Relative Retrieval Efficiency Analysis of Local Binary Pattern variants in Color Images

C.Callins Christiyana, J.Merlin Sheeba Rani, V.Rajamani

Abstract— Content Based Image Retrieval (CBIR) technique is used to retrieve relevant images from the Image database based on image content in the query image. Feature extraction is the key process in Content Based Image Retrieval. Many CBIR systems are being developed as in the way of feature extraction techniques used in them. Image features such as color, texture and shape are symbolized as a result of feature extraction. There are many ways to represent the image features. The choice of feature representation is depended on the nature of image database and the intended applications. This article is aimed to experiment how texture oriented feature representation acts upon in color images. Recent studies depict that texture is effectively signified by Local patterns. The well-known local patterns such as local binary pattern (LBP), local tri-directional pattern (LTP) and local neighborhood intensity pattern (LNP) are considered in this work. The relative efficiency of above-mentioned local patterns is compared in the retrieval of color images. Wang database is taken for the experimentation and the color images are considered as a grey scale image by combining three color planes into a single plane. The experimental results conclude that the relative retrieval efficiency of local patterns is not same for the retrieval of color images as in the retrieval of texture images.

Index Terms— CBIR, Local Binary Pattern, Local tri-directional pattern, Local neighborhood intensity pattern, Precision, Recall, Wang Database, Color Images.

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1 INTRODUCTION

OWADAYS due to the development of internet and technologies there is a huge growth of digital images. Different fields like: government, hospital and commerce uses these images for various functionalities. It is necessary to store and retrieve these images effectively. In order to do so image retrieval techniques are being used. There are two types of image retrieval techniques: Text based image retrieval (TBIR) and Content based image retrieval (CBIR).

In TBIR, images are searched by means of text or keywords. Though TBIR is the fast image retrieval technique it is inefficient for large image database because of its manual annotation work. CBIR overcomes this issue since it retrieves the images based on the content inherent in the images. The features such as color, shape and texture are derived as the image content. Color is the first and most straightforward visual feature for indexing and retrieving images. Most commonly used color descriptors are color moments, color histograms, color coherence vector and color correlogram [1].

Objects shape in an image is often used for image comparison, along with color and texture features. Shape features are represented by boundary based and region based methods. Polygonal Models, boundary partitioning and Fourier Descriptors are some familiar boundary based methods. The shape feature is used as the auxiliary feature in many of the CBIR systems since it requires segmentation as the pre process work [2].

Color feature alone is not sufficient to retrieve images perfectly. Since two different images may have same color property for eg: Leaf image and Grass image. They will be differentiated by their textural property. Texture is the most prominent feature. Texture feature provides the spatial arrangement of pixel intensities in an image [3]. It is extracted based on two approaches. They are statistical and structural approaches. Structural approach perceives the set of textures in some regular or repeated pattern. Statistical approach sees image texture as an arrangement of intensities in a region. Statistical Texture analysis discriminates texture as the same way how human discriminates the texture [4]. The most popular statistical representations of texture are: Tamura features [5], Grey Level Co-occurrence Matrix [6], Laws texture energy measures [7], and wavelet transform [8].

The features are drawn out by locally or globally. In global method, the image is represented as an one multidimensional feature vector describing the information in the whole image whereas in local method, an image is divided into regions and represents the local characteristic features[9]. Features are extracted based on neighborhood operation no matter whether they are extracted by globally or locally. The local features are also useful to express the local patches and multiple interest regions of the image [10].

The most popular local characteristic feature is Local Binary Patterns (LBP). The LBP is an efficient texture operator and it labels the pixels of an image based on binary

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thresholding. LBP is computationally fast and it is an illumination invariant operator. Many numbers of local binary pattern variants were developed for various purposes of image retrieval. Among various LBP variants, Local Tri-directional Pattern (LTP) [11] and Local Neighborhood Intensity Pattern (LNP) [12] were proved as superior features for the retrieval of textured images due to their consideration of magnitude patterns. The concern of this work is to experiment the behaviour of the above local patterns in the retrieval of color images. The texture features from grey version of color images are extracted for this purpose. Three color channels are merged and the color image is treated as the grey scale image for the experimentation. Prithaj Banerjee et al. [12] proved that the retrieval efficiency of LNP is more as compared to LTP and LBP for texture images retrieval. The objective of this work is to test whether the relative retrieval efficiency of the LNP, LTP and LBP is maintained in the retrieval of color images while combining all the color channels in the color image.

The sections of the paper are organized as follows. The related color feature based image retrieval systems are given in section II. The section III describes the methodology used for framing image retrieval systems using LBP, LTP and LNP features. Experiments over Wang database were carried out in section IV. Section V gives the conclusion of the work.

2 Related Work

This section presents various local patterns used in the retrieval of color images. Jun Yue at al. [13] presented CBIR system for color images. The system extracted features from HSV color space. Global Color histogram, Local Color histogram and texture features from co-occurrence matrix are extracted and fused to retrieve the color images. Wang et al. [14] exploited color co-occurrence matrix to extract the texture feature and color components as well as distributions to represent the color feature for the retrieval of color images. Jeena Jacob et al. [15] retrieved images from color image database using local oppugnant color texture pattern. The pattern finds complemented link between color and texture. The combinations of pair of color channels are used to extract the pattern.

Manisha verma et al. [16] have given Local Extrema Co-occurrence Pattern (LECoP) for the retrieval of color and texture images. The HSV color space is used for extracting the features in color images. The histograms of Hue and saturation components as well as histogram of LECoP of value component are concatenated to form a feature vector of color images. Yesubai et al. [17] contributed local mesh color texture pattern for the retrieval of color images. The pattern unites color along with local spatial information to represent an image. Three color spaces such as I1QCb, YCbCr and YIQ are utilized to extract the pattern. Chandan singh et al. [18] utilized the combination of LBP for color images, LBP of hue component in HSV color space and color histogram as a feature for the retrieval of color images. They proved that the above combination of feature has low dimension and outruns the state of the art color-texture feature regarding retrieval speed and accuracy. Mohamood Sotoodeh et al. [19] used Radial Mean Completed Local Binary Pattern (RMCLBP) followed by Prototype Data Model to retrieve color images. The pattern is extracted from all the color channels individually and combined.

It is observed from the related work that the local patterns for color images are extracted by considering the information from all the color channels of the color images. But this work combines all the color channels into a single plane and experiment the working of local pattern developed for grey scale textured images. Two superior patterns LTP and LNP along with LBP are considered for the experimentation.

3 Materials and Methods

3.1 Local Binary Pattern (LBP)

It is proposed by Ojala et al.[20] and found as powerful feature for texture classification. Due to its simplicity, it is also used in medical tracking, facial expression recognition, medical imaging, and image classification. LBP assigns the LBP label for every pixel in the image by considering every pixel as a center pixel in an overlapping window. Fig.1 gives how the LBP assigns the LBP value of center pixel based on its neighboring pixels. The histogram of LBP value represents the feature vector of the image.

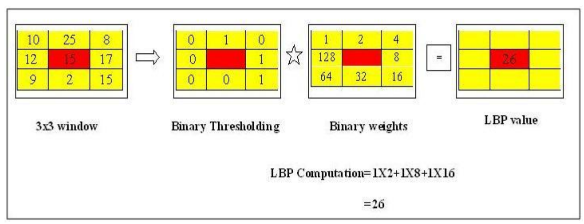

Fig.1. LBP Computation of a center pixel in 3X3 window

3.2 Local Tri-Directional Pattern (LTP)

Local tri-directional pattern is an extension of LBP. In a neighborhood of 3X3, rather considers the relationship between the center pixel and its surrounding neighbors; the LTP considers the relationship of surrounding neighbors with its two adjacent pixels and the center pixels. The two adjacent pixels are either vertical or horizontal pixels as they are closest to the considered neighboring pixel in the same window. The LTP provides both directional pattern and magnitude pattern based on relationship of surrounding neighbors with its adjacent pixels and center pixel.

The advantages of local tri- directional pattern are: additional relationships among the surrounding pixels of 3X3 neighborhood as well as magnitude pattern has been observed. It gives more information compared to LBP because for every surrounding pixel in the window, along with the relationship of center neighborhood pixels, mutual relationships of adjacent neighboring pixels are also obtained. Direction and Magnitude pattern is derived from the relationships. Fig.2 explains how the surrounding neighbors are related to center pixel and its two closest adjacent pixels.

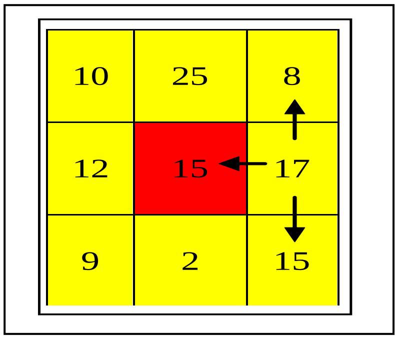

Fig.2. Surrounding Neighbors relations in LTP

In Fig.2, '17' is the intensity of one of the surrounding neighbors in 3X3 window. The pixel '17' is related to the center pixel '15' and its two closest neighbors '8' and '15' for LTP computation. The histograms of direction pattern and the magnitude pattern are used to form the feature vector of the image.

3.3 Local Neighborhood Intensity Pattern (LNP)

LNP is also the extension of LBP. It considers the relative intensity difference between the particular surrounding pixel and the center pixel in a 3X3 window by considering its adjacent neighbors (in all directions) and generates the sign and magnitude pattern. The sign and magnitude patterns persist in harmonizing information to each other. The histograms of these two patterns are concatenated into a single feature descriptor to generate a more concrete and useful feature descriptor for an image [21]. Fig.3 illustrates how the surrounding neighbors are related to its closest neighbors and the center pixel for LNP computation.

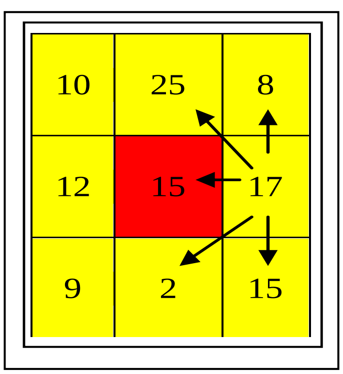

Fig.3. Surrounding Neighbors relations in LNP

The similarity between LNP and LTP is both draw sign and magnitude pattern and reflects on the relationships of surrounding pixels with its adjacent neighbors. The difference between the both is how the adjacent pixels relations are taken into account. Fig.3 describes clearly how pixel relation in LNP is different from LTP. For the pixel '17', the relationships between all the adjacent pixels (irrespective of the direction) and the center pixel are considered. This is not the case in LTP.

3.4 Similarity Matching

The similarity matching is a significant task in retrieval of images as it yields the results by matching the feature vector of database image and the query image [22]. This can be achieved by comparing the feature vector of the query image and the images in database using the distance measures. Some familiar distance measures used in the retrieval system are Euclidian Distance, Manhattan distance, Chi-square distance

$$\mathrm{Euclidian}(D_i, q) = \sum_{j=1}^{L} \sqrt{D_{ij}^2 - q_j^2} \quad (1)$$

$$\mathrm{Manhattan}(D_i, q) = \sum_{j=1}^{L} \left| D_{ij} - q_j \right| \quad (2)$$

$$\mathrm{Chi-square}(D_i, q) = \frac{1}{2} \sum_{j=1}^{L} \frac{(D_{ij} - q_j)^2}{D_{ij} + q_j} \quad (3)$$

$$d1(D_i, q) = \sum_{j=1}^{L} \frac{(D_{ij} - q_j)}{(1 + D_{ij} + q_j)} \quad (4)$$

and d1 distance. If Di is the i[th] image in the da... and q is the query image then the distance between them by various distance measures are as follows.

The term 'j' in (1) to (4) represents the length of the feature vector.

3.5 Image Retrieval Algorithm

Step 1 : Feature vectors of the images in the database are constructed using LBP, LTP and LNP.
Step 2: Query image from database is inputted into the retrieval system.
Step 3: Feature vector of query image is also composed using LBP,LTP and LNP.
Step 4: The feature vectors of query image and all the images in the database are compared using distance measures and similarity was measured.
Step 5: The most similar images of the query image are retrieved with respect to similarity list.

4 EXPERIMENTAL RESULTS AND DISCUSSIONS

This work experiments the performance of LBP, LNP and LTP based image retrieval algorithms on Wang database. Besides different feature extraction, the experiments are carried over on two distance measures such as Chi-square and d1.Chi-square distance measure is more suitable for histogram oriented feature[23] and d1 distance measure showed its excellence in local pattern based retrieval[24,25,26,27]. So these two distance measures are taken into account among various distance metrics. The Wang database has 1000 images in total, and they are distributed in 10 classes with 100 images in each class. The 10 classes are named as African people, beach, building, bus, Dinosaur, elephant, flower, food, horse, and mountain. Fig. 4 presents the sample image in each class.

Fig. 4. Sample images in each class of Wang Database

Each image in the database is keyed in as query to the retrieval system and the output is received. The competence of the image retrieval system is analyzed with two important parameters such as precision and recall. The precision and recall values of query image 'q' are calculated using (5) and (6) respectively.

$$Precision(q) = \frac{No\_of\_Relevant\_images\_Retrieved}{Total\_no\_of\_images\_Retrieved} \quad (5)$$

$$Recall(q) = \frac{No\_of\_Relevant\_images\_Retrieved}{Total\_no\_of\_Relevant\_images\_in\_Database} \quad (6)$$

Precision and recall values are examined by retrieving Top 1 to Top 10 images in the interval of 1, and Top 10 to Top 100 images in the interval of 10.

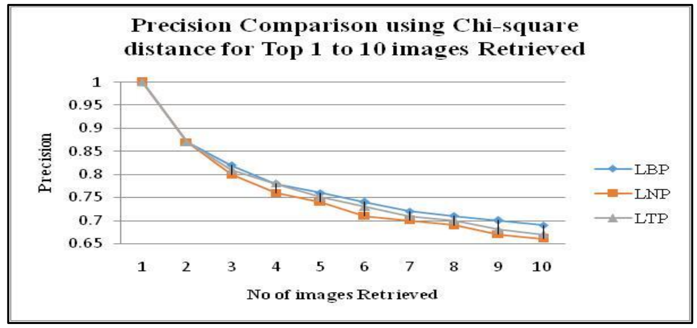

Fig. 5. Precision comparison of Retrieval systems in wang database with LBP, LTP and LNP using chi-square distance [interval 1 to 10]

Fig. 5 imparts the precision comparison of retrieval systems in wang database with LBP, LTP and LNP using chi-square distance. Top 1 to Top 10 retrieved images in the interval of 1 are considered for this analysis. It is observed that the precision values are same for Top1 and Top2 for all the descriptors. Afterwards LBP dominates LNP and LTP.

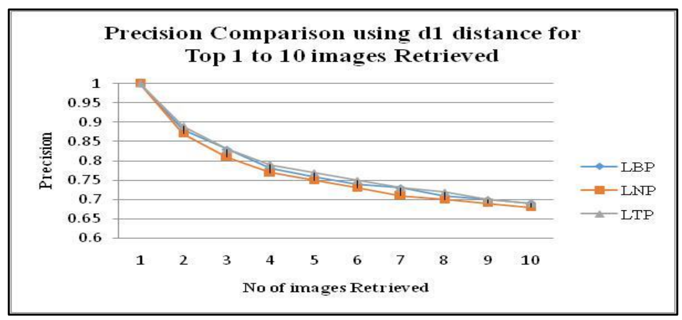

Fig 6. Precision comparison of Retrieval systems in wang database with LBP, LTP and LNP usingd1 distance [interval 1 to 10]

Fig.6 presents the precision comparison of retrieval systems in wang database with LBP, LTP and LNP using d1 distance. Top 1 to Top 10 retrieved images in the interval of 1 are considered for this analysis. It is noticed from Fig.6, LTP descriptor overlooks LBP and LNP, but in some positions the value of LBP and LTP are same.

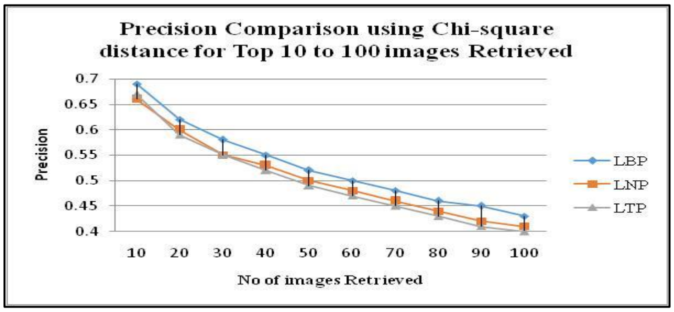

Fig. 7. Precision comparison of Retrieval systems in wang database with LBP, LTP and LNP using chi-square distance [interval 10 to 100]

Fig.7 imparts the precision comparison of retrieval systems in wang database with LBP, LTP and LNP using chi-square distance. Top 10 to Top 100 retrieved images in the interval of 10 are considered for this analysis. It is spotted that LBP descriptor rules LTP and LNP in all the Top positions.

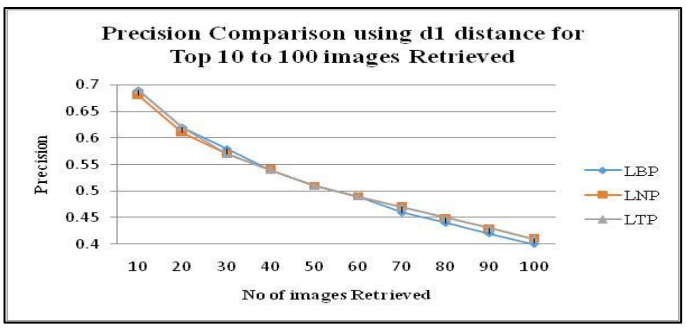

Fig 8. Precision comparison of Retrieval systems in wang database with LBP, LTP and LNP using d1 distance [interval 10 to 100]

Fig.8 presents the precision comparison of retrieval systems in wang database with LBP, LTP and LNP using d1 distance. Top 10 to Top 100 retrieved images in the interval of 10 are considered for this analysis. It is seen that no uniform dominance of descriptors in all the Top positions.

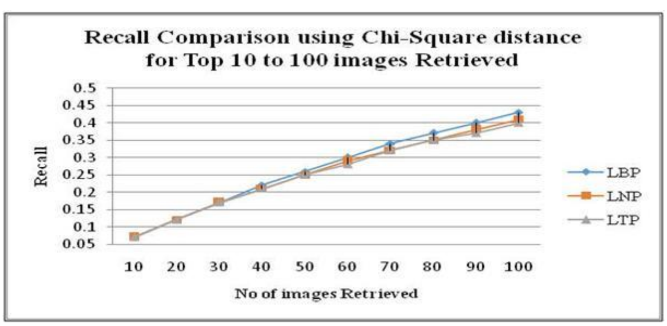

Fig. 9.Recall comparison of Retrieval systems in wang database with LBP, LTP and LNP using chi-square distance [interval 10 to 100]

Fig.9 imparts the recall comparison of retrieval systems in wang database with LBP, LTP and LNP using chi-square distance. Top 10 to Top 100 retrieved images in the interval of 10 are considered for this analysis. The supremacy of LBP is observed from Top 30 position onwards. All the descriptors performed same in the Top 10 and 20 positions.

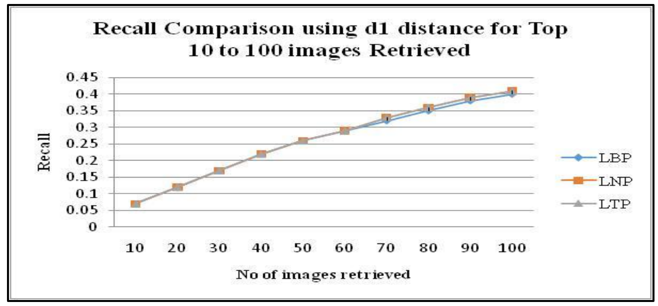

Fig. 10.Recall comparison of Retrieval systems in wang database with LBP, LTP and LNP using d1 distance [interval 10 to 100]

Fig.10 presents the recall comparison of retrieval systems in wang database with LBP, LTP and LNP using d1 distance. Top 10 to Top 100 retrieved images in the interval of 10 are considered for this analysis. There is no marginal performance difference between the descriptors in all the Top positions but LBP gets lower from Top 60 to Top 100.

The graphical representations from Fig.5 to Fig.10 depict that the local patterns are performed almost same in wang database for the retrieval applications. The difference in performance was identified with respect to the distance metric used in the retrieval system. LBP is dominating with chi-square distance and LTP is performing well with d1 distance. It is difficult to arrive the conclusion from the graphs shown. Hence, it is required to comprehend the performance of the features with single measure. Mean Average Precision (MAP) is such a measure. This is calculated by taking the mean value of average precision of all query images in the database. The average precision of query image is computed by considering the precision of the respected query image in all the top images retrieved. Since the most relevant images are expected as the output of the retrieval system for any query, this work respects the top 10 images retrieved in the interval of 1 for working out the average precision. The MAP comparison of the retrieval system using LBP, LNP and LTP features with chi-square and d1 distance measures is recorded in Table 1.

TABLE 1.MAP COMPARISON

METHOD/DISTANCE MEASURE USED	CHI-SQUARE	d1
LBP	0.78	0.78
LNP	0.76	0.77
LTP	0.77	0.79

From Table 1, it is clear that the LTP based system with d1 distance measure yields the better performance. The LTP with d1 distance based image retrieval algorithm is suitable to extract texture features from color images when the color components are united into a single plane. The observations from the Table 1 are as follows: The performance of retrieval system using LBP in two distance measures is same. The performance of LTP based system in both distance metrics is superior to the performance of LNP based system in both distance metrics. The inference from the observation is the relative retrieval efficiency of local patterns in color images is not same as in the retrieval of texture images. It was proved that LNP overruns LBP and LTP in the retrieval of texture images. This is not the case in the retrieval of color images from the experimental result shown in this section.

5 CONCLUSION

This work analyzed the performance of LBP, LTP and LNP in color images retrieval. There are many numbers of local patterns extract color-texture feature in color images without ignoring the information from every color component. In contrast to the previous works, this work considers the color image as a grey by fusing the color components into single plane. LTP and LNP are superior local patterns to extract the texture in textured image database. But what is the position of them in the retrieval of contacted color image. That was the experiment here. Wang database is considered for this experimentation. The efficiency of LBP, LTP and LNP are analyzed with the consideration of two similarity measures: chi-square and d1 distances. Results of the experiments show that LTP with d1 gives the best results as compared to others for color images retrieval. But the efficiency is not very high with respect to all other patterns as in textured image retrieval. The local patterns are functioned almost equal in color images. This is because of leaving the color information in color images. Hence, this work concludes that color component should be interleaved in texture as the feature representation for the retrieval of color images.

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