus several researchers are working on it to maintain the large amount of databases. Problem with the previous approach leads to another path of accessing the image on the basis of their features. This trend of image retrieval was rely on special properties and contents that are included in the images themselves called as Content-Based Image Retrieval.

CBIR uses the visual contents of an image to representation of an image as well as indexing of an image. CBIR system can be understood as a building blocks that communicate with each other to retrieve the database images according to a given query. In normal CBIR system, the visual contents/features of the images in the database are extracted by multi-dimensional feature vectors. To retrieve images, users provides query images to the retrieval system and then changes the query image into its internal representation of corresponding feature vectors. The similarities between the feature vectors as well as dissimilarities between the feature vector of the query image and the images in the archives are then matched. We noted some Characteristics of CBIR include like Image retrieval by image content, visually similar images to Query image, No keywords, Low level features like color, shape are used, image indexing techniques, etc. In this paper, we proposed changes in LTrP technique so that the accuracy should raise at consistent level as well the performance of retrieval should be maintain.

The rest of the paper is as follows. Section 2 briefs the considered different schemes based on CBIR for the analysis and image indexing techniques. Section 3 represents the proposed system considering different features. Section 4 represents the similarity measurement, Section 5 represents the image indexing techniques and the paper concludes with section 6.



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## II. LITERATURE SURVEY

From the last decade, the search for heavily used and efficient techniques of CBIR is a locus of research. The comprehensive works of talwar [3], Bansal [9] provide some of the most useful surveys on the CBIR. The extensive work of Singh [2], Chaudhari[4], Daisy [6] and Apurva [10] also outstands to describe the functionality of CBIR systems with proper references of past systems. Pujari [1], Sarvanan [7] done a great work with color feature. Finally, the recent study of Xie [5], Gui [8] and Demir [11] gives an actual overview of the enhanced of CBIR and tackle its major future challenges by implementing the relevance feedback using supervised learning algorithms (machine learning algorithms). But after feature extraction, some image indexing techniques are evolved. The local binary pattern (LBP) feature has been emerged in recent year in the field of "texture" classification and retrieval. Ojala et al. proposed LBPs [12], which are converted to a rotational invariant version for texture classification [13], [14] as well as improved LBP variance with global matching [15]. Some of the extensions of the LBP like dominant LBPs [16], completed LBPs [17], joint distribution of local patterns with Gaussian mixtures [18], etc., are proposed for rotational invariant texture classification. The LBP on facial expression recognition is successfully reported in [18] and [19]. Xi Li et al. proposed a multiscale heat-kernel-based face representation as heat kernels are known to perform well in characterizing the topological structural information of face appearance for the purpose of capturing texture information of the face appearance [20]. Zhang et al. proposed local derivative patterns (LDPs), here they assumed the LBP as first-order non-directional local patterns for face recognition collected from the first-order derivatives [21]. Lei et al. [22] proved that exploiting the image information jointly in image space, scale, and orientation domains can provide richer clues, which are not evident in any one individual domain. This process involves two phases, where the first phase, the face image is decomposed into different scale and orientation responses by convolving with multi-scale and multi-orientation Gabor filters. In the second phase, LBP analysis is used to describe the neighbouring relationship not only in image space but also in different scale and orientation responses. In our previous paper [26], we studied all these in detail. Thus, it is evident that the performance of these methods can be improved by differentiating the edges in more than two directions. This all observation has emphasis them to propose the quad-direction code, commonly known as local tetra patterns (LTrPs) for CBIR.

## III. PROPOSED SYSTEM

The basis of any content-based image retrieval technique is a visual feature extraction further classified as high-level features and low-level features. In a wider sense, features might include both color as well as shape features and text-based features (key-words, annotations). One of the keys of a CBIR system is the selection of the features to represent an image exactly query given to it. Also due to perception subjectivity of visual data it is hard to use only single content. Multiple approaches have been introduced for each of these visual features and each of them characterizes the feature from a different perspective [3].

### A. LTrP

The idea of local patterns (the LBP, the LDP, and the LTP) has been adopted to define LTrPs. The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel  $g_c$  (center of pixel in  $I$ ). Given image, the first-order derivatives along 0 and 90 directions are denoted as  $I_{\theta 0}^1(g_p)$  where  $\theta = 0^\circ, 90^\circ$ . let  $g_h, g_v$  and  $g_d$  denote the horizontal, vertical and diagonal neighbourhoods of  $g_c$ , respectively. The direction of the center pixel can be calculated as



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$$I_{Dir}^1(g_c) = \begin{cases} 1. \text{ if } I_{0^0}^1(g_c) \geq 0 \text{ and } I_{90^0}^1(g_c) \geq 0 \\ 2. \text{ if } I_{0^0}^1(g_c) \geq 0 \text{ and } I_{90^0}^1(g_c) < 0 \\ 3. \text{ if } I_{0^0}^1(g_c) < 0 \text{ and } I_{90^0}^1(g_c) \geq 0 \\ 4. \text{ if } I_{0^0}^1(g_c) < 0 \text{ and } I_{90^0}^1(g_c) < 0 \\ 5. \text{ if } I_{0^0}^1(g_c) \geq 0 \text{ and } I_{90^0}^1(g_c) < 0 \\ 6. \text{ if } I_{0^0}^1(g_c) < 0 \text{ and } I_{90^0}^1(g_c) \geq 0 \\ 7. \text{ if } I_{0^0}^1(g_c) \geq 0 \text{ and } I_{90^0}^1(g_c) \geq 0 \\ 8. \text{ if } I_{0^0}^1(g_c) < 0 \text{ and } I_{90^0}^1(g_c) < 0 \end{cases}$$

and the first-order derivatives at the center pixel can be written as

$$I_{0^0}^1(g_p) = I(g_h) - I(g_c)$$

$$I_{90^0}^1(g_p) = I(g_v) - I(g_c)$$

It is evident that the possible direction for each center pixel can be either 1, 2, 3, . . . or 8 and eventually, the image is converted into eight values, i.e., directions.

The second-order LTrP( $g_c$ ) is defined as

$$LTrP^2(g_c) = \{ f_3 (I_{Dir}^1(g_c), I_{Dir}^1(g_1)), f_3 (I_{Dir}^1(g_c), I_{Dir}^1(g_2)) \dots, f_3 (I_{Dir}^1(g_c), I_{Dir}^1(g_P)) \}_{P=8}$$

$$f_3 (I_{Dir}^1(g_c), I_{Dir}^1(g_p)) = \begin{cases} 0, & I_{Dir}^1(g_c) = I_{Dir}^1(g_p) \\ I_{Dir}^1(g_p), & \text{else.} \end{cases}$$

Similarly, the remaining 3 tetra patterns for remaining 2 directions of center pixels are inverted to binary patterns. Thus, we get 8 (4 x 2) binary patterns. Most of the literatures proved that, the sign component extracts more useful information as compared with the magnitude component. Still exploiting the combination of sign and magnitude components can provide better clues, which are not evident in any one individual component.

$$M_{T1} = \sqrt{(I_{0^0}^1(g_p))^2 + (I_{90^0}^1(g_p))^2}$$

For the local pattern with neighbourhoods,  $2^P$  combinations of LBPs are possible, resulting in the feature vector length of  $2^P$ . The computational cost of this feature vector is very high. To reduce the actual computational cost, we take the uniform patterns. These pattern refers to the uniform appearance pattern that has restricted discontinuities in this binary representation. In this survey, we represent those patterns that have less than two discontinuities in the binary representation are refer as the uniform patterns, and the other remaining patterns are referred to as non-uniform pattern. Thus, the distinct uniform patterns for a given query image would be  $P(P-1)+2$ . Here the actual process become fast but the accuracy remains same w.r.t. size of dataset.

## B. PROPOSED LTrP

The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel  $g_c$  (center of pixel in I). Given image, the first-order derivatives along 0, 45 and 90 directions are denoted as  $I_{\theta^0}^1(g_p)$  where  $\theta = 0^\circ, 45^\circ, 90^\circ$ . let  $g_h, g_v$  and  $g_d$  denote the horizontal, vertical and diagonal neighborhoods of  $g_c$ , respectively. Then, the first-order derivatives at the center pixel can be written as

$$I_{0^0}^1(g_p) = I(g_h) - I(g_c)$$

$$I_{45^0}^1(g_p) = |I_{0^0}^1(g_p) - I_{90^0}^1(g_p)|$$

$$I_{90^0}^1(g_p) = I(g_v) - I(g_c)$$

and the direction of the center pixel can be calculated as



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It is evident that the possible direction for each center pixel can be either 1, 2, 3, . . . or 8 and eventually, the image is converted into eight values, i.e., directions.

The second-order LTrP( $g_c$ ) is defined as

$$\begin{aligned} LTrP^2(g_c) &= \{ f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_1)), f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_2)) \\ &\quad \dots, f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_P)) \} |_{P=8} \\ f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_p)) &= \begin{cases} 0, & I_{Dir}^1(g_c) = I_{Dir}^1(g_p) \\ I_{Dir}^1(g_p), & \text{else.} \end{cases} \end{aligned}$$

Similarly, the remaining 3 tetra patterns for remaining 3 directions of center pixels are inverted to binary patterns. Thus, we get 12 (4 x 3) binary patterns. Most of the literatures proved that, the sign component extracts more useful information as compared with the magnitude component. Still exploiting the combination of sign and magnitude components can provide better clues, which are not evident in any one individual component. This concept has motivated us to propose the 13th binary pattern by using the magnitudes of horizontal and vertical first-order derivatives using

$$M_{I^1} = \sqrt{(I_{0^0}^1(gp))^2 + (I_{45^0}^1(gp))^2} + \sqrt{(I_{45^0}^1(gp))^2 + (I_{90^0}^1(gp))^2}$$

For the local pattern with neighbourhoods,  $2^P$  combinations of LBPs are possible, resulting in the feature vector length of  $2^P$ . The computational cost of this feature vector is very high. To reduce the actual computational cost, we take the uniform patterns. These pattern refers to the uniform appearance pattern that has restricted discontinuities in this binary representation. In this survey, we represent those patterns that have less than two discontinuities in the binary representation are refer as the uniform patterns, and the other remaining patterns are referred to as non-uniform pattern. Thus, the distinct uniform patterns for a given query image would be  $P(P-1)+2$ . Here the actual process become slow but the accuracy increases w.r.t. size of dataset.

## IV. EXPERIMENTS AND EVALUATION

This section presents the analysis and evaluation of the proposed scheme. Wang's Image Database [3] is used for experiment. This database contains total of 180 images of 9 different classes. Each image class consists of almost 20 images. Out of the total 180 images, 135 images (15 images from each class) are used for the training purpose and 45 images (5 images from each class) are used for testing. A query image is provided by the user. Then similar images from database are selected and displayed in range of 1 to 20. For testing purpose, total 5 test images are randomly selected from the database to show the performance of the proposed scheme.

### A. Design Considerations:

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The experiments were taken on a standalone machine with high storage capability. Machine is equipped with Intel core i5 processor having a clock speed of 2.5 GHZ and 4GB of RAM. The algorithm is implemented using Matlab. It's a real time application which need dataset to train the system. We have to implement a system which having capability of different feature extraction like color, texture, etc. which done the process image retrieval according to similarity between the images given as query image. Also we are using LBP, Ltrp and proposed Ltrp indexing techniques.

### B. Image Dataset description:

In our proposed system, using Color and texture, we manage different image clusters like Buses, Cats, Flowers, Dogs, Dinosaurs, Foxes, Tiger and Buildings

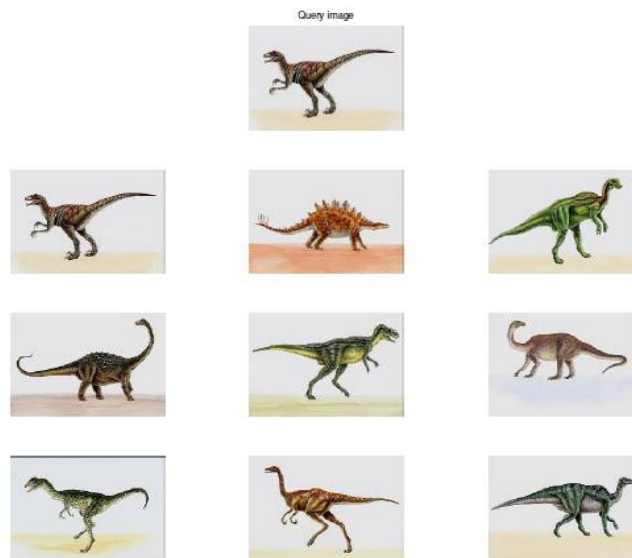


Fig 1. Sample Images from dinosaurs cluster

Figure 1 shows sample images from dinosaurs cluster given to our system to train the system according to feature we have. Then we have to perform different feature extraction and image indexing techniques to proposed better one for image retrieval.

## V. SIMULATION RESULTS

By looking at the results provided by proposed algorithm and the results obtained by study different feature extraction system compared against various factors and following points are worth noted. The retrieval performance of proposed technique is shown in terms of Precision and Recall. These two measures are given by equations (1) and (2) respectively. Again for other factors we have to calculate the Psignal as the mean of pixel values as well as the Pnoise and the standard deviation or error value of the pixel values. Finally we have to take the ratio or may use  $SNR=10\log_{10}(P_{signal}/P_{noise})$  to express the result.

$$\text{Precision} = \frac{\text{No.of relevant images retrieved}}{\text{Total no.of images retrived}} \dots\dots\dots (1)$$

$$\text{Recall} = \frac{\text{No.of relevant images retrieved}}{\text{Total no.of relevant images}} \dots\dots\dots (2)$$



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$$\begin{aligned}
 PSNR &= 10 \cdot \log_{10} \left( \frac{MAX_I^2}{MSE} \right) \\
 &= 20 \cdot \log_{10} \left( \frac{MAX_I}{\sqrt{MSE}} \right)
 \end{aligned}$$

Table 1 shows the Comparison between Color, LBP, Ltrp & Proposed Ltrp based on Number of images return correctly. Here we show the comparison how previous systems and our proposed system deals with the images given to them and the process gives us the output images aggregated with respect to the image clusters. Number of features increases the accuracy of the system. The requester has been provided requested images by our proposed system on the basis of different features. Figure 2 shows difference between Color, LBP, Ltrp & Proposed Ltrp with respect to Number of images retrieved.

No. of images returned	Color	LBP	Ltrp	Proposed Ltrp
1	YES	YES	YES	YES
2	YES	YES	YES	YES
3	NO	YES	YES	YES
4	NO	NO	YES / NO	YES
5	NO	NO	NO	NO

Table 1: Comparison between Color, LBP, Ltrp & Proposed Ltrp based on Number of images return correctly

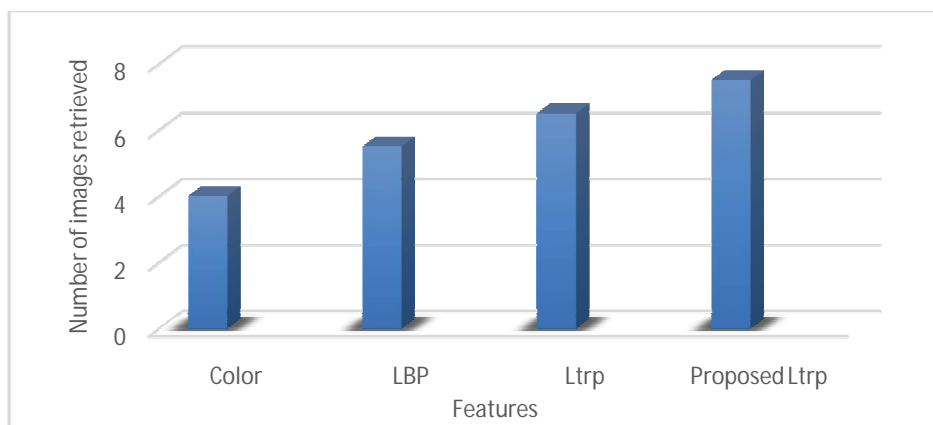


Figure 2: Comparison between Color, LBP, Ltrp & Proposed Ltrp based on Number of images retrived correctly

From the Table 2, we show the Comparison between Color, LBP, Ltrp & Proposed Ltrp using Image Clusters. First we consider the image clusters like Buses, Cats, Flowers, Dogs, Dinosaurs, Foxes, Tiger and Buildings. There are many feature extraction type which is covered in our proposed system. Now according to our algorithm here bus image are properly classified as 60%, cat image are properly classified as 80%, Flowers are properly classified as 80%, metro image are properly classified as 80% only, Dogs image are properly classified as 80%, Dinosaurs image are properly classified as 80%, Foxes image are properly classified as 60%, Tiger image are properly classified as 60% and Buildings image are properly classified as 60% tends to overall accuracy of system is 70% only still quite good with earlier system.

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Image Cluster	Color	LBP	Ltrp	Proposed Ltrp
Buses	40%	60%	60%	60%
Cats	40%	40%	60%	80%
Flowers	60%	60%	80%	80%
Dogs	40%	60%	60%	80%
Dinosaurs	60%	60%	60%	80%
Foxes	40%	60%	60%	60%
Tiger	40%	40%	60%	60%
Buildings	40%	60%	60%	60%

Table 2: Comparison between Color, LBP, Ltrp & Proposed Ltrp using Image Clusters

Figure 3 shows the Comparison between Color, LBP, Ltrp & Proposed Ltrp based on number of images process. This shows clearly that the proposed system make difference with efficiency compare to existing system. Now according to our algorithm here 50 images are properly classified as 70%, 100 images are properly classified as 66%, 150 images are properly classified as 61% still quite good with earlier system.1

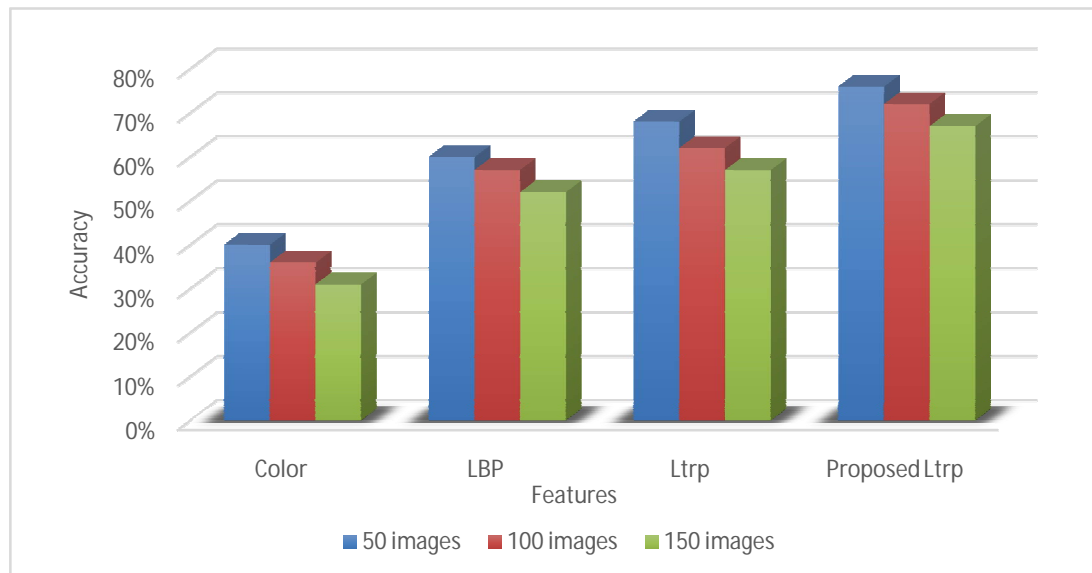


Figure 3: Comparison between Color, LBP, Ltrp & Proposed Ltrp based on number of images process

Table 3 shows the Comparison between Color, LBP, Ltrp & Proposed Ltrp based on number different parameters like precision, recall, SNR, PSNR and overall Accuracy. This shows clearly that the proposed system make difference with efficiency compare to existing system. Now according to our algorithm we getting highest precision recall value as well as highest accuracy among other system.



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Image Cluster	No. of images in Database	No. of images retrieve	No. of relevant images	Precision	Recall	Average SNR (Signal to Noise Ratio)	Average PSNR (Peak Signal to Noise Ratio)	Accuracy
Color	150	125	95	0.76	0.63	29.25	36.85	0.69
LBP	150	132	111	0.84	0.74	22.44	29.74	0.79
LTrP	150	138	119	0.86	0.79	31.55	38.03	0.83
Proposed LTrP	150	145	128	0.88	0.85	26.19	32.10	0.86

Table 3: Overall Comparison between Color, LBP, Ltrp & Proposed Ltrp using different factors

## VI. CONCLUSION AND FUTURE WORK

In this paper, horizontal, vertical as well as diagonal pixels have been used for derivative calculation to improve the result by considering the diagonal pixels for derivative calculations in addition to horizontal and vertical directions. Due to the effectiveness of the proposed method, it can be also suitable for other pattern recognition applications such as face recognition, fingerprint recognition, etc. Here we studied different image indexing techniques. In future relevance feedback also be our aim of research.

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ISSN(Online): 2320-9801  
ISSN (Print): 2320-9798

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(An ISO 3297: 2007 Certified Organization)

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