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CONTENT-BASED IMAGE RETRIEVAL USING FEATURESEXTRACTED FROM HALFTONING-BASED BLOCK TRUNCATION CODING

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ABSTRACT:

In this paper we proposed a new method to index color images using the features extracted from the error diffusion block truncation coding(EDBTC). The EDBTC produces a bitmap image and two color quantizers, which are further processed using vector quantization (VQ) to generate the image feature descriptor. Here we computed color histogram feature (CHF) and bit pattern histogram feature (BHF), to measure the similarity between a query image and database image. The CHF and BHF are computed from the VQ-indexed color quantizer and VQ-indexed bitmap image, respectively. The distance computed from standard formula , the proposed indexing method outperforms the former BTC based image indexing and the other existing image retrieval schemes with natural and textural data sets. Thus, the proposed EDBTC is not only examined with good capability for image compression but also offers an effective way to index color images for the content based image retrieval system with less computational time.

I.INTRODUCTION:

Many former schemes have been developed to improve the retrieval accuracy in the content-based image retrieval (CBIR) system. One type of them is to employ image features derived from the compressed data stream. As opposite to the classical approach that extracts an image feature descriptor from the original image, this retrieval scheme directly generates image features from the compressed stream without first performing the decoding process. This type of retrieval aims to reduce the time computation for feature extraction since most of the multimedia images are already converted to compressed domain before they are recorded in any storage devices. The image features are directly constructed from the typical block truncation coding (BTC) or halftoning-based BTC compressed data stream without performing the decoding process. These image retrieval schemes involve two phases, indexing and searching, to retrieve a set of similar pictures from the database. The indexing phase extracts the image features from all the images in the database which is later stored in database as feature vector. In the searching phase, the retrieval system derives the image features from a picture submitted by a user (as query image), which are later utilized for performing similarity matching on the feature vectors stored in the database. The image retrieval system finally returns a set of pictures to the user with a specific similarity criterion, such as color similarity and texture similarity.

II.EXISTING SYSTEM:

The concept of the BTC is to look for a simple set of representative vectors to replace the original images. BTC compresses an image into a new domain by dividing the original image into multiple non overlapped image blocks, and every block is then represented with two extreme quantizers (i.e., high and low mean

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values) and bitmap image. Two subimages constructed by the two quantizers and the corresponding bitmap image are produced at the end of BTC encoding stage,which are later transmitted into the decoder module through the transmitter. To generate the bitmap image, the BTC scheme performs thresholding operation using the mean of every image block such that a pixel value greater than the mean value is regarded as one (white pixel) and vice versa.

2.1. Drawbacks:

BTC method doesn't improve the image quality or compression ratio compared with JPEG or JPEG 2000. It often suffers from blocking effect and false contour problems. Making it less satisfactory for human perception.

III. Error Diffusion Block Truncation Coding (EDBTC):

The EDBTC produces two color quantizers and a bitmap image, which is further, processed using vector quantization (VQ) to obtain the image feature descriptor. Herein two features are introduced, namely, color histogram feature (CHF) and bit pattern histogram feature (BHF), to measure the similarity between a query image and the target image in database. The CHF and BHF are computed from the VQ-indexed color quantizer and VQ-indexed bitmap image, respectively.

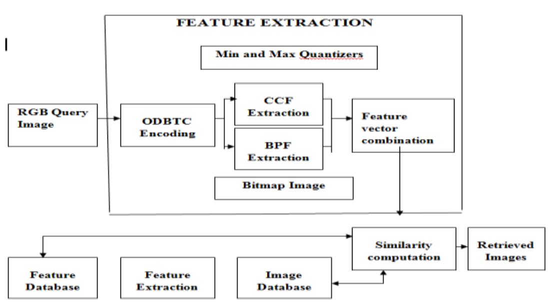

Fig.1. Schematic diagram of the proposed image retrieval framework.

ADVANTAGES:

The halftoning - based BTC, namely, Error Diffusion BTC (EDBTC) is proposed to overcome the three above disadvantages of the BTC. EDBTC scheme produces higher image quality compared with the classical BTC approaches.

3.1.EDBTC FOR COLOR IMAGES

This section presents a review of the EDBTC with its extension to color image compression. The EDBTC compresses an image in an effective way by incorporating the error diffusion kernel to generate a bitmap image. Simultaneously, it produces two extreme quantizers, namely, minimum and maximum quantizers. The EDBTC scheme offers a great advantage in its low computational complexity in the bitmap image and two extreme quantizers' generation. Additionally, EDBTC scheme produces better image quality compared with the classical BTC approaches. The detail explanation and comparison between EDBTC and BTC-based image compression can be found at [3] and [4]. BTC and EDBTC have the same characteristic in which the bitmap image and the two extreme values are produced at the end of the encoding stage. In BTC scheme, the two quantizers and its image bitmap are produced by computing the first moment, second moment, and variance value causing a high computational burden. Suppose a color image of size $M \times N$ is partitioned into multiple non-overlapping image blocks of size $m \times n$. Let $f(x, y) = \{f_R(x, y), f_G(x, y), f_B(x, y)\}$ be an image block, where $x = 1, 2, \ldots, m$ and $y = 1, 2, \ldots, n$.

For each image block, the EDBTC produces a single bitmap image $bm(x, y)$ and two extreme (color) quantizers (q_{min} and q_{max}). The bitmap image size is identical to that of the original image size. EDBTC employs the error kernel to generate the representative bitmap

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image. The error diffusion kernels for Floyd–Steinberg, Stucki, Sierra, Burkers, Jarvis, and Stevenson are the different error kernels yield different bit/halftoning patterns. The EDBTC exploits the dithering property of the error diffusion to overcome the false contour problem normally occurred in BTC compression. Moreover, the blocking effect can also be eased by its error kernel since the quantization error on one side of the boundary can be compensated by the other side of the boundary. The correlation on both sides of a boundary between any pair of resulting image blocks can be maintained. The EDBTC bitmap image can be obtained by performing thresholding of the inter-band average value with the error kernel. In a block-based process, the raster-scan path (from left to right and top to bottom) is applied to process each pixel in a given image. Suppose that f (x, y) and f¯(x, y) denote the original and inter-band average value, respectively. The inter-band average value can be computed as

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

The fR(x, y), fG(x, y), and fB(x, y) denote the image pixels in the red, green, and blue (RGB) color channels, respectively. The inter-band average image can be viewed as the gray scale version of a color image.

The EDBTC performs the thresholding operation by incorporating the error kernel. We first need to compute the minimum, maximum, and mean value of the inter-band average pixels as

$$x_{\min} = \min_{\forall x,y} \bar{f}(x, y)$$
$$x_{\max} = \min_{\forall x,y} \bar{f}(x, y)$$
$$\bar{x} = \sum_{x=1}^{m} \sum_{y=1}^{n} \bar{f}(x, y).$$

The bitmap image h(x, y) is generated using the following rule:

$$h(x, y) = \begin{cases} 1, & \text{if } \bar{f}(x, y) \geq \bar{x} \\ 0, & \text{if } \bar{f}(x, y) < \bar{x}. \end{cases}$$

The intermediate value o(x, y) is also generated at the same time with the bitmap image generation. The value o(x, y) can be computed as

$$o(x, y) = \begin{cases} x_{\max}, & \text{if } h(x, y) = 1 \\ x_{\min}, & \text{if } h(x, y) = 0. \end{cases}$$

The residual quantization error of EDBTC can be computed as

$$e(x, y) = \bar{f}(x, y) - o(x, y).$$

The EDBTC thresholding process is performed in a consecutive way. One pixel is only processed once, and the residual quantization error is diffused and accumulated into the neighboring unprocessed pixels. The value f¯(x, y) of unprocessed yet pixel is updated using the following strategy:

$$\bar{f}(x, y) = \bar{f}(x, y) + e(x, y) * \epsilon$$

Where ∈ is the error kernel to diffuse the quantization residual into its neighboring pixels which have not yet been processed in the EDBTC thresholding. The symbol ∗ denotes the convolution operation. Several error kernels can be used to perform the diffusion operation, such as Jarvis error kernel [63], Burkers [65], Floyd–Steinberg [61], Sierra [65], Stucki [62], and Stevenson [64. The reason of choosing the extreme values to represent an image block is to generate a dithered result (bit pattern illusion) to reduce the annoying blocking effect or false contour inherently existing in BTC images. Notably, the error at the boundary of an image block should be diffused to its neighboring blocks, thus the blocking effect can be significantly eased in the EDBTC reconstructed image. The two extreme quantizers consist of RGB color information obtained by searching the minimum and maximum of value in an image block for each RGB color space. Two EDBTC color quantizers are computed by looking for the minimum and maximum of all image pixels in each image block as

$$q_{\min}(i,j) = \{\min_{\forall x,y} f_R(x,y), \min_{\forall x,y} f_G(x,y), \min_{\forall x,y} f_B(x,y)\}$$

$$q_{\max}(i,j) = \{\max_{\forall x,y} f_R(x,y), \max_{\forall x,y} f_G(x,y), \max_{\forall x,y} f_B(x,y)\}.$$

Fig.2 shows the schematic diagram of the EDBTC image compression system. The EDBTC is not only able to compress an image but also able to index an image in a CBIR system

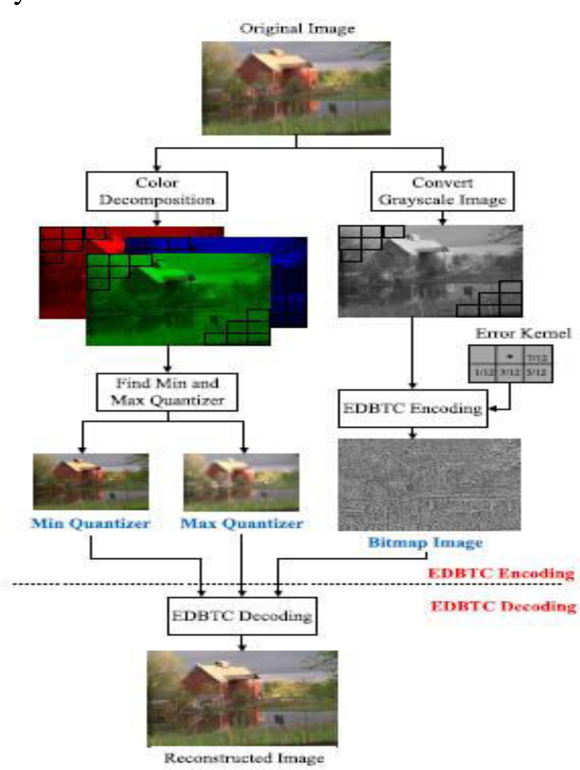

Fig.2. Schematic diagram of EDBTC processing for color image.

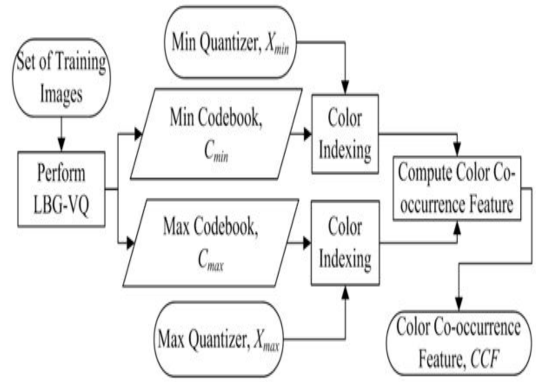

Fig. 3. Illustration of CHF computation.

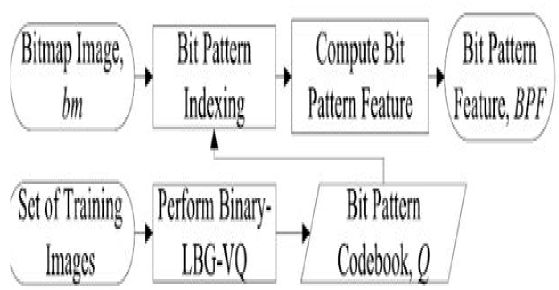

Fig. 4. Illustration of BHF computation..

At the end of the EDBTC encoding process, two color quantizers and a bitmap image are sent to the decoder via a transmission channel. The decoder simply replaces the bitmap image which has value 1 with the maximum quantizer, while the value 0 is substituted with the minimum quantizer. There is no computation needed in the decoder side, making it very attractive in the real-time application.

IV.PROPOSED SYSTEM:

4.1 ODBTC Encoding

.Given an original RGB color image of size $M \times N$. This image is firstly divided into multiple non-overlapping image blocks of size

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$m \times n$, and each image block can be processed independently.

$$B = \left\{ b(i,j); i = 1,2,\ldots,\frac{M}{m}; j = 1,2,\ldots,\frac{N}{n} \right\} \text{ --------4.1}$$

The original image block *b(i, j)* is firstly converted into the inter-band average image by

$$\bar{b}_{k,l}(i,j) = \frac{1}{3}\left[b_{k,l}^{red}(i,j) + b_{k,l}^{green}(i,j) + b_{k,l}^{blue}(i,j)\right]; \text{ ------4.2}$$
$$k = 1,2,\ldots,m; \quad l = 1,2,\ldots,n,$$

The inter-band average computation is applied to all image blocks. The classical BTC approach performs the thresholding operation with a single threshold value obtained from the mean value of the pixels in an image block. A pixel of a smaller value compared to the threshold is turned to 0 (black pixel); otherwise it turns to 1 (white pixel) to construct the bitmap image representation.

Subsequently, the ODBTC performs the thresholding on the inter-band average image with the scaled version of dither array for each image block to obtain the representative bitmap image *bm(i, j)*.

Except for sending the image bitmap to the decoder, ODBTC also transmits the two extreme color quantizers (minimum and maximum quantizers) to the decoder. The RGB color space is employed in this paper, thus the minimum and maximum quantizers are also in the RGB color representation.

The set of minimum and maximum quantizers from all image blocks is given as

$$X_{min} = \left\{ x_{min}(i,j); i = 1,2,\ldots,\frac{M}{m}; j = 1,2,\ldots,\frac{N}{n}, \right\}$$
$$X_{max} = \left\{ x_{max}(i,j); i = 1,2,\ldots,\frac{M}{m}; j = 1,2,\ldots,\frac{N}{n}, \right\} \text{ ----------4.3}$$

where $x_{min(i,j)}$ and $x_{max(i,j)}$ denote the minimum and maximum values, respectively, over red, green, and blue channels on the corresponding image block *(i, j)*.

The two values can be formally formulated as

$$x_{min}(i,j) = \left[\min_{\forall k,l} b_{k,l}^{red}(i,j), \min_{\forall k,l} b_{k,l}^{green}(i,j), \min_{\forall k,l} b_{k,l}^{blue}(i,j)\right],$$
$$x_{max}(i,j) = \left[\max_{\forall k,l} b_{k,l}^{red}(i,j), \max_{\forall k,l} b_{k,l}^{green}(i,j), \max_{\forall k,l} b_{k,l}^{blue}(i,j)\right], \text{ -----------4.3}$$

At the end of the ODBTC encoding, the bitmap image, b_m, the minimum quantizer, X_{min}, and maximum quantizer, X_{max} , are obtained and considered as encoded data stream, which are then transmitted to the decoder module over the transmission channel. The receiver decodes this encoded data stream to reconstruct the image. The decoder simply replaces the elements of value 0 in the bitmap by the minimum quantizer, and elements of value 1 in the bitmap by the maximum quantizer.

It is clear that the ODBTC yields better reconstructed image quality compared to the traditional BTC scheme. The blocking effect and false contour are reduced in the ODBTC reconstructed image because of the halftoning-illusion from the dithering strategy. Except for the image compression, ODBTC compressed data stream, i.e., the bitmap image and two extreme color quantizers, can be further utilized as an image descriptor. A simple method for CBIR task is developed in this paper using the image feature derived from the ODBTC encoded data stream.

4.2 CCF Extraction

The ODBTC employed in the proposed method decomposes an image into a bitmap image and two color quantizers which are subsequently exploited for deriving the image feature descriptor. Two image features are introduced in the proposed method to

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characterize the image contents, i.e., Color Co-occurrence Feature (CCF) and Bit Pattern Feature (BPF). The CCF is derived from the two color quantizers, and the BPF is from the bitmap image.

The color distribution of the pixels in an image contains huge amount of information about the image contents. The attribute of an image can be acquired from the image color distribution by means of color co-occurrence matrix. This matrix calculates the occurrence probability of a pixel along with its adjacent neighbors to construct the specific color information. This matrix also represents the spatial information of an image.

Color Co-occurrence Feature (CCF) could be derived from the color co-occurrence matrix. In the proposed scheme, CCF is computed from the two ODBTC color quantizers. The minimum and maximum color quantizers are firstly indexed using a specific color codebook. The color co-occurrence matrix is subsequently constructed from these indexed values. Subsequently, the CCF is derived from the color co-occurrence matrix at the end of computation. In general, the color indexing process on RGB space can be defined as mapping a RGB pixel of three tuples into a finite subset (a tuple) of codebook index (the most representative codeword). LBG Vector Quantization (LBGVQ) generates a representative codebook from a number of training vectors.

Let $C_{min} = \{c_{min1}, c_{min2}, \ldots, c_{min\ Nc}\}$ and $C_{max} = \{c_{max1}, c_{max2}, \ldots, c_{max\ Nc}\}$ be the codebooks generated from the minimum quantizer, $Xmin$, and maximum quantizer, X_{max}, respectively. Herein, $c_{min\ i}$, $c_{max\ i}$, and Nc denote the codewords from minimum quantizer, codeword from maximum quantizer, and color codebook size, respectively.

The color indexing process of the ODBTC minimum quantizer can be considered as the closest matching between the minimum quantizer value of each image block $x_{min(i,j)}$ and the codebook C_{min}. Similarly, the indexing for the maximum quantizer of each image block $x_{max(i,j)}$ with codebook C_{max} is formally defined. After performing the color indexing for minimum and maximum quantizers, the color co-occurrence matrix (i.e., Color Co-occurrence Features (CCF)) for a given image can be directly computed as

$$CCF(t_1, t_2) = \Pr\left\{\tilde{i}_{min}(i,j) = t_1, \tilde{i}_{max}(i,j) = t_2 \mid i = 1, 2, \ldots, \frac{M}{m}; j = 1, 2, \ldots, \frac{N}{n}\right\}, \quad \text{---------4.5}$$

4.3 BPF Extraction

Another feature, namely Bit Pattern Feature (BPF), characterizes the edges, shape, and image contents. The binary vector quantization produces a representative bit pattern codebook from a set of training bitmap images obtained from the ODBTC encoding process. Let $Q = \{Q_1, Q_2, \ldots, Q_{Nb}\}$ be the bit pattern codebook consisting N_b binary code words. These bit pattern codebooks are generated using binary vector quantization with soft centroids, and many bitmap images are involved in the training stage. At the codebook generation stage, all code vector components may have intermediate real values between zero (black pixel) and one (white pixel) as opposed to binary values. At the end of training stage, the hard thresholding performs the binarization of all code vectors to yield the final result.

Thus BPF is defined as

$$BPF(t) = \Pr\left\{\tilde{b}(i,j) = t \mid i = 1, 2, \ldots, \frac{M}{m}; j = 1, 2, \ldots, \frac{N}{n}\right\} \quad \text{---------4.6}$$

for all $t = 1, 2, \ldots N_b$.

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4.4 Texture Feature Extraction

For extracting the texture features, Gabor wavelet transformation is used.

Gabor filters are directly related to Gabor wavelets, since they can be designed for number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of biorthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created.

A Gabor filter can be viewed as a sinusoidal plane of particular frequency and orientation, modulated by a Gaussian envelope.

$$G(x,y) = s(x,y)\, g(x,y) \quad ....4.7$$

where $s(x,y)$ is complex sinusoid and $g(x,y)$ is 2D gaussian envelope

$$s(x,y) = \exp \quad ....4.8$$

$$g(x,y) = \exp \quad ....4.9$$

and characterize the spatial extent and bandwidth of along the respective axes, and are the shifting frequency parameters in the frequency domain. Using as the mother wavelet, the Gabor wavelets, a class of self-similar functions can be obtained by appropriate dilations and rotations of through:= where **(xsin , a>1,** indicates the number of orientations, S the number of scales in the multi resolution decomposition and a is the scaling factor between different scales. These parameters can be set according to reduce the redundant information (caused by the Non orthogonality of the Gabor wavelets) in the filtered images. Given an image I, the Gabor transform with orientation n and m scale can be computed as. Where indicates the complex conjugate. In our work, we set the Gabor filter to have S=4 scale levels and O=6 orientations. Gives the examples of the extracted Gabor features using the designed filter bank on T1, PD, T2 and FA images, respectively. As we can see, on different locations, scales and orientations, we need Gabor features from different modalities to best delineate the underlying structure. For instance, in the corpus callosum, since it is mainly white matter, Gabor features from FA image (computed from DTI) is expected to give stronger response.

4.5 Database Feature Extraction

Similar to Query feature extraction, the CCF, BPF and the texture features are extracted for all the images present in the database.

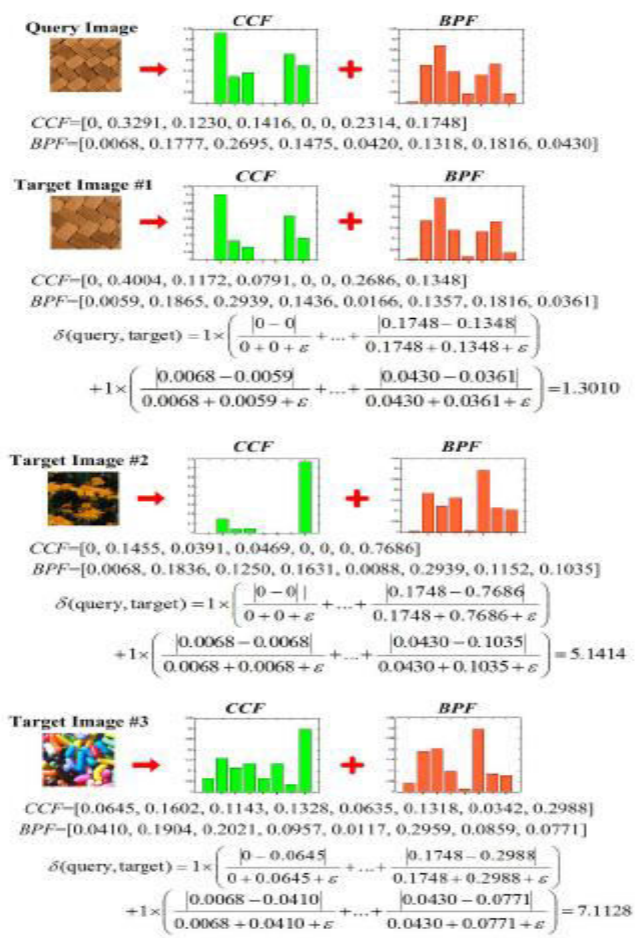

Figure 4.1 Example of similarity distance computation with $\alpha 1 = 1$, $\alpha 2 = 1$ and $\_\epsilon = 10^{-16}$

4.7 Image Retrieval Using Svm

In the image classification task, the proposed method performance is measured with the proportion correct classification (accuracy) from the nearest neighbor classifier. The classifier assigns a class label of testing set using the similarity distance computation as used in the image retrieval task. The similarity distance is computed and sorted in the ascending order between the query image *q* and target images in the database, and then the first *L* images are returned as a set of retrieved images. In image retrieval experiment, all images are turned as query image such that the performance evaluation is conducted by averaging the values over all query images.

Formally, the average precision *P(q)* and average recall *R(q)* measurements for describing the image retrieval performance are defined as below:

$$P(q) = \frac{1}{N_t L} \sum_{q=1}^{N_t} n_q(L),$$
$$R(q) = \frac{1}{N_t N_R} \sum_{q=1}^{N_t} n_q(L), \qquad \text{---------4.11}$$

where *L*, *Nt*, and *NR* denote the number of retrieved images, the number of images in database, and the number of relevant images on each class, respectively. The symbols *q* and *nq (L)* denote the query image and the number of correctly retrieved images among *L* retrieved images set, respectively.

Image Retrieval With EDBTC Feature

The similarity distance computation is needed to measure the similarity degree between two images. The distance plays the most important role in the CBIR system since the retrieval result is very sensitive with the chosen distance metric. The image matching between two images can be performed by calculating the distance between the query image given by a user against the target images in the database based on their corresponding features (CHF and BHF). After the similarity distance computation, the system returns a set of retrieved images ordered in ascending manner based on their similarity distance scores. The similarity distance between the two images, namely, query and target images, can be formally

defined as

$$\delta(\text{query}, \text{target}) = \alpha_1 \sum_{k=1}^{N_c} \frac{|\text{CHF}_{\min}^{\text{query}}(k) - \text{CHF}_{\min}^{\text{target}}(k)|}{\text{CHF}_{\min}^{\text{query}}(k) + \text{CHF}_{\min}^{\text{target}}(k) + \varepsilon} + \alpha_2 \sum_{k=1}^{N_c} \frac{|\text{CHF}_{\max}^{\text{query}}(k) - \text{CHF}_{\max}^{\text{target}}(k)|}{\text{CHF}_{\max}^{\text{query}}(k) + \text{CHF}_{\max}^{\text{target}}(k) + \varepsilon} + \alpha_3 \sum_{k=1}^{N_b} \frac{|\text{BHF}^{\text{query}}(k) - \text{BHF}^{\text{target}}(k)|}{\text{BHF}^{\text{query}}(k) + \text{BHF}^{\text{target}}(k) + \varepsilon}$$

where α1, α2, and α3 are the similarity weighting constants representing the percentage contribution of the CHF and BHF in the proposed image retrieval process. The value 1 means that the color or bit pattern feature is catered in the similarity distance, while the value 0 meaning that the color or bit pattern feature is disabled in the distance computation. A small number ε is added into denominator to avoid the mathematic division error. The CHF query and BHF query denote the color and bit pattern feature descriptors of the query image, respectively, while the symbols CHF target and BHF target represent the image descriptors of the target image in database.

V.EXPERIMENTAL RESULTS

In this section, extensive experiment results are reported to demonstrate the effectiveness of the proposed EDBTC image indexing method. Several image databases consisting of the natural and textural images are utilized in this experiment to have an in-depth investigation of the successfulness of the proposed CBIR system. The proposed image retrieval system extracts the image features from all images in the database using the proposed CHF and BHF EDBTC features. The

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similarity between the query and target images is measured based on the similarity distance score from their descriptors. A set of retrieved images is returned by the system in ascending order based on the similarity distance values. In this experiment, the retrieval accuracy is measured using the average precision, average recall, or APR value over all query images. The higher average precision rate and APR value indicate that the system is able to retrieve a set of returned image which has more similar appearance with the query image.

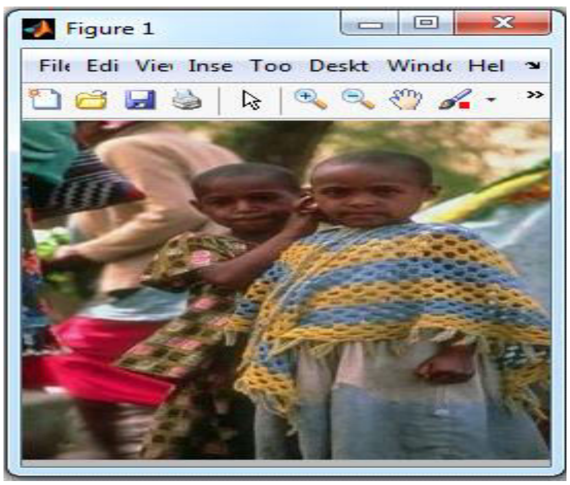

Fig: Input Query Image

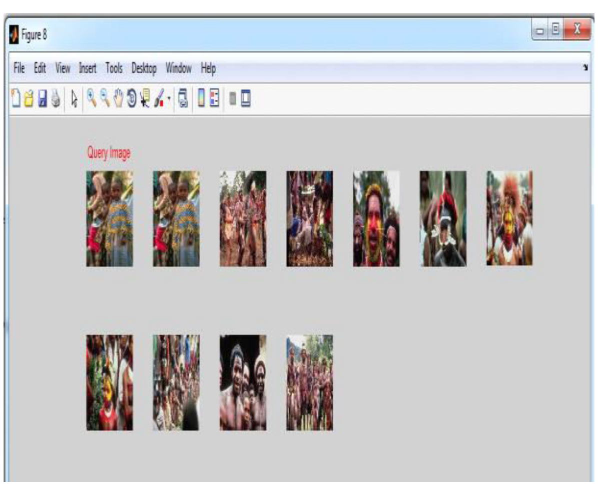

Fig: Retrieved Images

CONCLUSION

In this study, an image retrieval system is presented by exploiting the ODBTC encoded data stream to construct the image features, namely Color Co-occurrence and Bit Pattern features. Another features based on color and texture can be added along with CCF and BPF which act as additional approach of extracting the ODBTC features which enhance the overall efficiency in the retrieval task. The proposed scheme can provide the high accuracy rate when compared to various former schemes in the literature. As a result, the proposed scheme can be considered as a very competitive candidate in color image retrieval application. Another feature can be added by extracting the ODBTC data stream, not only CCF and BPF, to enhance the retrieval performance.

REFERENCES

[1] Z. Liu, H. Li, W. Zhou, R. Zhao, And Q. Tian, "Contextual Hashing for Large-Scale Image Search," IEEE Trans. Image Process., Vol. 23, No. 4, Pp. 1606-1614, Apr. 2014.

[2] Payal Dilip wankhade, Prof.S.V.Paranjape, "Texture based matching of Medical Images," International conference on Power, Automation and Communication (INPAC), Page. 107-111, Oct. 2014.

[3] Manimala Singha and K.Hemachandran, "Content Based Retrieval using Color and Texture," Signal & Image Processing: An International Journal (SIPIJ) Vol.3, No.1, February 2012

[4] C. C. Lai, and Y. C. Chen, "A user-oriented image retrieval system based on interactive genetic algorithm," IEEE Trans. Inst. Meas., vol. 60, no. 10, October 2011.

[5] Doaa Mohammed, Fatma Abou-Chadi, "Image Compression using Block Truncation

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Coding ," Journal of Selected Areas in Telecommunications (JSAT), Feb 2011.

[6] Ja-Hwung Su, Wei-Jyun Huang, Philip S. Yu, Fellow, "Efficient Relevance Feedback for Content-Based Image Retrieval by Mining User Navigation Patterns," IEEE Transactions on Knowledge and Data Engineering, Vol. 23, No. 3, March 2011.

[7] Jing-Ming Guo, Ming-Feng Wu, "Improved Block Truncation Coding Based on the Void-and-Cluster Dithering Approach," IEEE Transactions on Image Processing, vol. 18, no. 1, pp. 211-213, Jan 2009.

[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, Oct. 2008.

[9] Amit Jain, Ramanathan Muthuganapathy and Karthik Ramani, "Content-Based Image Retrieval Using Shape and Depth from an Engineering Database," Springer-Verlag Berlin Heidelberg pp. 255–264, 2007.

[10] M. R. Gahroudi, and M. R. Sarshar, "Image retrieval based on texture and color method in BTC-VQ compressed domain," Int. Symp. on Signal Processing and Its Application, 20th, Feb. 2007.

[11] Manesh Kokare, P. K. Biswas and B. N. Chatterji, "Rotation-Invariant Texture Image Retrieval Using Rotated Complex Wavelet Filters," IEEE Trans. Systems, Man, and Cybernetics, vol. 36, no. 6, Dec. 2006.

[12] Manesh Kokare, P. K. Biswas and B. N. Chatterji, "Texture Image Retrieval Using New Rotated Complex Wavelet Filters," IEEE Trans. Systems, Man, and Cybernetics, vol. 35, no. 6, Dec. 2005.

[13] Y. D. Chun, S. Y. Seo, and N. C. Kim, "Image retrieval using BDIP and BVLC moments," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 13. Pp. 951-957, Sept 2003.

[14] G. Qiu, "Color Image Indexing Using BTC," *IEEE Trans. Image Processing*, Vol. 12, No. 1, Jan. 2003.

[15] B. S. Manjunath, J. R. Ohm, V. V. Vasudevan, and A. Yamada, "Color and teture descriptors," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 11, pp. 703-715, Jun. 2001.

[16] C. S. Huang and Y. Lin, "Hybrid block truncation coding," *IEEE Signal Process. Lett.*, vol. 4, no. 12, pp. 328–330, Dec. 1997.