



## Enhanced LTrP For Image Retrieval

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**Abstract** - Local Tetra Pattern (LTrP) is an image retrieval and indexing algorithm for content based image retrieval (CBIR) which made a significant improvement in the precision and recall rates of the retrieved images. Enhanced LTrP for Image Retrieval (ELIR) proposes a novel method of image retrieval by adding additional features to LTrP together with the features of coarseness, contrast, directionality and busyness. The experimental results show that precision and recall of image retrieval improved from that of using LTrP alone.

**Keywords:** Busyness, CBIR, Coarseness, Contrast, Directionality, LTrP



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## INTRODUCTION

### A. Motivation

Medical imaging technology has seen great advancement in recent years. The use of CT, MRI, X-ray imaging help diagnose diseases and to provide adequate treatment to patients. Hence it is necessary to acquire, analyze, classify and store these images. Physicians and researchers take data from these images for studying a case. This lead to a new field of research called Medical Image Retrieval (MIR). This is similar to earlier existing image retrieval methods. But retrieval in MIR must be more accurate as it is a real time application.

Content based image retrieval (CBIR) methods use feature extraction. Features can be general or related to a specific domain. Commonly used features include shape, texture, color. Feature extraction can be done at the local, global or pixel level. Pixel level feature extraction is the simplest of all. It involves extracting features at the basic pixel level. All the images are scaled down to a common size. Local level feature extraction involves dividing an image into small sub images and extracting features from these sub images. Global features tend to describe the images in an average fashion. The low-level features constitute the color, texture, and shape [1]. The Local Tetra Pattern [3] is a prominent method in the field of texture classification and retrieval. LTrP finds the correlation between the referenced pixel and its neighbours by computing the gray-level difference. The LTrP encodes the images by taking into consideration the direction of pixels calculated by horizontal and vertical derivatives.

In this paper we propose a novel method of image retrieval by constructing a feature vector using LTrP, perceptual textural features and more features generated using shift operation on LTrP.

### B. Related Works

As per the previous work study conducted by [4], a number of authors have proposed using the direction of the image gradient alone for image comparison. In some cases, the motivations for this has been that the gradient direction is also invariant to changes in offset and gain in the image and indeed to any monotonic change in image intensity. Chen et al. [5] provide a statistical analysis to show that the direction of gradient is also insensitive to changes in lighting direction for nonisotropic scenes. There are many possible ways to compare images using gradient direction. The simplest is to compute the sum of squares of the differences between two gradient direction images. Images are classified as nonisotropic and isotropic. Properties of nonisotropic surface change rapidly in one direction and slowly in another. An isotropic surface will be one in which variation is more or less similar in both directions.

In [6] a new method was introduced to estimate set of perceptual textural features, namely coarseness, directionality, contrast and busyness.

The local binary pattern (LBP) feature has emerged as a silver lining in the field of texture classification and retrieval. The successful binary patterns are:

#### LBP:

**Local binary patterns** (LBP) is a type of feature used for classification in computer vision. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification. Ojala *et.al.* proposed LBPs [4], which are converted to a rotational invariant version for texture classification [5], [6]. Various extensions of the LBP, such as LBP variance with global matching [7], dominant LBPs [8], completed LBPs [9], joint distribution of local patterns with Gaussian mixtures [10], etc., are proposed for rotational invariant texture classification.

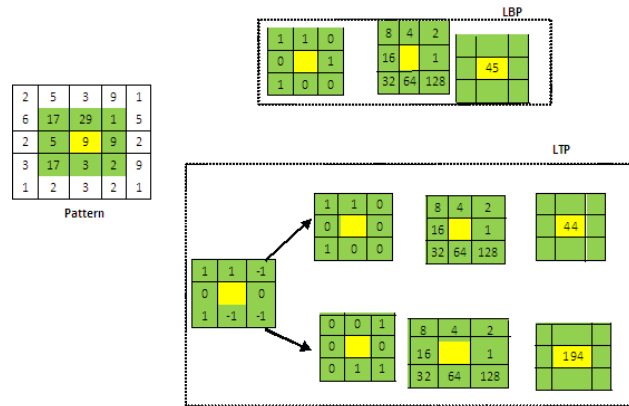
LBPs are a computationally efficient nonparametric local image texture descriptor. They have been used with considerable success in a number of visual recognition tasks including face recognition [11], [12], [13]. LBP features are invariant to monotonic gray-level changes by design and thus are usually considered to require no image preprocessing before use [14].

The LBP operator was introduced by in [5] for texture classification. Given a center pixel in the image, the LBP value is computed by comparing its gray value with its neighbors, as shown in Fig. 1, based on

$$LBP_{P,R} = \sum_{p=1}^P 2^{(p-1)} \times f_1(g_p - g_c) \quad (1)$$

$$f_1(x) = \begin{cases} 1, & x \geq 0 \\ 0, & \text{else} \end{cases} \quad (2)$$

Where  $g_c$  is the gray value of the center pixel,  $g_p$  is the gray value of its neighbors,  $P$  is the number of neighbors, and  $R$  is the radius of the neighborhood.



**Fig. 1. Calculation of LBP and LTP operators. In the LTP, the obtained ternary pattern is further classified into upper and lower binary patterns. The upper pattern is obtained by retaining a 1 and replacing 0 for -1 and 0. Lower pattern is coded by replacing -1 with 1 and 0 for 1 and 0.**

In practice the reliability of LBP decreases significantly under large illumination variations. Lighting effects involve complex local interactions and the resulting images often violate LBP's basic assumption that gray level changes monotonically. Another limitation of LBP is its sensitivity to random and quantization noise in uniform and near-uniform image regions such as the forehead and cheeks.

#### LTP (Local Ternary Pattern):

Tan and Triggs [14] developed a simple and efficient image preprocessing chain that greatly reduces the influence of illumination variations, local shadowing and highlights while preserving the elements of visual appearance that are needed for recognition which addresses the problem of large illumination variations. Also they extended LBP to Local Ternary Patterns (LTP), a 3-valued coding that includes a threshold around zero for improved resistance to noise. LTP inherits most of the other key advantages of LBP such as computational efficiency.

In LTP gray values in the zone of width  $\pm t$  around  $g_c$  are quantized to zero, those above  $(g_c + t)$  are quantized to +1, and those below  $(g_c - t)$  are quantized to -1, i.e., indicator  $f_1(x)$  is replaced with three-valued function (3) and the binary LBP code is replaced by a ternary LTP code, as shown in Fig. 1, i.e.,

$$f_1(x, g_c, t) = \begin{cases} +1, & x \geq g_c + t \\ 0, & |x - g_c| < t \\ -1, & x \leq g_c - t \end{cases} \quad (3)$$

#### LTrP (Local Tetra Pattern):

The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel  $g_c$ . The LDP (Local Derivative Pattern) encodes the relationship between the  $(n-1)^{\text{th}}$ -order derivatives of the center pixel and neighbors in  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$ ,  $135^\circ$  directions separately, whereas the LTrP encodes the relationship based on the direction of the center pixel and its neighbors, which are calculated by combining  $(n-1)$ th-order derivatives of the  $0^\circ$  and  $90^\circ$  directions [3].

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

$$I_{0^\circ}^1(g_c) = I(g_h) - I(g_c) \quad (4)$$

$$I_{90^\circ}^1(g_c) = I(g_v) - I(g_c) \quad (5)$$

and the direction of the center pixel can be calculated as

$$I_{Dir}^1(g_c) = \begin{cases} 1, & I_{0^\circ}^1(g_c) \geq 0 \text{ and } I_{90^\circ}^1(g_c) \geq 0 \\ 2, & I_{0^\circ}^1(g_c) < 0 \text{ and } I_{90^\circ}^1(g_c) \geq 0 \\ 3, & I_{0^\circ}^1(g_c) < 0 \text{ and } I_{90^\circ}^1(g_c) < 0 \\ 4, & I_{0^\circ}^1(g_c) \geq 0 \text{ and } I_{90^\circ}^1(g_c) < 0 \end{cases} \quad (6)$$

From (6) it is evident that the possible direction of each central pixel can be 1, 2, 3 or 4 and eventually the image is converted into four directions.

Using the second order derivative,  $LTrP^2(g_c)$ , 8-bit tetra pattern for each central pixel is obtained. All patterns are separated into four parts based on direction of center pixel. Finally the tetra patterns of each part (direction) are converted into three binary patterns. Similarly the other three tetra patterns for the remaining three directions of center pixels are converted to binary patterns. Thus, 12 (4 x 3) binary patterns are obtained.

The LTrP method used the 13<sup>th</sup> binary pattern (LP) which can be calculated by using the magnitudes of horizontal and vertical first-order derivatives:

$$M_{I^1(g_p)} = \sqrt{(I_{0^{\circ}}^1(g_p))^2 + (I_{90^{\circ}}^1(g_p))^2} \quad (7)$$

$$LP = \sum_{p=1}^P 2^{p-1} \times f_1 \left( M_{I^1(g_p)} - M_{I^1(g_c)} \right) |_{P=8} \quad (8)$$

After identifying the 13<sup>th</sup> binary pattern, their histogram is calculated and query image is compared with the images of the given database. During comparison, the  $n$  best images similar to query image are selected. The experimental results confirmed that LTrP outperforms LBP, LDT and LTP in terms of retrieval and is able to extract more detailed information from the image.

A perception-based approach to content-based image representation and retrieval is proposed by Nouredine Abbadeni in [6]. A new method to estimate a set of perceptual textural features, namely coarseness, directionality, contrast and busyness is presented in this paper.

**Coarseness:** This feature determines the existence of texture in an image. Coarseness measures the size of the primitives that constitutes the texture. A coarse structure is composed of large primitives and is characterized by a high degree of local uniformity of grey-levels. A fine texture is constituted by small primitives and is characterized by a high degree of local variations of grey-levels.

**Directionality** is a global property in an image. It measures the degree of visible dominant orientation in an image. An image can have one or several dominant orientation(s) or no dominant orientation at all. In the latter case, it is said isotropic. The orientation is influenced by the shape of primitives as well as by their placement rules.

**Contrast** measures the degree of clarity with which one can distinguish between different primitives in a texture. A well contrasted image is an image in which primitives are clearly visible and separable. Among the factors that influence contrast, the grey-levels in the image; the ratio of white and black in the image; and the intensity change frequency of grey-levels.

**Busyness** refers to the intensity changes from a pixel to its neighborhood: a busy texture is a texture in which the intensity changes are quick and rush; a nonbusy texture is a texture in which the intensity changes are slow and gradual. One can say, therefore, that busyness is related to spatial frequency of the intensity changes in an image. If these intensity changes are very small, they risk to be invisible. Consequently, the amplitude of the intensity changes has also an influence on busyness.

## PROPOSED METHOD

The complete overview of the work is shown in Fig. 2. The query image is loaded initially and converted to grayscale. The query and database images are resized to a standard dimension. Feature extraction is done using LTrP. A shift is applied on these features to generate 13 more features. Textural features like coarseness, contrast, directionality and busyness were also calculated. Thus a total of 30 features were obtained. Similarly 30 features of database images are obtained. Histograms are obtained for query and database images using these features. Euclidean distance measure is used for finding the nearest matching images. Images which has distance measure less than or equal to the threshold value are retrieved.

### A. Calculation of Textural features:

#### Coarseness

$$C_s = \frac{1}{\frac{1}{2} \times \left( \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} Max_x(i,j)}{n} + \frac{\sum_{j=0}^{m-1} \sum_{i=0}^{n-1} Max_y(i,j)}{m} \right)} \quad (9)$$

where  $Max_x(i,j) = 1$  if pixel  $(i,j)$  is maximum on rows and  $Max_x(i,j) = 0$  if pixel  $(i,j)$  is not a maximum on rows. Similarly  $Max_y(i,j) = 1$  if pixel  $(i,j)$  is maximum on columns and  $Max_y(i,j) = 0$  if pixel  $(i,j)$  is not a maximum on columns.

#### Contrast:

$$C_t = \frac{M_a \times N_t \times C_s^{\frac{1}{\alpha}}}{n \times m} \quad (10)$$



where  $M_a$  represents average amplitude,  $N_t$  ( $n \times m$ ) represents percentage of pixels having an amplitude superior than threshold  $t$ , and  $1/\alpha$  is a parameter to make  $C_s$  significant against the quantity  $(M_a \times N_t) / (n \times m)$ .

**Directionality:**

$$N_{\theta_d} = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} \theta_d(i, j)}{(n \times m) - N_{\theta_{nd}}} \quad (11)$$

where  $\theta_d$  is the dominant orientation,  $N_{\theta_{nd}}$  the number of non oriented pixels.

**Busyness:**

$$B_s = 1 - C_s^{\frac{1}{\alpha}} \quad (12)$$

## B. Calculating additional features:

LtrP is used to extract 13 features from which three binary patterns are derived. If we shift an image, the output image is same but for the shift applied [20] and it is observed in [3] that increase in number of features will increase the accuracy of image retrieval. These are the reasons which tempted us to use the shift operation for generating additional features. Circular right shift is applied on the binary patterns four times to generate additional 12 features.

## C. Euclidean Distance:

This method uses Euclidean Distance Measure (EDM) [15]. EDM determines the pixel-wise quadratic distance between both images. It is one of the common Distance Based Similarity measure to estimate similarity between two images. Let  $x_1, x_2, \dots, x_n$  be  $n$  different features extracted. Then the Euclidean distance between the query image  $Q$  and Database image  $P$  is calculated as follows.

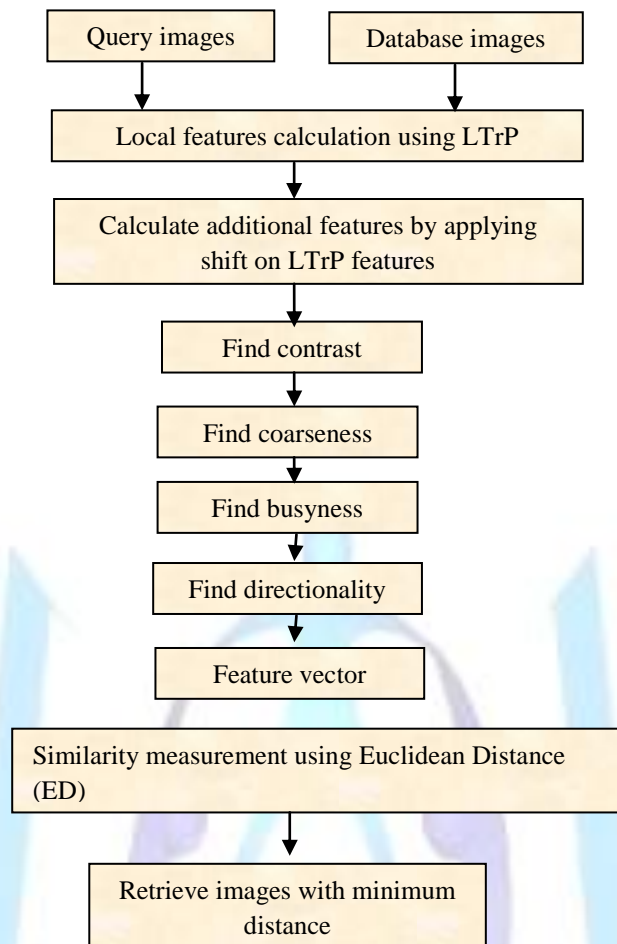
$$ED(P, Q) = \sqrt{\sum_{j=1}^n (x_j(P) - x_j(Q))^2} \quad (13)$$

## D. Proposed Framework:

**Algorithm:**

*Input: Query Image; Output: Matching images*

1. Load the image and convert it to grayscale.
2. Calculate tetra patterns and divide them into three binary patterns.
3. Construct binary patterns.
4. Calculate magnitude using (7).
5. Calculate histograms of binary patterns.
6. Apply shift on the binary patterns.
7. Calculate histogram of shifted patterns.
8. Calculate histogram of magnitude.
9. Combine histograms calculated from steps 5, 7 and 8.
10. Calculate contrast using (10)
11. Calculate busyness using (12).
12. Using (9) find coarseness.
13. Calculate directionality using (11).
14. Construct the feature vector using results of steps 9, 10, 11, 12 and 13.
15. Compare query images with images from the database using (13).
16. Retrieve the images with minimum distance.



**Fig 2: Overview of proposed work.**

### E. Performance Parameters:

The performance of the proposed method can be identified by using precision and recall. Precision is the fraction of retrieved images that are relevant to the query image, while recall is the fraction of relevant images that are retrieved from the database. Both precision and recall are therefore based on an understanding and measure of relevance.

Let NR=Number of retrieved images relevant to the query image.

TR = Total Number of images retrieved

TD = Total Number of Relevant images in the database

$$precision = NR/TR \quad (14)$$

$$recall = NR/TD \quad (15)$$

Using Eq. (14) and Eq. (15), the precision and recall values for the query image are calculated for the proposed method and also for the existing methods.

## RESULTS AND DISCUSSIONS

Experiments were conducted on MRI Brain images on a dataset of 500 images. Images are taken from the WTA[16], Radiological Anatomy [17], google's brain database[18], and MedPix's Medical Image database and Atlas[19].

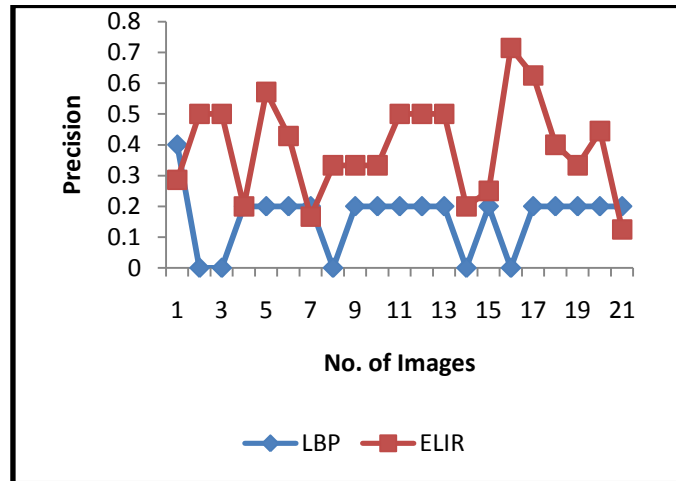


Fig 3: Comparison of Average Precision against No. of MRI Brain images between LBP and ELIR

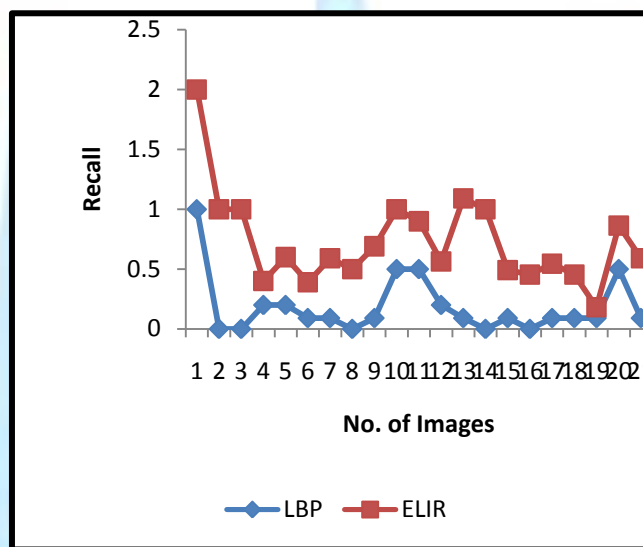


Fig 4: Comparison of Average Precision against No. of MRI Brain images between LBP and ELIR

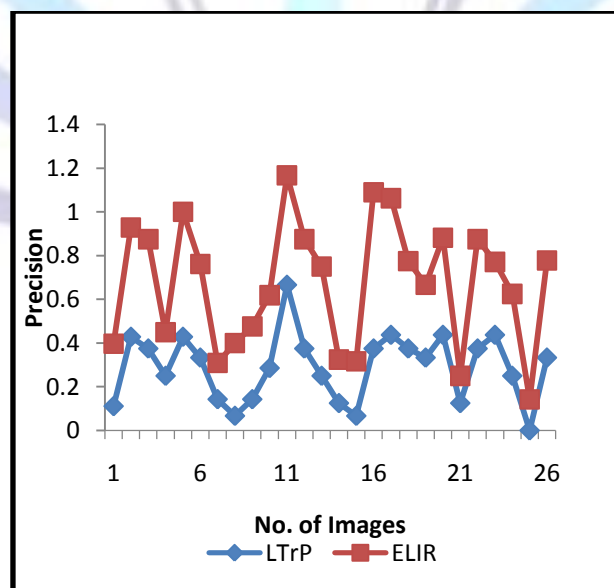
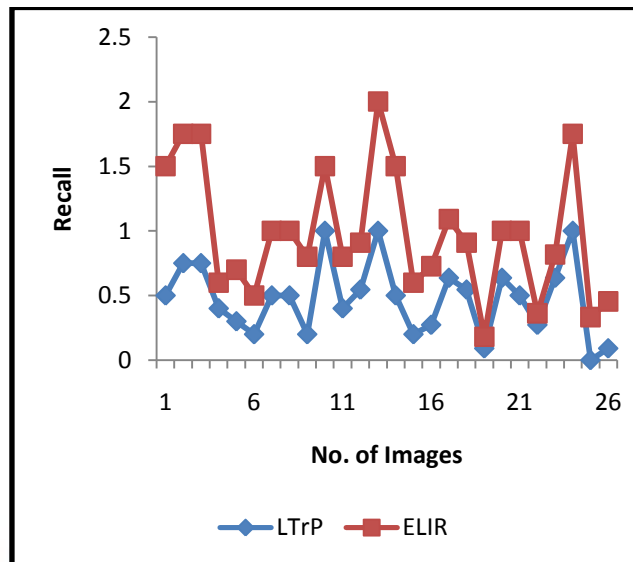


Fig 5: Comparison of Average Precision against No. of MRI Brain images between LTrP and ELIR



**Fig 6: Comparison of Average Recall against No. of MRI Brain images between LTrP and ELIR.**

The comparison charts of Figs 5 and 6 shows that the proposed method proved to produce more efficient retrieval than that of the earlier method of using LTrP alone. The precision improved from 28.95% to 38.62% and the recall improved from 47.79% to 50.42%.

## CONCLUSION

In this paper, a new technique of content based image retrieval system for medical images is presented. This paper also includes feature set calculation using Local Tetra Pattern technique, contrast, coarseness, busyness and directionality and more features are calculated by applying shift on LTrP features. Experiments are carried out on MRI brain images from datasets of google, Harvard university and Wayne university. Results show an improvement of precision by 9.67% and recall by 2.63% from LTrP.

Further works include combining image annotation along with the image retrieval using enhanced LtrP method and text based image retrieval.

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