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Research paper

Tri-Chrominance Texture Pattern: A New Feature Descriptor

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Abstract

Feature extraction plays a vital role in the information management system. This paper proposes Tri-Chrominance Texture Pattern (TCTP), a feature descriptor for extracting the features from images. This pattern helps to extract the inter-channel chrominance relationship, along with texture information of the image. The analysis were done in a natural image dataset, Corel database (DB1), pure colored texture database, Colored Brodaz Texture database (DB2) and a biometric dataset, Indian Face Image database (DB3). The proposed work outperforms the existing works in all the datasets. The analysis on DB1 shows significant improvement over the previous works like Local Binary Pattern (LBP) (78.64%/57.35%), Local Tetra Pattern (LTrP) (79.84%/56.8%) and Local Oppugnant Color Texture Pattern (LOCTP) (82.64%/58%) as 83.25%/58.2% in terms of Average Precision/ Average Recall. The analysis made in the Colored Brodaz database (DB1) shows the result of TCTP as improved from LBP (91.75%/75.18%), LTrP (91.64%/76%) and LOCTP (99.21%/89.38%) to (99.8%/93.47%). The Average Recognition Rate (ARR) of face recognition in DB3 database using the proposed work shows considerable improvement from LBP (78.2%), LTrP (91.9%) and LOCTP (89.1%) as 88.5%. The computational complexity of the proposed work is much lesser than LTrP and LOCTP.

Keywords: *Biometrics, Content-Based Image Retrieval, Feature Descriptor, Tri-Chrominance Texture Pattern*

1. Introduction

Images play a vital role in diversified fields. The enormous advances in technology and inventions such as the computer, television and photography play a remarkable role in facilitating the capture and communication of images [25]. Since databases of medicine, satellite and art works are attracting a lot of users from various fields, effective accessing of desired images from huge and wide-ranging image databases is now a necessity. As a result, the retrieval of relevant information in the large space of image and video databases has become more demanding. The processing and extraction of the needed information from images are done by feature extraction which is based on the low level features like color, shape and texture.

2. Related Work

Texture measures [12, 23, 27, 30, and 31] extract the visual patterns of the images and their spatial definition. The texture is modelled as a two-dimensional gray level variation to extract the feature. The texture [24] is represented by properly defined primitives (microtexture) and spatial arrangements (macrotextue) of the microtexture. Many researchers [20, 21] made their contribution to retrieve the relevant images by using their texture features. Various filters were described by Randen and Hussy [35] and Rivero-Moreno and Bres [36]. The transformations comprise wavelets [15, 34], wavelet packets [22] and curvelets [39]. Recent technological advances allow exploration of human perception of more elaborate techniques [7, 8]. In these works, the authors used functional Magnetic Resonance Imaging (fMRI) to explore the perception of color and shape. Filip et al [9] exploited gaze tracking device to identify salient areas on textured surfaces. The texture of an image can also be represented by the proper distribution of local intensity gradients. This can be implemented by using Histogram of Oriented Gradient (HOG) descriptors [5, 18]. Alvarez et al [2] decomposed texture into blobs in the shape of an ellipse and characterize the texture by a histogram of these blobs. This method is not able to capture blobs' relations or their interactions as crossings. The LBP operator [32] is another texture feature which is being applied in many applications like texture classification [27, 28, 34] texture segmentation [33], face recognition [1] and facial expression recognition [40]. LBP is a histogram of micro texture patterns. For each pixel, a circular neighborhood around the pixel is sampled, and then the sampled values are thresholded by the central pixel value. A drawback of the original LBP feature is that complex patterns usually do not have enough occurrences in a texture, which introduces a statistical error.

3. Proposed Work

There is no single best representation of an image for all perceptual subjectivity, because the user may take the photographs in different conditions (view angle, illumination changes, etc.). Making a suitable representation of these images is an open issue. The detailed study on the researches in perceiving the images with human color vision [25] is done. For perceiving the images with human vision, they suggest to work on separated color spaces [3, 6, 30]. Even though the texture information provides effective feature, many researches [6, 10-14] show that combining other features along with it may give better results. At the conclusion of these studies to incorporate both information about color and texture and to exhibit the human color vision, local texture feature is combined with color feature in opponent color space. This work is motivated by [19, 34].

The contributions of this work include

1. The spatio-chromatic feature is extracted instead of only gray level information.
2. Three different patterns are extracted instead of a single pattern, which extracts more reliable feature.
3. The incorporation of three colors helps to get all color information.

The Tri-Color Channel Texture Pattern (TCTP) code is generated by creating three different inter-channel interaction codes from an image. This is done by generating six different sequences of patterns for each inter-channel interaction, which have different color combinations in distinct positions. The pattern is calculated by using Equation (1). This extracts the information of an image in R-G-B, G-B-R and B-R-G interactive planes by replacing $C_1C_2C_3$ with respective color information.

$$[Pattern_{\,c_1c_2c_3}]_{ij} = f(i,j)]_{i=1\ldots m, j=1\ldots n} \tag{1}$$

The TCTP code provides the inter-relation between the neighbouring pixels which are taken from various color models. Six different combinations of pattern sequences are used in this work, which varies for odd and even rows and for three alternative columns. The following Equations (2) to (16) are used for calculating the $(f(i,j)$. The Equation (2) gives the values of each odd and even row, which are defined in Equation (3) and (4).

$$f(i,j) = \begin{cases} g(i,j), & if\ i\ is\ odd \\ h(i,j), & if\ i\ is\ even \end{cases} \tag{2}$$

$$g(i,j) = \begin{cases} u(i,j), & j = 1,4,7,\ldots \\ v(i,j), & j = 2,5,8,\ldots \\ w(i,j), & j = 3,6,9,\ldots \end{cases} \tag{3}$$

$$h(i,j) = \begin{cases} x(i,j), & j = 1,4,7,\ldots \\ y(i,j), & j = 2,5,8,\ldots \\ z(i,j), & j = 3,6,9,\ldots \end{cases} \tag{4}$$

The odd rows of the code have the value $g(i,j)$ whose values varies for different columns (columns-1,4,7,..., columns-2,5,8,..., columns- 3,6,9,...) as $u(i,j)$, $v(i,j)$ and $w(i,j)$ using Equations (5), (6) and (7) respectively and even rows of the code have the value $h(i,j)$, whose values varies for different columns (columns-1,4,7,..., columns-2,5,8,..., columns- 3,6,9,...) as $x(i,j)$, $y(i,j)$ and $z(i,j)$ using Equations (8), (9) and (10) respectively.

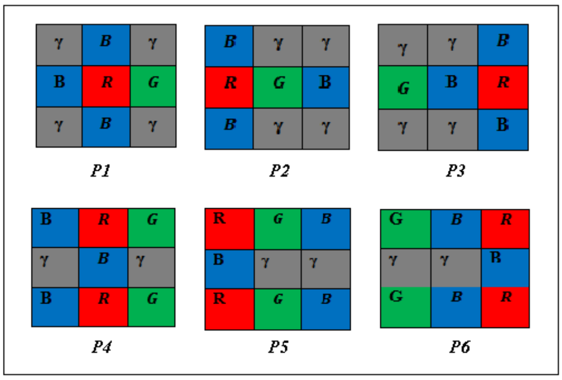

Fig. 1: Six sequences of patterns used for TCCTP

$$u(i,j) = \sum_{l=0}^{7} \begin{cases} 2^l, & \text{if } \big(a(l) - \alpha_1(i,j)\big) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$$v(i,j) = \sum_{l=0}^{7} \begin{cases} 2^l, & \text{if } \big(b(l) - \alpha_2(i,j)\big) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$$w(i,j) = \sum_{l=0}^{7} \begin{cases} 2^l, & \text{if } \big(c(l) - \alpha_3(i,j)\big) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

$$x(i,j) = \sum_{l=0}^{7} \begin{cases} 2^l, & \text{if } \big(d(l) - \alpha_4(i,j)\big) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

$$z(i,j) = \sum_{l=0}^{7} \begin{cases} 2^l, & \text{if } \big(f(l) - \alpha_6(i,j)\big) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

The texture information in relation to the color is extracted by using these equations for each column. The mid pixel value for each sequence of pattern is assigned as the color value in specified $f(i,j)$. $\alpha_1(i,j)$ is taken as the red component value, $\alpha_2(i,j)$ is taken as green component value, $\alpha_3(i,j)$ is taken as the blue component value and $\alpha_4(i,j)$ is taken as blue component value in the corresponding position. Also, $\alpha_5(i,j)$ is taken as γ value and $\alpha_6(i,j)$ is taken as γ value. l represents the number of neighboring pixels (0 to 7). The γ value is assigned to a much lesser value than that of other color component values, which is used for maximizing the difference between the pixel values. This helps to obtain much more complementary texture features for improving the retrieval performance, as compared with gray scale texture feature extraction, where only the luminance of an image is taken into account. Three patterns are extracted from RG, GB and BR planes. Figure 1 shows the nine sequences of patterns formed for RG plane and Figure 2 shows example for extracting the pattern sequences for a block (7X6) from an image. The values $a(l)$, $b(l)$, $c(l)$, $d(l)$, $e(l)$ and $f(l)$ provide the local neighbourhood pixel values used for calculating the pattern code of each center pixel in RGB plane by using the Equations (11) to (16). The same values for other planes can be found out by replacing corresponding color values.

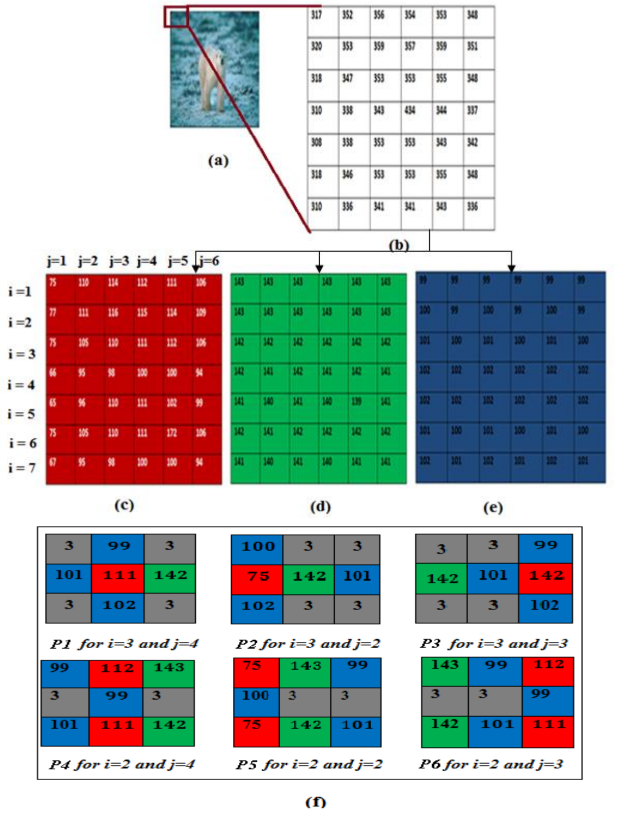

Fig. 2: Example for extracting the pattern sequences for a block (7X6) from an image.

$$a(l)_{rgb} = [\beta, b_{r-1,c}, \beta, g_{r,c+1}, \beta, b_{r+1,c}, \beta, b_{r,c-1}] \quad (11)$$

$$b(l)_{rgb} = [b_{r-1,c-1}, \beta, \beta, b_{r,c+1}, \beta, \beta, b_{r+1,c-1}, r_{r,c-1}] \quad (12)$$

$$c(l)_{rgb} = [\beta, \beta, b_{r-1,c+1}, r_{r,c+1}, b_{r+1,c+1}, \beta, \beta, g_{r,c-1}] \quad (13)$$

$$d(l)_{rgb} = [b_{r-1,c-1}, r_{r-1,c}, g_{r-1,c+1}, \beta, g_{r+1,c+1}, r_{r+1,c}, b_{r+1,c-1}, \beta] \quad (14)$$

$$e(l)_{rgb} = [r_{r-1,c-1}, g_{r-1,c}, b_{r-1,c+1}, \beta, b_{r+1,c+1}, g_{r+1,c}, r_{r+1,c-1}, b_{r,c-1} \quad (15)$$

$$f(l)_{rgb} = [g_{r-1,c-1}, b_{r-1,c}, r_{r-1,c+1}, b_{r,c+1}, r_{r+1,c+1}, b_{r+1,c}, g_{r+1,c-1}, \beta] \quad (16)$$

Thus TCTP code ($Pattern_{c_1c_2c_3}$) is generated by following the above steps. By replacing the color information of other interactive planes, two more pattern codes are calculated.

4. Experimental Results and Analysis

The experiments are done on two different databases which vary in nature. The major finding of this study is texture features can be represented well by the distribution of a pixel in relation with the neighbouring pixel in the other planes. This helps to incorporate the pixel information in terms of color and texture.

Fig. 3: Example images from DB1

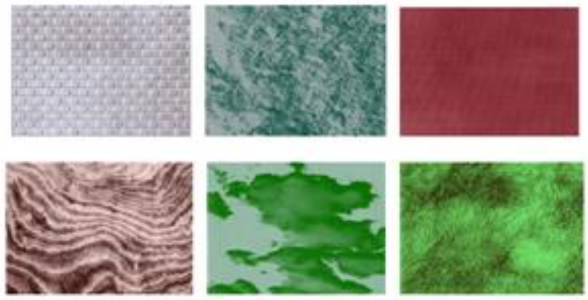

Fig. 4: Example images from DB2

In Experiment 1, images from the Corel-1000 database (DB1) [5] have been used. For this experiment, 1000 images have been collected to form database DB1. Corel database comprises of large amount of images of various contents ranging from animals, outdoor sports to natural images. These images are pre-classified into different categories of size 100 by domain professionals. Some researchers think that this database meets all the requirements to evaluate an image retrieval system because of its large size and heterogeneous content. In this experiment, 1000 images are collected which are about 10 different categories. The ten different categories provided in the database are bears, dogs, buses, dinosaurs, elephants, roses, horses, mountains, buildings and ladies. Each category has 100 images and these have either 187×126 or 126×187 sizes. Figure 3 shows sample images from DB1 database.

Fig. 5: Example images from DB3

In Experiment 2, database DB2 [38] database is used, which consists of 110 different textures from Colored Brodatz texture photographic album. The size of each texture is 640X 640. Each 640X640 image is divided into twenty five 128 X 128 non-overlapping sub images, thus creating a database of 2750 (110 X 25) images. Figure 4 shows sample images from DB2 database. In Experiment 3, Indian Faces database (DB3) [16] which is published by IIT Kanpur in India is used. In this database images of 50 persons with 10 sample images with different orientations and views are available. There are 25 female subjects and 25 male subjects available in Indian Face database. The resolutions of this database images are changed into 128 x 128 for computational purpose and one normal face of each subject is used for training. This experiment uses 240 expressions variant and 357 pose variant faces up to 180º for testing. Figure 5 shows sample images from DB3 database.

4.1. Experiment 1

In Experiment 1, DB1 is used. The performance analysis is done among LBP [28], LTrP [29], LOCTP [17] and TCTP. From the figures and tables, it is evident that the TCTP gives a considerable improvement over the other methods.

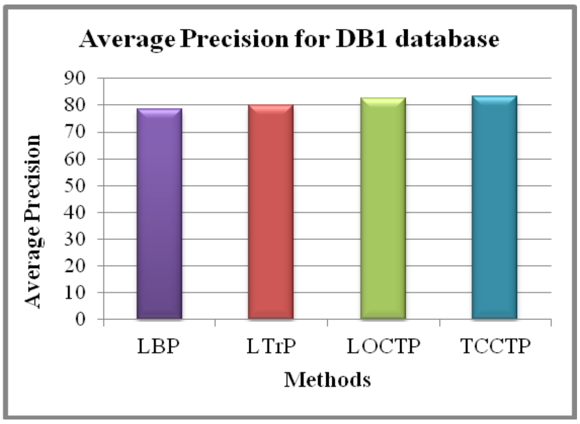

Fig. 6: Average precision of DB1 database

Table 1: Average precision of previous and proposed methods for top number of matches retrieved in DB1 database

Methods	10	30	50	70	90
LOCTP	82.64	73.9	66.14	61.39	58.53
LBP	78.64	69.7	64.2	61.2	59.44
LTrP	79.84	71.2	64.71	61.13	59.11
TCTP	83.25	73.38	66	62	60

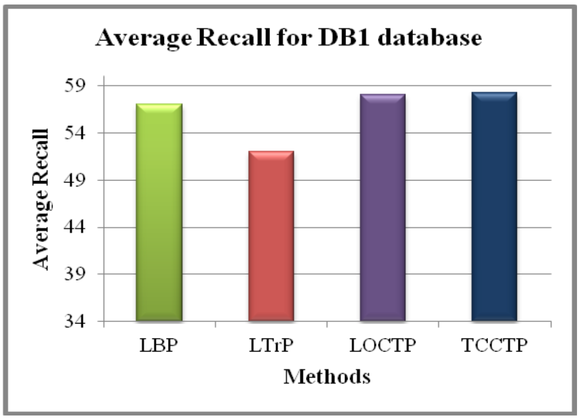

Fig. 7: Average recall of DB1 database

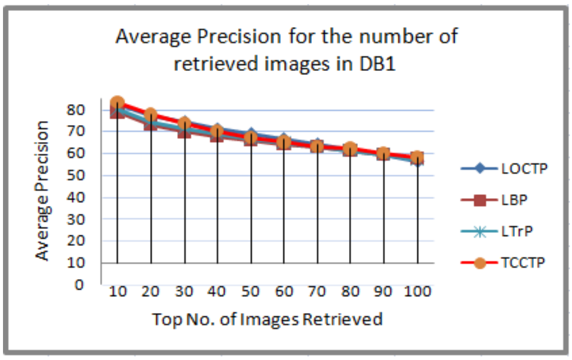

Fig. 8: Average Precision for top number of images retrieved in DB1 database

Table 1 shows average precision of the proposed method and existing methods for top number of matches retrieved. In all cases the results of the proposed method show improvement than that of the previous work. Figures 6, 7 and 8, illustrate the comparison between proposed method and other existing methods in terms of average precision (AP), the average recall (AR), average precision for top number of images retrieved in DB1 database respectively. From these, the following points are observed that average precision/average recall of the DB1 database shows an increase in retrieval result from LBP (78.64%/57.35%), LTrP (79.84%/56.8%) and LOCTP (82.64%/58%) to 83.25%/58.2%. It is clear that the proposed method shows a significant improvement in terms of all evaluation measures as compared with other existing methods for DB1.

4.2 Experiment 2

In Experiment 2, images from the Colored Brodatz texture database (DB2) have been used. Each image is analysed by making all others as the training image. Table 2 shows the average precision for top number of images retrieved in DB2 database.

Table 2: Average precision (in %) of LBP, LTrP, LOCTP and proposed method for top number of matches retrieved in DB2 database

Methods	5	10	15	20	25
LOCTP	99.21	97.72	95.78	93.39	89.38
LBP	91.75	87.37	83.72	79.88	75.18
LTrP	91.64	87.55	83.86	80.03	75.52
TCTP	99.8	99.21	98.21	96.93	94.22

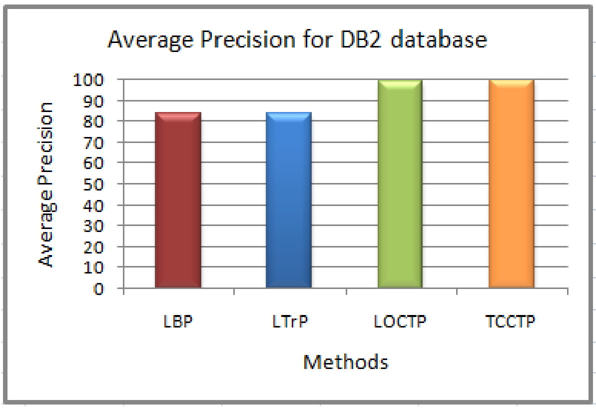

Fig. 9: Average precision for DB2 database

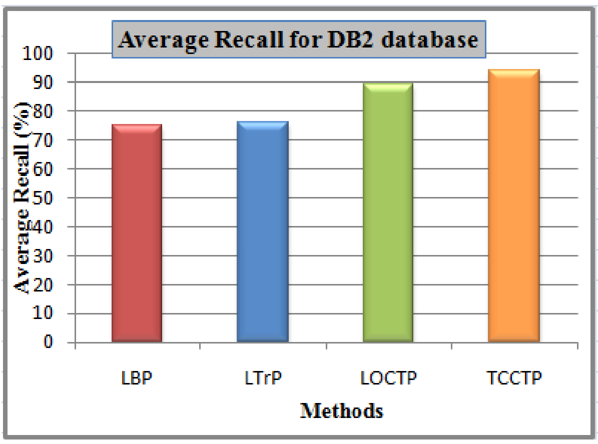

Fig. 10: Average recall for DB2 database

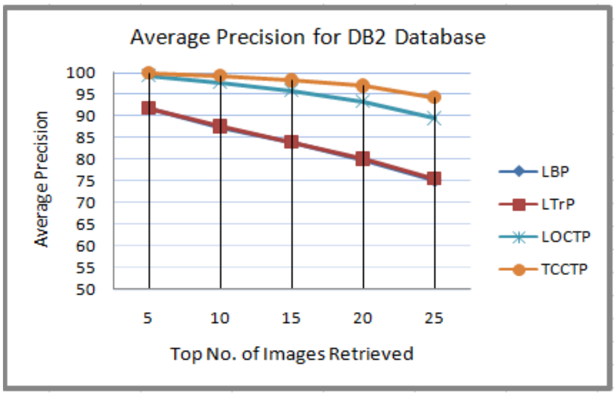

Fig. 11: Average Precision for top number of images retrieved from DB1 database

Figures 9, 10 and 11 show the comparison between proposed method and other existing methods in terms of average precision (AP), the average recall (AR), average precision for top number of images retrieved in DB2 database respectively. From these table and figures it can be viewed that the TCCTP gives better improvement in retrieval result than that of LBP (91.75%/75.18%), LTrP (91.64%/75.52%) and LOCTP (99.21%/89.38%) as 99.8%/94.22% in terms of average precision/average recall for DB2.

4.2. Experiment 3

Experiment 3 is done in DB3 database. The analysis is done between TCTP with LBP, LTrP and LOCTP. The analysis is given in the following figures and table.

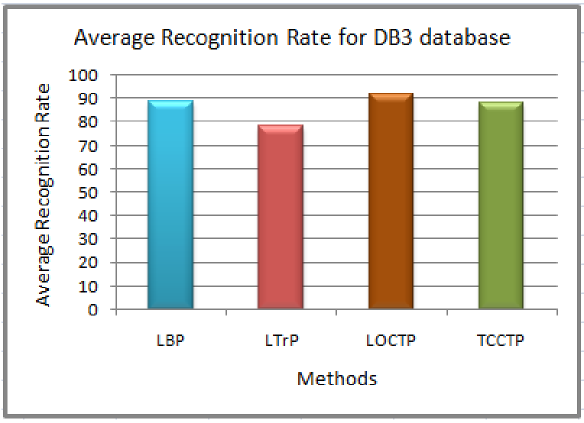

Fig. 12: ARR for DB3 database

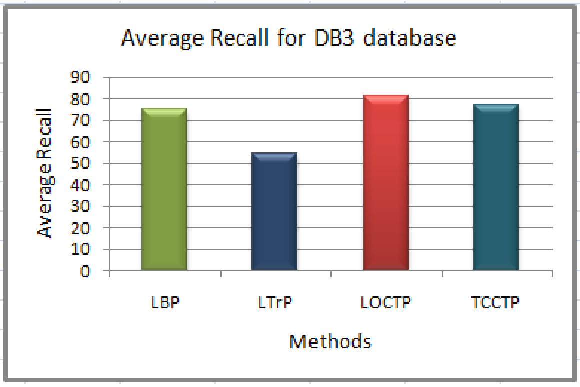

Fig. 13: Average recall for DB3 database

Table 3: Average precision of LBP, LTrP, LOCTP and proposed method for top number of matches retrieved in DB3 database

Methods	2	4	6	8
LOCTP	89.1	78.9	70.87	64.7
LBP	78.2	61.35	54.53	48.8
LTrP	91.9	84.05	78.1	72.62
TCTP	88.5	78.05	71.77	61.82

Figures 12 and 13 illustrate the comparison between proposed method and other existing methods in terms of average retrieval rate (ARR) and average recall (AR) respectively. Table 3 gives the average precision of LBP, LTrP, LOCTP and proposed method for top number of matches retrieved in DB2 database.

4.3 Performance Analysis

Table 4: Feature vector length of an image for different methods

Methods	Feature vector length
LOCTP	3 X 13 X 59
LBP	59
LTrP	13 X 59
TCTP	3 X 59

Table 5: Computation time for feature extraction in different databases

Methods	DB1	DB2	DB3
LOCTP	1122.23	471.3	440.94
LBP	114.39	23.79	19.23
LTrP	285.47	187.31	174.3
TCTP	115.85	54.92	57.5

Table 6: Computation time for query retrieval in different databases

Methods	DB1	DB2	DB3
LOCTP	139.8	1239.15	1020.84
LBP	25.61	176.43	132.3
LTrP	62.39	472.73	398.4
TCTP	26.53	179.7	152.76

The feature vector lengths for the databases are given in Table 4. From this it can be observed that the feature vector length is compared to be lesser equal than in all the other methods. Tables 5 and 6 show the computation time of feature extraction and query retrieval for LBP, LTrP, LOCTP and TCTP methods. The computation time for TCTP is almost equal or less than in the other methods.

5. Conclusion

The proposed work, TCTP works well for DB1, DB2 and DB3 databases. Since TCTP uses all three colors in a pattern sequence, it could able to extract the texture information along with the color feature. The extraction of individual texture features from all the three pairs of opponent color spaces helps to get the interrelated features of chromatic-texture pattern. The different sequences of patterns in TCTP give different results. This work may further improve by incorporating region-based feature extraction.

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