An Efficient Content Based Image Retrieval using Block Truncation Coding

[1] R.Sahaya Jeya Sutha,[2] D.S. Mahendran, [3]S.John Peter
[1]Research Scholar, Department of Computer Science, St.Xavier's College, Palayamkottai, India
[2]Principal, Aditanar College of Arts and Science, Tiruchendur, India
[3]Asso.Professor & Head, Department of Computer Science, St.Xavier's College, Palayamkottai, India

Abstract—

Content based image retrieval (CBIR) systems used to retrieve the related images from a large image database according to the query image. Existing methods for CBIR usually suffer from the limitations of retrieval time and high length feature vector. This paper presents CBIR using global features for Block Truncation Coding (BTC) compressed images. BTC is a compression technique, which is also suitable for indexing the images in database for image retrieval. The features extracted directly from the BTC compressed image without decompressing it, reduces retrieval time. To achieve an image retrieval from a large database, texture and color attributes integrated in this work. HSV Color Histogram extracts color information, while Gray Level Co-occurrence Matrix (GLCM) of BTC codeextracts the texture information. The experimental results prove that the proposed method is able to achieve higher performance as compared to traditional retrieval scheme using BTC. The proposed method tested on Wang image database having 1000 images across 10 categories with 100 images in each category of RGB color space. To compare the performance precision and recall computed, and they showed our approach is outperformed.

Index Terms—*Block truncation coding (BTC), Content based image retrieval (CBIR), global feature descriptors, HSV Color Histogram, Gray Level Co-occurrence Matrix (GLCM)*

DOI Number: 10.14704/nq.2022.20.8.NQ44087 **Neuro Quantology 2022; 20(8):812-823**

I. INTRODUCTION

The emergence of digital cameras, mobile phones and other hand held devices, almost everyone projected to sharing and browsing for images from collection of images database. Content Based Image Retrieval (CBIR) used to retrieve the relevant images according to the query image based on automatically derived image features.

Many researchers proposed various strategies to increase content-based image retrieval accuracy in an acceptable period of time. Today's CBIR systems suffer from main problems like unsatisfactory results and the long response time, because of the inaccurate existing methods and large memory required for storing a large scale image dataset.

CBIR having important role in copyright detection, medical diagnosis, crime prevention, military and engineering design. An efficient, accurate and fast image retrieval is still a challenging task for all these applications.

Image retrieval operated in two domains Pixel and Compressed domain. In the pixel domain approach, features extracted directly from images [5]. These feature extractions are very time consuming while comparing with all images in the database. In the compressed domain, features extracted from the compressed data stream so that it allow faster feature extraction.

Compressed domain CBIR classified into DCT, Wavelet, and Vector Quantization (VQ) based. Block Truncation Coding (BTC) is one of the famous VQ based compression method.

BTC is a lossy image compression technique invented by Delp and Mitchell, [1] which uses moment preserving quantization method for compressing digital gray scale images.GuopingQiu et al.,[4] used this BTC image compression technique for contentbased image retrieval from image databases. In this method,image features extracted directly from the typical BTC or BTC based compressed data stream without performing the decoding process.

This paper elaborates the global feature descriptors for BTC based CBIR for retrieving images that enhances the performance of the CBIR. This scheme involves three phases: compression, feature extraction and searching.

In the compression phase, RGB color image is compressed using traditional BTC method and it yields two color quantizer and one bitmapimage.

The feature extraction phase retrieves image features from color quantizers and bitmap images, which are then saved as feature vectors in the database.Global featuresused to compute the feature extraction.The discriminating information contained in the Local and Global features, which allows one object to be distinguished from others. Local features describe image patches, whereas global features describe the whole image.

In the searching phase, the feature vector extracted from the user submitted query image as the same way and it is matched with the feature vectors in the database by similarity assessments. For similarity measurement, Euclidean distance is used.

The image retrieval system finally returns a set of related images to the user. The proposed method is tested on Wang image database having 1000 images across 10 categories with 100 images in each category of RGB color space. Finally, the precision and recall computed for comparing the performance of the results.

The rest of this paper organized as follows. In section II, details of related works. In section III, details of proposed method described. In section IV, gives the results of the proposed method. Conclusions presentedinSection V.

II. RELATEDWORKS

This chapter presents a comprehensive survey of existing techniques related to this work.

Long et al., [5] elaborates the fundamental theories for contentbased image retrieval. It explains in detail about some widely used methods for visual content descriptions.

GuopingQiu et al.,[4] presents a method to derive image features directly from the BTC compressed images without decoding it. Both color and texture feature derived, one termed the Block Color Co-occurrence Matrix (BCCM) and the other Block Pattern Histogram (BPH). The color feature characterizes the statistics of the color correlation between the blocks, and the texture feature characterizes the statistics of the spatial patterns of the blocks

Suresh P, et al., [9]proposed a method of indexing the image in JPEG compressed domain and extracting the statistical features from that. In the YCbCr plane, image compression happens more efficiently. To extract the features directly from the luminance (Y) and chrominance (Cb, Cr) components for retrieval purposes. Texture information extracted from the luminance plane and color information from the two-chrominance planes.

Kekre et al., [10], proposed the BTC based CBIR. In this method red, green and blue planes of image considers together to compute feature vector. Here augmented this BTC based CBIR as BTC-RGB and Spatial BTC-RGB. In BTC-RGB, feature vector computed by considering red, green and blue planes of the image independently.

Rao et al., [11] projected the CBIR using Dynamic Dominant Color, Texture and Shape features. Here the image partitioned into eight equal parts. Then finds the centroid of each parts and consider it as Dominant Color. Texture feature was obtained using the Gray Level Co-occurrence Matrix (GLCM). Then the color and texture features are normalized. To capture the Shape feature, edges of image calculated using Gradient Vector Flow fields and it recorded using Invariant moments.

Guo et al., [14] proposed a new approach for CBIR in compressed domain using Dot-Diffused Block Truncation Coding (DDBTC) compressed data stream. RGB color space used for constructing color descriptor. The DDBTC effectively compresses an image by decomposing an image into two quantizers and its corresponding bitmap image. Then, from the DDBTC quantizers and bitmap image, the Color Histogram Feature (CHF) and Bit Pattern Feature (BPF) were retrieved. The variants of BTC discussed [12]-[16] by this author.

Liu et al., [17] proposed the Local Binary Pattern (LBP) based feature for texture image retrieval. For extracting texture feature, neighboring pixel values are considered. A joint histogram derived from the LBP code used as a feature descriptor. By adding an additional color feature called Color Information Feature (CIF), color information of the image retrieved.

Sutha *et al.,* [19]-[20] discussed in detail of BTC Compression technique and its variants how utilized for content based image retrieval. Various feature extraction techniques and color models are reviewed and surveyed elaboratively.

Jamil *et al.,*[21] proposed an optimal codebook for a content-based image retrieval system in JPEG compressed domain. To extract features from JPEG images only requires partial decoding of images. The codebook generated by selecting an optimum number of training images. Even though the current JPEG compressed domain-based image retrieval approaches have achieved good retrieval results, it contains the problems of feature vector length is large and need to be optimized.

Garg et al., [22] presented a novel method to retrieve colored images using GLCM features and texture fused LBP variants. This technique focuses on extraction and reduction in multiple features. The work divided into of four steps. The first step is decomposition, in which multi-scale decomposition is performed separately using discrete wavelet transformation (DWT) for channels R, G, and B. The second is concatenation of all three channels R, G, and B achieved from the set of functions. The third is reduction in features using the PSO algorithm to pick the most differentiating features. The last step is classification where three classifiers used to assess the category of images evaluated. The three classifiers are support vector machine (SVM), K-nearest neighbor (KNN) and decision tree (DT).

III. PROPOSED METHOD

A. BTC based CBIR

The benefit of BTC based CBIR is that the feature vector of image is independent of the image dimensions, i.e. There is no requirement that all database images be the same size as the query image. The BTC compression produced two color quantizers and a bitmap image, which further processed to generate the image feature vector. The feature vectors are compared by using suitable similarity measures between a query image and the target image in database. Based on the distance computed from similarity measures, a set of relevant images retrieved.

B. BTC compression

Block Truncation Coding (BTC) is a good, simple, and effective image compression method that also helps with image retrieval.

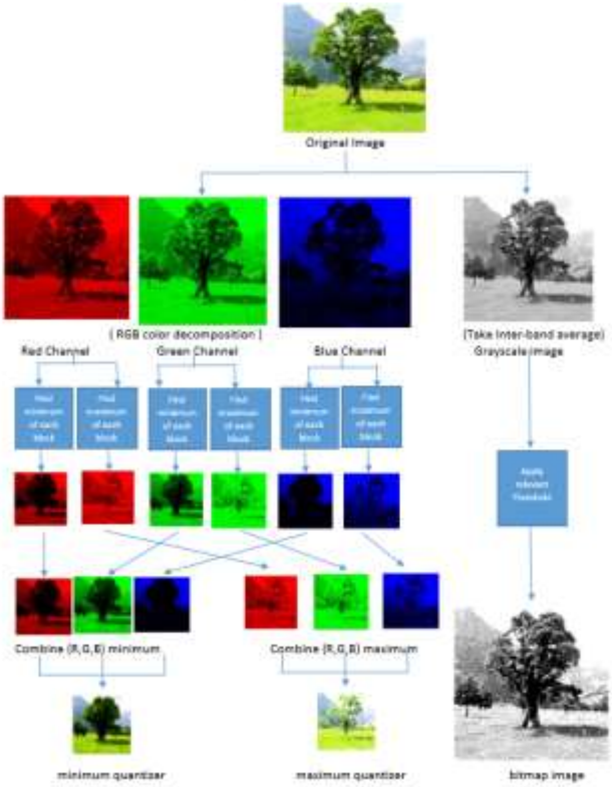


Fig. 1 Schematic diagram of Compression phase

As seen in [1,] Delp and Mitchell proposed the BTC approach for image compression in 1979. Improved methods of BTC compressions are Ordered Dither Block Truncation Coding (ODBTC) [12], Error Diffusion BTC (EDBTC) [13], Dot diffusion BTC (DDBTC) [14], etc.

In BTC, the original RGB color image F of size $M \times N$ is divided into fixed-size non-overlapping image blocks of size $m \times n$. To avoid the edge blurring and blocking effect, can pick the small block size. Let f_R, f_G, f_B is the red, green, and blue color channel of the image F. The output of BTC is two color quantizer and one bitmap image.

Combine the minimum pixel value over red, green, and blue color spaces to determine the minimum quantizer for each image block.The maximum quantizer was also derived in the same way.The color quantizer size reduced as $\frac{M}{m} \times \frac{N}{n}$ from the original image size $M \times N$. Here the maximum quantizer is looking brighter than that of the minimum quantizer.

To find the bitmap image, first convert the color image into grayscale image by its inter-band average value as

$$\bar{f}(x,y) = \frac{1}{3}[f_R(x,y) + f_G(x,y) + f_B(x,y)]$$

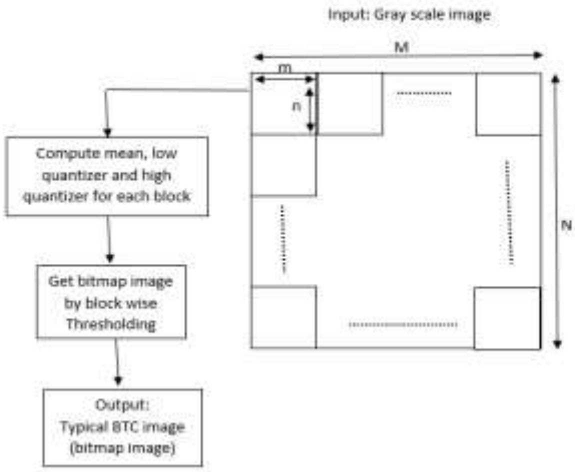


Fig 2: Block Diagram of Typical BTC for Gray scale image

Now construct the bitmap image from the grayscale image by applying the following typical BTC compression technique. The grayscale image is separated into $m \times n$image blocks of defined size that do not overlap, to avoid the effect of edge blurring and blocking.Compute mean, low quantizer ($\mathrm{X_L}$), high quantizer ($\mathrm{X_H}$) for each block. Now construct the bitmap image from the grayscale image by applying mean as a threshold value. If a pixel value is lesser than the threshold then it returns 0 else it returns 1. The resultant output bitmap image produced with the same size$M \times N$.

Algorithm of Typical BTC

Input: Gray Scale Image

Output: Bitmap Image

Step 1: Split the image into non-overlapping $m \times n$ size blocks.

Step 2: Compute $\bar{x}$ (mean), $\mathrm{X_L}$(low quantizer) and $\mathrm{X_H}$ (high quantizer) for each block.

Step 3: Compare the pixels with its block mean as a threshold value.

Step 4: Assign '0' for less than the threshold value pixels, otherwise assign '1'.

Step 5: Repeat the steps 2 to 4 until all blocks completed to get the final bitmap image.

Step 6: $\mathrm{X_L}$(low quantizer) and $\mathrm{X_H}$ (high quantizer) of each block produced two quantizers. It used for reconstructing the compressed image.

Step 7: To reconstruct the Bitmap image, value of '1' replaced by one mean pixel value ($\mathrm{X_H}$), otherwise replaced by another mean pixel value ($\mathrm{X_L}$).

C. HSV Color Histogram

The proposed method uses the HSV (Hue Saturation Value) color histogram for global color feature extraction. In HSV, 'Hue' denotes the colors, 'Saturation' denotes the amount of that color that is mixed with white, and 'Value' denotes the amount of that color that is combined with black (Gray level).

Color information and brightness cannot be separated in RGB. To isolate image brightness from color information, HSV is used.

A color histogram of an image depicts the distribution of the image's color composition. It represents the various types of colors that appeared, as well as the amount of pixels in each type of color.

Color histograms computed in two ways: globally or locally. Only the global color histogram features considered in this proposed work, which depicts the entire image with a single color histogram.

To derive the color feature from the two color quantizers of BTC compression, the RGB color space is transformed to HSV color space in order to retrieve the color histogram. The color histogram is made up of 12 bins that are evenly quantized into 8 levels of hue, 2 levels of saturation, and 2 levels of value. This procedure was used for both the min and max color quantizers. As a result, the size of the color feature vector is 24 (12+12).

Algorithm to convert RGB to HSV

Step 1: To modify R,G,B values range from 0..255 to 0..1, divide the R,G,B numbers by 255.

$$\mathrm{R}' = \frac{\mathrm{R}}{255}$$

$$G' = \frac{\mathrm{G}}{255}$$

$$B' = \frac{\mathrm{B}}{255}$$

Step 2: Compute $C_{max}, C_{min},\ \Delta\,(difference)$

$$C_{max} = \max(R', G', B')$$

$$C_{min} = \min(R', G', B')$$

$$\Delta = C_{max} - C_{min}$$

Step 3: Compute 'Hue'value

$$H = \begin{cases} 0^{\circ}, & if\ \Delta = 0 \\ 60^{\circ} \times \left(\frac{G' - B'}{\Delta}\ mod\ 6\right), & if\ C_{max} = R' \\ 60^{\circ} \times \left(\frac{B' - R'}{\Delta} + 2\right), & if\ C_{max} = G' \\ 60^{\circ} \times \left(\frac{R' - G'}{\Delta} + 4\right), & if\ C_{max} = B' \end{cases}$$

Step 3: Compute 'Saturation'value

$$S = \begin{cases} 0, & if\ C_{max} = 0 \\ \frac{\Delta}{C_{max}}, & if\ C_{max} \neq 0 \end{cases}$$

Step 4: Compute 'Value'

$$V = C_{max}$$

D. Gray Level Co-occurrence Matrix (GLCM)

The proposed method uses the GLCM for extracting global texture feature extraction.Before finding the GLCM, BTC bitmap is converted into BTC code matrix by multiplying 255 with every 3x3 blocks average values. The extraction of GLCM features can be done in two steps. The co-occurrence matrix calculated in the first step;then texture features are computed from theco-occurrence matrix.

The size of the co-occurrence matrix is $N \times N$,where N is the number of gray-valuesi.e., the rows & columns represent the set of possible pixel values.The co-occurrence matrix shows how frequently different combinations of grey levels co-occur in an image. In other words, spatial relationship between pixels in an image.

It is calculated based on the following parameters$d\ and\ \theta$. Where d represents the Relative distance between the pixel pair, measured in pixel difference number such as 1, 2, …. and θ represents the Relative orientationi.e., rotational angle. (e.g., 0º, 45º, 90º, 135º, …)

The co-occurrence matrix can be calculated as the following equation:

$$C_{d,\theta}(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, if I(p,q) = i and I(p+\Delta x, q+\Delta y) = j \\ 0, otherwise\end{cases}$$

where,$C_{d,\theta}(i,j)$, is the number of occurrences of the pair of gray levels i and j, with d,θ are the distance and angularity respectively. Here, $I(p,q)$, is the intensity of p^{th} row and q^{th} column of animage.

The proposed work considers 4 directions $\theta = 0^{o}, 45^{o}, 90^{o}, 135^{o}$ with $d = 1$. Thus, the pair $(d = 1, \theta = 0^{o})$ is the nearest horizontal pixel. Moreover, co-occurrence matrixes $(\theta = 90^{o})$ for vertical and diagonal axes $(\theta = 90^{o}, 135^{o})$.

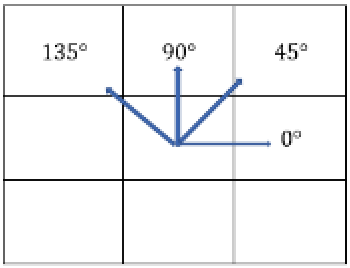


Fig.3 GLCM Directions

GLCM is a statistical texture analysis method of the second order. It describes the spatial relationship between pixels in an image.Some of the GLCM statistical features are Contrast, Correlation,Energy, homogeneity, Entropy,Inverse Difference Moment. Inthispaper,four GLCM features contrast, correlation, energy, and homogeneity are calculated from the BTC compressed imagefor 4 directions and used to describe the image texture feature. The number of distinctive parameters utilized to characterize the texture is 16. The feature dimension is greatly reduced when compared with existing techniques.

The GLCM feature calculated as follows:

1. *Contrast:* Measures the local variation in the graylevel co-occurrence matrix, which also called as Variance.

$$\sum_{i,j} P_{i,j}.(i-j)^2$$

2. *Correlation:* Measures the correlation between a pixel to its neighbor, its range between -1 to 1.

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)P_{i,j}}{\sigma_i \sigma_j}$$

3. *Energy:* Provides the sum of squared elements in the GLCM, which also called as Uniformity.

$$\sum_{i,j} {P_{i,j}}^2$$

4. *Homogeneity*: The closeness of element distribution is measured.

$$\sum_{i,j} \frac{P_{i,j}}{1+|i-j|}$$

Where$P_{i,j}$represents the number of gray occurrences.

Algorithm for Texture feature extraction:

(1) Select BTC based compression method and find the compressed image as bitmap.

(2) Bitmap image is converted into BTC code matrix.

(3) Select the distanced=1, and four direction θ=0°,45°,90°and 135° to obtain four GLCM.

(4) The contrast, correlation, energy and homogeneity of each GLCM are calculated, and the 4 feature values calculated.

E. Similarity measures

Some of the important distance measures are $\mathrm{L_1, L_2, \ldots, L_n}$ distances, Fu distance, Canberra distance, etc. The distance plays the most important role in the CBIR system since the retrieval result is very sensitive with the chosen distance metric. The similar images to the query image returned and ordered based on their similarity distance score.The image with the lowest score is the most similar to the query image.

The proposed method uses the Euclidean distance (L_2 distance) for calculating the similarity between two images of a query image and the set of images in the database as target image.The similarity distances between the two images $\delta(query, target)$ can be formally defined under Euclidean distance metrics as follows:

$$\boldsymbol{\delta(query, target)} = \sqrt{\sum |query_i - target_i|^2}$$

IV. EXPERIMENTAL RESULTS

The proposed method was implemented in a MATLAB 2017 and tested on Wang image database having 1000 images across 10 categories with 100 images in each category of RGB color space. All the images are stored in JPEG format with size 384 x 256 or 256 x 384. There are different categories which include 100 people, 100 old building,100 horses,100 dinosaur, 100 rose flowers,100 beaches,100 elephants,100 mountains,100 foods, and 100 buses.Some of the sample images shown in the following figure.

Fig.4 Sample Corel 1K images

The following figures shows the stages of resultant images: the input image, inter band image, BTC compressed binary image, minimum and maximum color quantized images.

Fig. 5Input Image

Fig. 6 Inter-band Average Image

Fig. 7BTC Compressed binary image

Fig. 8 Minimum and Maximum color Quantized images of the input image

The color and texture feature vectors obtained from the quantized image and BTC compressed images. The results stored in a database. The similarity metrics applied to the query images and target images feature vector directly. The top 10 most relevant retrieved images shown from the compared results.

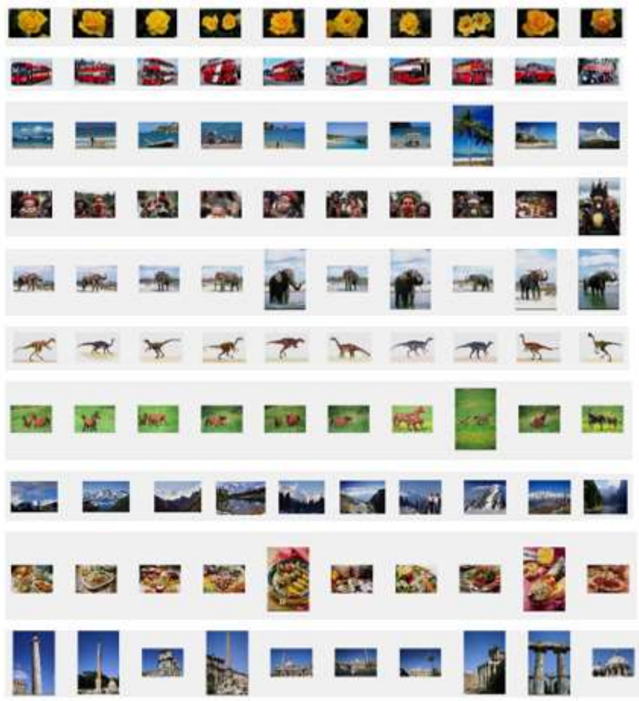


Fig. 9: Retrieved similar images

In this research, two image feature descriptors and two color spaces areinvolved for performing the retrieval task. Two features are theHSV Color Histogram and GLCM for retrieving color and texture features. TheRGB and HSV color spaces are investigated for the CBIR system.

It generates the min and max color quantizers are RGBmin, RGBmax respectively. HSVmin, HSVmax feature vectors generated from the respective quantizers. In this work, 8 levels of Hue, 2 levels of Saturation, and 2 levels of Value considered. So the color feature vector size is 24 by 12 HSVmin+12 HSVmax.When compared to previous approaches, this is an extremely short feature vector.

V. PERFORMANCE MEASURES

In CBIR, precision and recall are the most important measure of evaluation system to find the accuracy of the images retrieved. Precision is used to measure the accuracy whereas recall is used to measure the completeness. The precision and recall for a query image is defined as follow.

A. Precision

The ratio of the number of retrieved relevant images to the total number of retrieved images is known as Precision.

$$\text{Precision} = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ retrieved}$$

B. Recall

The number of recovered relevant images divided by the total number of relevant images in the database is known as Recall.

$$\text{Recall} = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ relevant\ images\ in\ the\ database}$$

Our experimental approach is organized into three classes to determine the significance of proposed features. Only the HSVcolor histogram, Only the GLCM, and combined descriptor. The results are superior when combining theboth color and texture features, as shown in Table I.

Table 1. Results of proposed methods Precision on Corel–1K database

Categories	Color Feature	Texture Feature	Both Color & Texture
Africans	90	75	95
Beaches	70	60	85
Buildings	55	75	75
Buses	90	75	100
Dinosaurs	95	95	100

Elephants	75	60	80
Roses	90	80	100
Horses	90	75	95
Mountains	65	55	70
Food	80	75	90
Average	**80**	**72.5**	**89**

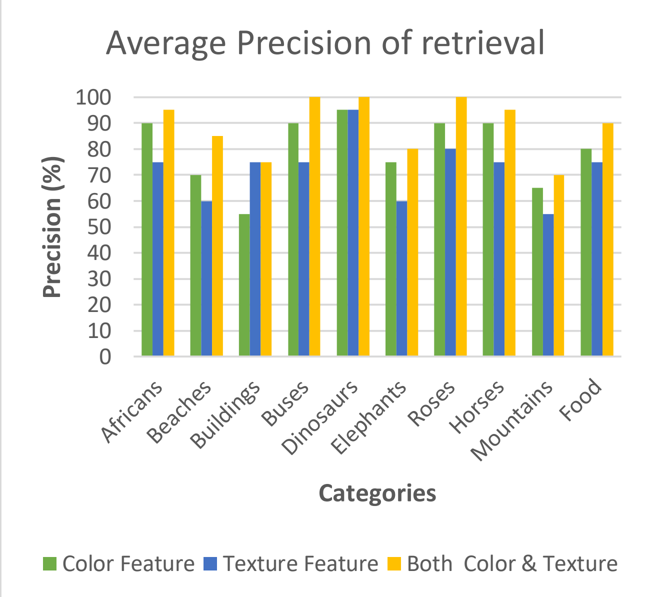


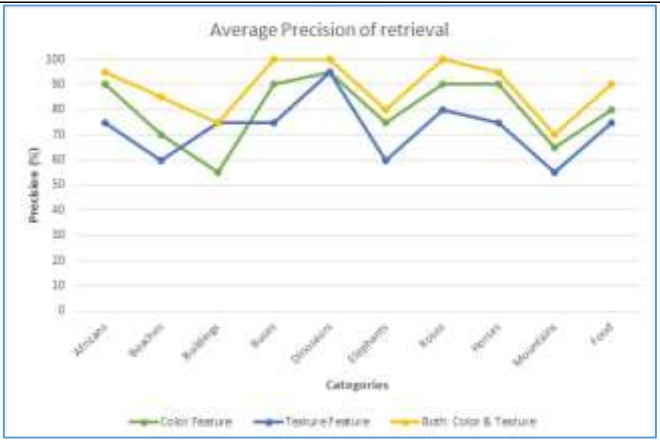
Fig. 7: Comparison of Precision Graph Corel-1K image categories

The Fig.7 proves the proposed method gives better result when considering both the color and texture features. In the above experiment we have considered 50% color feature and 50% texture feature.

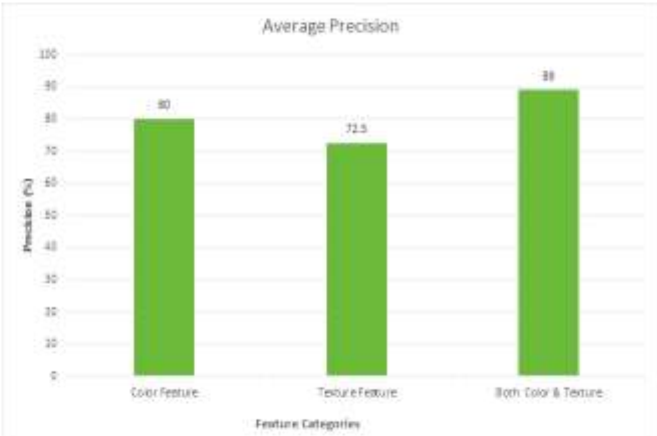
Table II. Comparison of Average Precision(P) And Recall (R)On Top 20 Retrieval Images (in %) with different methods

Categories	LBP		Dominant Color		Proposed method	
	P (%)	R (%)	P (%)	R (%)	P (%)	R (%)
Africans	90	18	80	16	95	19
Beaches	85	17	55	11	85	17
Buildings	80	16	55	11	75	15
Buses	90	18	90	18	100	20
Dinosaurs	100	20	80	16	100	20
Elephants	80	16	60	12	80	16
Roses	85	17	75	15	100	20
Horses	90	18	55	11	95	19
Mountains	70	14	50	10	70	14
Food	80	16	75	15	90	18

In Table II, the comparison of Average Precision and Recall on top 20 Retrieval Images with different methods are shown. The proposed work given the outperformed results. The Fig. 8 shows its graphical representation.



(a)



(b)

Fig.8 (a) & (b): The retrieval performance comparison of the proposed methods features for Corel-1k

The Table III compares the retrieval images on top 10, 20, 30 images. Obviously, it shows the up to 20 images it gave better results. When the count less, the Precision and Recall are very high. Fig. 9 shows its comparison result graphically.

Table III. Comparison of Average Precision(P) And Recall (R) On Top 10, 20, 30 Retrieval Images (in %) of LBP, Dominant Color and Proposed methods

	Precision (in %)			Recall (in %)		
No. of retrievals	LBP	DC	Prop-osed	LBP	DC	Prop-osed
10	92	77	98	9	8	10
20	85	68	89	17	14	18
30	72	59	80	22	18	24

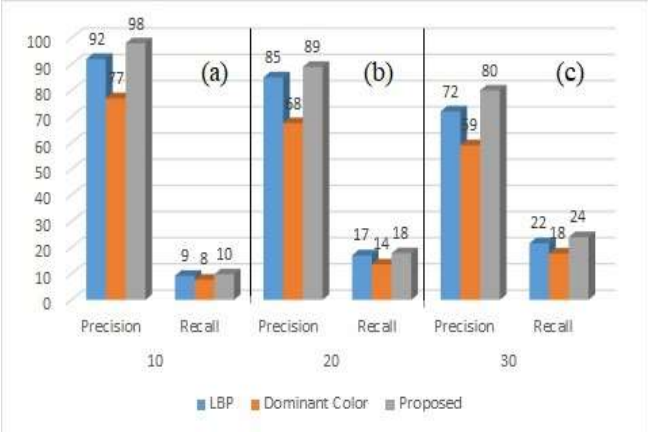


Fig9. The retrieval performance comparison for Corel-1k: (a) on Top 10 Retrieval images (b) on Top 20 Retrieval Images (c) on Top30 Retrieval Images

VI. CONCLUSION

This work presented an efficient method for content based image retrieval using BTC based compression technique. The global features HSV color histogram and GLCM used for color and texture feature extractions respectively. Euclidean distance applied for similarity checking between query and target image database. As a result, the proposed image retrieval scheme works effectively for CBIR. The retrieval time and feature vector size are both reduced due to BTC compressed images.This method can be extended for video retrieval. And also, it can be extended to different color spaces instead of RGB/HSV color space. The variants of BTC compression techniques can be considered for future works.

REFERENCES

[1] E.J. Delp, O.R. Mitchell, “Image compression using block truncation coding”, IEEE Transactions on Communications COMM-27 (September 1979) 1335–1342.

[2] D. E. Knuth, “Digital halftones by dot diffusion”, ACM Trans. Graph., Vol. 6, No. 4, pp. 245–273, Oct. 1987.

[3] J. Huang et al., “Image indexing using color correlogram,” in Proc.CVPR97, 1997, pp. 762–768.

[4] GuopingQiu, “Color Image Indexing Using BTC”, IEEE Transactions on Image Processing, Vol.12, No.1, pp.93-101, Jan. 2003.

[5] F. Long, H. J. Zhang, D. D. Feng (2003) , ‘Fundamentals of content – based image retrieval’, in: D. D. Feng, W. C. Siu, H. J .Zhang(Eds.), Multimedia Information Retrieval and Management—Technological Fundamentals and Applications, Springer, pp.1–27.

[6] Z. M. Lu, and H. Burkhardt, “Colour image retrieval based on DCT-domain vector quantization index histograms,” Electronics Letters, vol. 41, no. 17, 2005.

[7] Kim, Tae-Su& Kim, Seung-Jin& Lee, Kuhn-Il. (2005). Image Retrieval Based on Co-occurrence Matrix Using Block Classification Characteristics. 3767. 946-956. 10.1007/11581772_83.

[8] Y. D. Chun, N. C. Kim, and I. H. Jang, Content -based image retrieval using multiresolution color and texture features, IEEE Trans. Multimedia, Vol. 10, No. 6, Pp. 1073 1084, Oct. 2008.

[9] Suresh, P., Sundaram, R. M. D., & Arumugam, A. (2008, December). Feature extraction in compressed domain for contentbased image retrieval. In *2008 International Conference on Advanced Computer Theory and Engineering* (pp. 190-194). IEEE.

[10]Kekre, H. B., &Thepade, S. D. (2009, January). Image retrieval using augmented block truncation coding techniques. In *Proceedings of the International Conference on Advances in Computing, Communication and Control* (pp. 384-390).

[11]Rao, M. B., Rao, B. P., & Govardhan, A. (2011). CTDCIRS: content based image retrieval system based on dominant color and texture features. *International Journal of Computer Applications*, *18*(6), 40-46.

[12]Guo, J. M., Prasetyo, H.,“Content-Based Image Retrieval Using Features Extracted From Halftoning-Based Block Truncation Coding”, IEEE Transaction on Image Processing , Vol. 24 , No. 3, Mar. 2015.

[13]Guo, J. M., Prasetyo, H. and Jen-Ho Chen, “Content-Based Image Retrieval Using Error Diffusion Block Truncation Coding Features”, IEEE Transactions On Circuits And Systems For Video Technology, Vol. 25, No. 3, Mar. 2015.

[14]Guo, J. M., Prasetyo, H. and N. J. Wang, "Effective image retrieval system using dot-diffused block truncation coding features," IEEE Trans. on Multimedia, Vol. 17, No. 9, Sep. 2015.

[15]Guo, J. M., Prasetyo, H."Performance Evaluation of Error Diffusion Block Truncation Coding Feature for Color Image Retrieval" Chapter 4, publically available in the link http://sciencegatepub.com/books/gcsr/gcsr_vol4/GCSR-Vol4-Ch4.pdf

[16]Guo, J. M., Prasetyo, H., Lee, H., & Yao, C. C. (2016). Image retrieval using indexed histogram of void-and-cluster block truncation coding. *Signal Processing*, *123*, 143-156.

[17]Liu, P., Guo, J. M., Chamnongthai, K., &Prasetyo, H. (2017). Fusion of color histogram and LBP-based features for texture image retrieval and classification. *Information Sciences*, *390*, 95-111.

[18]Sutha, R. S. J., Mahendran, D. S., & Peter, S. J. (2017). An Overview of Content Based Image Retrieval Techniques. *International Journal of Advanced Research Trends in Engineering and Technology (IJARTET) Vol*, *4*.

*[19]*Sutha, R. S. J., Mahendran, D. S., & Peter, S. J. A survey on Block Truncation Coding based Content Based Image Retrieval.*International Journal of Computer Application. Vol, 7, No. 6,.DOI:*10.26808/rs.ca.i7v6.03

[20]Sutha, R. S. J., Mahendran, D. S., & Peter, S. J. (2019). A Review on Feature Extraction Techniquesfor CBIR with different BTC methods. Journal of Emerging Technologies and Innovative Research (JETIR), February 2019, Vol 6, No. 2, DOI:http://doi.one/10.1729/Journal.27613

[21]Jamil A, Majid M, Anwar SM. An optimal codebook for content-based image retrieval in JPEG compressed domain. Arabian Journal for Science and Engineering. 2019 Nov;44(11):9755-67.

[22]Garg M, Dhiman G. A novel content-based image retrieval approach for classification using GLCM features and texture fused LBP variants. Neural Computing and Applications. 2021 Feb;33:1311-28.

R. Sahaya Jeya Sutha received the B.Sc. (Computer Science), M.C.A. (Computer Applications) and M.Phil. (Computer Science) degrees in 1995, 2000 and 2006, respectively from the Manonmaniam Sundaranar University, Tirunelveli. She has qualified the Tamilnadu State Eligibility Test (SET) Lectureship in 2016. She is currently pursuing Ph.D. degree in Computer Applications at the Manonmaniam Sundaranar University, Tirunelveli. She is a life member of ISTE. Her research interests include image retrieval, video retrieval, data hiding and image compression.

Dr. D.S.Mahendran is working as the Principal, Aditanar College of Arts and Science, Tiruchendur. He received the M.Sc. Physics and PGDCA degrees from Madurai Kamaraj University and M.Phil. andPh.D. degrees in Computer Science from Alagappa University, Karaikudi. His research interest includes Computer algorithms, Ad-Hoc Networks, Network Security and Green Network.

Dr. S. John Peter is working as Associate Professor in Computer Science at St.Xavier's College, Palayamkottai, Tirunelveli. He received his M.Sc. and M.Phil. degrees in Computer Science from Bharadhidasan University,Tiruchirappalli. He also earned his Ph.D. degree from Manonmaniam Sundaranar University, Tirunelveli. He has published many research papers on clustering algorithms in various conferences, national and international journals.