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SVM BASED CBIR USING FEATURES EXTRACTED FROM HALFTONING-BASED BLOCK TRUNCATION CODING

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***Abstract*— —** Our propose work presents a technique for Content-Based Image Retrieval (CBIR) by exploiting the advantage of low complexity Ordered-Dither Block Truncation Coding (ODBTC) for the generation of image content descriptor. In encoding step, ODBTC compresses an image block into corresponding quantizers and bitmap image. Two image features are proposed to index an image, namely Color Co-occurrence Feature (CCF) and Bit Pattern Features (BPF), which are generated directly from ODBTC encoded data streams without performing the decoding process. The CCF and BPF of an image are simply derived from the two ODBTC quantizers and bitmap, respectively, by involving the visual codebook. SVM (Support Vector Machine Classification) is used for improve the retrieval accuracy based on feature extractions of images.

Keywords – CBIR, ODBTC , CCT, BPF , Support Vector Machine

I INTRODUCTION

With the advancement in internet and multimedia technologies, a huge amount of multimedia data in the form of audio, video and images has been used in many fields like medical treatment, satellite data, video and still images repositories, digital forensics and surveillance system. This has created an ongoing demand of systems that can store and retrieve multimedia data in an effective way. Many multimedia information storage and retrieval systems have been developed till now for catering these demands. The most common retrieval systems are Text Based Image Retrieval (TBIR) systems, where the search is based on automatic or manual annotation of images. A conventional TBIR searches the database for the similar text surrounding the image as given in the query string. The commonly used TBIR system is Google Images. The text based systems are fast as the string matching is computationally less time consuming process. However, it is sometimes difficult to express the whole visual content of images in words and TBIR may end up in producing irrelevant results. In addition annotation of images is not always correct and consumes a lot of time. For finding the alternative way of searching and overcoming the limitations imposed by TBIR systems more intuitive and user friendly content based image retrieval systems (CBIR) were developed. A CBIR system uses visual contents of the images described in the form of low level features like color, texture, shape and spatial locations to represent the images in the databases. The system retrieves similar images when an example image or sketch is presented as input to the system. Querying in this way eliminates the need of describing the visual content of images in words and is close to human perception of visual data. Some of the representative CBIR systems are Query by Image Content (QBIC) [15a] Flickner et al., Simplicity [26] Wang et al. and Blob world [5] Carson et al.

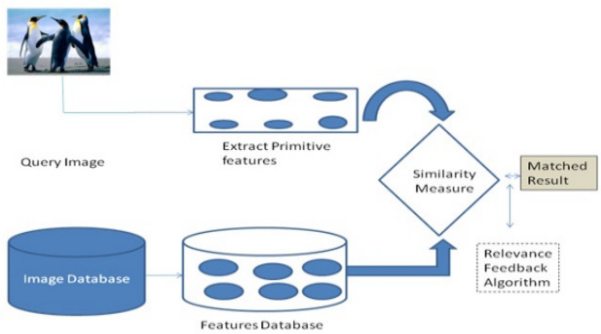

Fig: 1 Architecture of CBIR

In a typical CBIR system (Figure 1.1), image low level features like color, texture, shape and spatial locations are represented in the form of a multidimensional feature vector. The feature vectors of images in the database form a feature database. The retrieval process is initiated when a user query the system using an example image or sketch of the object. The query image is converted into the internal representation of feature vector using the same feature extraction routine that was used for building the feature database. The similarity measure is employed to calculate the distance between the feature vectors of query image and those of the target images in the feature database. Finally, the retrieval is performed using an indexing scheme which facilitates the efficient searching of the image database. Recently, user's relevance feedback is also incorporated to

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further improve the retrieval process in order to produce perceptually and semantically more meaningful retrieval results. In this chapter we discuss these fundamental techniques for content- based image retrieval.

II RELATED WORKS

Y.Bengio, A.Courville, P.Vincent et.al [1] proposed method A new technique for image compression called Block Truncation Coding (BTC) is presented and compared with transform and other techniques. The BTC algorithm uses a two-level (one-bit) nonparametric quantizer that adapts to local properties of the image. The quantizer that shows great promise is one which preserves the local sample moments. This quantizer produces good quality images that appear to be enhanced at data rates of 1.5 bits/picture element. No large data storage is required, and the computation is small. The quantize is compared with standard (minimum mean-square error and mean absolute error) one-bit quantizers. Modifications of the basic BTC algorithm are discussed along with the performance of BTC in the presence of channel errors.

Y.Boureau, F.Bach, Y.LeCun [2] proposed this source encoding of the outputs of a block truncation coder (BTC), namely, the overhead statistical information and the truncated block. The statistical overhead and the truncated block exhibit properties which can be effectively used for their quantization as vectors. Vector quantization of these BTC outputs results into reduction of the bit rate of the coder. The bit rate reduces up to 1.5 bits/ pel if vector quantization is used on one of the outputs; i.e., either the overhead information or the truncated block. By vector quantizing both the BTC outputs the bit rate can he reduced up to 1.0 bits/pel without introducing many perceivable errors in the reconstructed output.

A.Bolovinou, I.Pratikakis, S.Perantonis [3] proposed a hybrid BTC-VQ-DCT (Block Truncation Coding, Vector Quantization, and Discrete Cosine Transform) image coding algorithm is presented. The algorithm combines the simple computation and edge preservation properties of BTC and the high fidelity and high-compression ratio of adaptive DCT with the high-compression ratio and good subjective performance of VQ, and can be implemented with significantly lower coding delays than either VQ or DCT alone. The bit-map generated by BTC is decomposed into a set of vectors which are vector quantized. Since the space of the BTC bit-map is much smaller than that of the original 8-b image, a lookup-table-based VQ encoder has been designed to `fast encode' the bit-map. Adaptive DCT coding using residual error feedback is implemented to encode the high-mean and low-mean sub images. The overall computational complexity of BTC-VQ-DCT coding is much less than either DCT and VQ, while the fidelity performance is competitive. The algorithm has strong edge-preserving ability because of the implementation of BTC as a precompress decimation. The total compression ratio is about 10:1.

C-C.Chang, C.-J. Lin, LIBSVM [4] proposed a hybrid block truncation coding (BTC) is presented. In the hybrid BTC, a universal codebook using Hamming codes and a differential pulse code modulation (DPCM) are employed, respectively, to the bit plane and the side information of BTC to reduce coding rate. Simulation results reveal that the performance of the proposed algorithm is only slightly worse than that of the hybrid BTC using vector quantization (VQ) techniques, but with much lower computational or hardware complexity.

R.Datta, D.Joshi, J. Li, J.Z.Wang [5] proposed a moment preserving and visual information dominance technique to achieve the low-bit rate block truncation coding (BTC). Compared with other existing strategies as transform coding and vector quantization, conventional BTC compression has the advantage of simple and fast computation. Nevertheless the compression ratio is limited by its low efficiency. Our proposed technique accomplishes the goal of simple computation with variable bit rate selection by the moment preservation and information extraction algorithm. The proposed technique has the advantage of simple operations and it does not require complicated mathematical computations. Thus, the overall computation does not increase the burden compared with ordinary BTC. The simulations are carried with natural images to evaluate the performance. The generated decoded images have moderate quality with a bit rate of 0.5-1.0 bit/pixel.

N. Dalal, B. Triggs [6] proposed a new quantization method that uses the criterion of preserving sample absolute moments is presented. This is based on the same basic idea for block truncation coding of Delp and Mitchell but it is simpler in any practical implementation. Moreover, output equations are those for a two-level nonparametric minimum mean square error quantizer when the threshold is fixed to the sample mean. The application of this method to single frame color images is developed. A color image coding system that uses absolute moment block truncation coding of luminance and chroma information is presented. Resulting color images show reasonable performance with bit rates as low as 2.13 bits/pixel.

T. Deselaers, D. Keysers, H. Ney [7] proposed a method of Block truncation coding (BTC) is an efficient technology for image compression. An improved BTC algorithm, namely ordered dither block truncation coding (ODBTC), is presented in this study. In order to provide better image quality, the void-and-cluster half toning is combined with the BTC. The ODBTC results show that the image quality is improved when it is operated in high coding gain applications. Another feature of the ODBTC is the dither array look up table (LUT), which significantly reduces the complexity compared to the BTC.

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III PROBLEM FORMULATION

From the above literature, it is found that in the existing content based information retrieval systems texture based, shape based algorithms are used. The methods like block truncation coding, rotation invariant methods are used for compression. Due to high complexities of these algorithms, the existing systems provide less accuracy results, consumes more time for retrieval process. Hence, a new system is needed for CBIR with more accuracy, low complexity and less time. So, this paper proposes a new hybrid SVM based CBIR.

IV PROPOSED WORK

Content based image retrieval (CBIR):

It has gained much attention in the past decade. However, the gap between low-level features and high-level semantic meanings usually leads to poor performance for CBIR. Relevance feedback is a powerful tool to involve the user in the loop to enhance CBIR's performance. Recently, many RF methods have been introduced. Feature selection-based methods adjust weights associated with various dimensions of the feature space to enhance the importance of those dimensions that help in retrieving the relevant images and reduce the importance of those dimensions that hinder image retrieval. Alternatively, features can be selected by the boosting technique in which a strong classifier is obtained as a weighted sum of weak classifiers along the different feature dimensions.

Probabilistic model-based methods use entropy to minimize the expected number of iterations. discriminant analysis-based methods either find row dimensional subspace of the feature space, such that the positive and negative samples are well seperated after projection to this subspace or define a (1+x)-class problem (biased discriminant analysis and find a subspace within which to discriminant the one positive class and the unknown number of negative sample classes. More recently the direct kernel based discriminant analysis was developed and reported to outperform the BDA in both linear space and the nonlinear kernel space. Support vector machine (SVM)-based methods either estimate the density of positive instances or regard

RF as a classification problem with the positive and negative samples as training sets. SVM active learning, which plays an important role in CBIR RF research, selects the samples near the SVM boundary and queries the use for labels, then, after training; the points near the SVM boundary are regarded as the most-informative images while the most-positive images are the farthest ones from the boundary on the positive side. Recently, SVM active learning is also combined with a multimodal concept-dependent process for CBIR, constrained similarity measure (CSM). CSM-based SVM learns a boundary that separates all the images in the database into two clusters and the image inside the boundary are ranked by their Euclidean distances to the query image.

Derived from one-class SVM in a biased SVM is proposed, which can better model the relevance feedback problem and reduce the performance degradation caused by the imbalanced data set problem i.e., the number of the positive feedback samples is much less than the number of the negative feedback samples. These conventional schemes have been successfully in solving some samples of the problems in CBIR RF.

Shape based image retrieval:

In recent years, content based image retrieval has been studied with more attention as huge amounts of image data accumulate in various fields, e.g., medical images, satellite images, art collections, commercial images and general photographs. Image databases are usually very big, and in most cases, the images are indexed only by keywords given by a human.

Although keywords are the most useful in retrieving images that a user wants, sometimes the keyword approach is not sufficient. Instead, Query-by-example or pictorial-query approaches make the system return similar images to the example image given by a user. The example images can be a photograph, user-painted example, or line-drawing sketch. In this method, images are retrieved by their contents: color, texture, shape, or objects.

Thus, the degree of similarity between query images and images in databases can be measured by color distribution, texture distribution, shape similarity, or object presence between the two images. There have been many works done with color and texture property. Searching for images using shape features has attracted much attention. Shape representation and description is a difficult task. This is because when a 3-D real world object is projected onto a 2-D image plane, one dimension of object information is lost.

As a result, the shape extracted from the image only partially represents the projected object. To make the problem even more complex, shape is often corrupted with noise, defects, arbitrary distortion and occlusion.

There are many shape representation and description techniques in the literature. Marr and Nishihara and Braddy have thoroughly discussed representation and sets of criteria for the evaluation of shape. Soffer and Samet proposed a pictorial query specification technique that enables the formulation of complex pictorial queries including spatial constraints between query- image objects which are predefined symbolic images and contextual constraints which specify how many objects should be in the target Image.

The predefined symbolic query- images are represented by shape feature, e.g., moment, circularity, eccentricity, rectangularity, etc. Folkers and Samet extended this tool to permit query-images that have spatial extent such as ellipses, rectangles, polygons, and B- splines.

The query-images are represented by Fourier descriptors which serve powerful boundary- shape representation tools because of invariance property in affine transformation. However, there is a limit to expressing an object by its boundary because the boundary itself does not represent inside shape feature of the object. In and, shapes were represented using a Fourier expansion of the function of their tangent angle and their arc length. The lower- order Fourier coefficients were then used to represent the shape. Lie determined points of high curvature of a shape and represented them in polar form. These methods were invariant to translation and scale. However, the Fourier descriptor has several shortcomings in shape representation.

Bernier and Landry use a polar transformation of the shape points about the geometric center of object, the distinctive vertices of the shape are extracted and used as comparative parameters to minimize the difference of shape distance from the center. But it was not designed to be tolerant to occlusion.

Seldom works have been done with shape similarity since we need to have go od representation and description algorithm to use shape similarity in retrieving images and the state of the algorithms are still primitive. In this paper, shape-based image retrieval problem is handled especially in a colour image database. A program that extracts the proposed shape features from database images, compares these features with query image features and retrieves the image based on similarity between these two feature sets was implemented.

The shape feature representation's performance was evaluated in terms of how effective the above goal was met by testing the results from queries performed on a colour image database.

In the proposed work the basic idea is to use the centroid-radii model to represent shapes. In this method, lengths of the shape's radii from centroid to boundary are used to represent the shape. If a shape is used as feature, edge detection might be the first step to extract that feature. In our work, the canny edge detector is used to determine the edge of the object in the scene.

After the edge has been detected the important step is tracing the contour of the object in the scene. For this the edge image is scanned from four directions (right to left, left to right, top to bottom, bottom to top) and the first layer of the edge occurred is detected as image contour. To avoid discontinuities in object boundary the contour image is then re-sampled. After the object contour has been detected the first step in shape representation for an object is to locate the central point of the object.

Fig: Image Retrieval in shape based Approaches

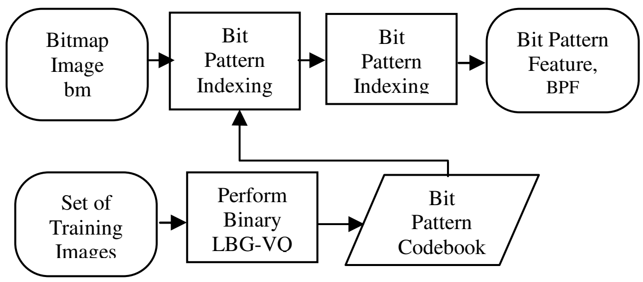

Fig 3. bit pattern feature

Figure 3.the schematic diagram for deriving the BPF. 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 codevector 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. An example of bit pattern codebook over various codebook sizes.

The bitmap of each block bm(i,j) is simply indexed based on the similarity measurement between this bitmap and the codeword Qq which meets the following criterion.

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$$\tilde{b}(i,j) = \underset{q=1,2,\dots,N_b}{\arg\min}\ \delta_H\{bm(i,j), Q_q\},$$

for all $i = 1,2,\dots,\frac{M}{m}$ and $j = 1,2,\dots,\frac{N}{n}$. The symbol $\delta_H\{\cdot,\cdot\}$ denotes the Hamming distance between the two binary patterns (vectors), i.e., bitmap image bm(i, j)and bit pattern codeword Q_q.

Subsequently, the BPF is simply derived as the occurrence probability of the bitmap image mapped into the a specific bit pattern code word Q_q. Thus, BPF is formally defined as

$$BPF(t) = \Pr\left\{\tilde{b}(i,j) = t \,\middle|\, i = 1,2,\dots,\frac{M}{m}; j = 1,2,\dots,\frac{N}{n}\right\},$$

$$\text{for all } t = 1,2,\dots,N_b.$$

The feature dimensionality of the BPF is N_b , i.e., identical to the bit pattern codebook size. The overall dimensionality of the proposed feature descriptor is $N_c + N_b$.

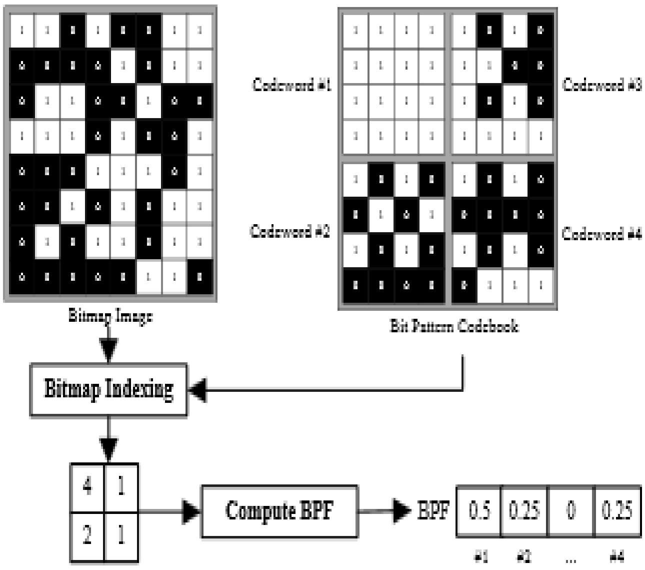

Fig.4. (a) Example of BPF Computation

Figure 3.4.(a) illustrates the BPF computation given an ODBTC bitmap image and a bit pattern codebook of size N_b. Similar to that of the CCF, the BPF only needs a simple computation, making it suitable for real applications where fast response is required.

Information modeling and steps of processing Compared to standard CBIR systems, at least three additional semantic levels of abstraction are needed to cope with the complex medical knowledge that is to be handled by a general system for content-based image retrieval in medical applications. A low-level of medical knowledge is determined by the imaging modality including technical parameters, the orientation of the patient position with respect to the imaging system, the body region examined, and the functional system under investigation. Based on prototype images, a mid-level of knowledge is described by regions of interest (ROIs) within the images, and a high-level is obtained from information regarding the spatial or temporal relationships of relevant objects. Consequently, IRMA splits the retrieval process into seven consecutive steps (Fig. 1). Each step represents a higher level of image abstraction, reflecting an increasing level of image content understanding .

ORDERED-DITHER BLOCKTRUNCATION CODING (ODBTC) AND ITS COLOR EXTENSION:

This section introduces the motivation of adopting the Ordered Dithered Block Truncation Coding (ODBTC) and its effectiveness in generating representative image features. In this paper, the ODBTC algorithm is generalized for color images in coping with the CBIR application. The main advantage of the ODBTC image compression is on its low complexity in generating bitmap image by incorporating the Look-Up Table (LUT), and free of mathematical multiplication and division operations on the determination of the two extreme quantizers. The traditional BTC derives the low and high mean values by preserving the first-order moment and second-order moment over each image block, which requires additional computational time. Conversely, ODBTC identifies the minimum and maximum values each image block as opposed to the former low and high mean values calculation, which can further reduce the processing time in the encoding stage. In addition, the ODBTC yields better reconstructed image quality by enjoying the extreme-value dithering effect compared to that of the typical BTC method as reported.

Given an original RGB color image of size M × N. This image is firstly divided into multiple non-overlapping image blocks of size m × n and each image block can be processed independently.

BLOCK DIAGRAM OF ODBTC ENCODING

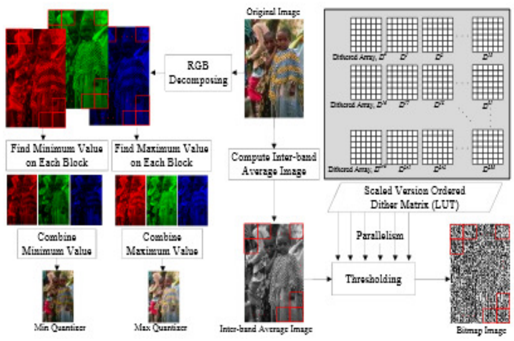

Fig 3.3 Block Diagram of ODBTC Encoding

Figure 3.3 shows the conceptual block diagram of the ODBTC encoding for a color image.

$$= \left\{b(i,j); i = 1,2,\dots,\frac{M}{m}; j = 1,2,\dots,\frac{N}{n}\right\}$$

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Let B be a set of image blocks of size m × n, containing the RGB color pixel information. The original image block b (i, j)is firstly converted into the inter - band average image

$\bar{b}_{k,l}(i,j)$ by

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

where (k, l) denotes the pixel coordinate on image block (i, j).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.

As opposed the single threshold utilized in classical BTC, the ODBTC employs the void-and-cluster dither array of the same size as an image block to generate the bitmap image. Let D(k,l) denotes the dither array coefficient at position (k, l), where k= 1,2,...,m and l=1,2,...,n. Let D ={D^0, D^1,...,D^{255}} be a set of scaled version of dither array which can be easily computed as

$$D^d(k,l) = d\,\frac{D(k,l) - D_{min}}{D_{max} - D_{min}},$$

Where D_{min} and D_{max} denote the minimum and maximum coefficient values in the dither array, respectively. The set D = {D^0,D^1,…,D^{255}} can be off-line pre-calculated and stored as a Look -Up-Table (LUT) for later usage. Using this strategy, the computational time can be significantly reduced, making it suitable for the practical applications. The variable d denotes the dither array index in LUT, defined as $d = \bar{b}_{max}(i,j) - \bar{b}_{min}(i,j)$. Since 0≤ d ≤255, it implies that all dither array coefficients $D^d(k, l)$ distribute in the range [0,255]. The variables represent the minimum and maximum values, respectively, of the inter-band average image on image block (i, j). These two values can be computed as

$$\bar{b}_{min}(i,j) = \min_{\forall k,l} \bar{b}_{k,l}(i,j), \quad (3)$$

$$\bar{b}_{max}(i,j) = \max_{\forall k,l} \bar{b}_{k,l}(i,j). \quad (4)$$

Subsequently, the ODBTC performs the thresholdingon 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). The thresholding process for the pixels $b_{k,l}(i, j)$in each image block is given by

$$bm_{k,l}(i,j) = \begin{cases} 1; if\ \bar{b}_{k,l}(i,j) \geq \bar{b}_{min}(i,j) + D^d(k,l) \\ 0; if\ \bar{b}_{k,l}(i,j) < \bar{b}_{min}(i,j) + D^d(k,l) \end{cases},$$

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

$$X_{min} = \{x_{min}(i,j); i = 1,2,\dots,\tfrac{M}{m}; j = 1,2,\dots,\tfrac{N}{n}\},$$

$$X_{max} = \{x_{max}(i,j); i = 1,2,\dots,\tfrac{M}{m}; j = 1,2,\dots,\tfrac{N}{n}\},$$

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

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

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

$$\text{for all } i = 1,2,\dots,\frac{M}{m} \text{ and } j = 1,2,\dots,\frac{N}{n}.$$

At the end of the ODBTC encoding, the bitmap image, bm, 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. the BTC and ODBTC reconstructed images over various image block sizes. 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 half toning-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

VI. EXPERIMENTAL RESULTS

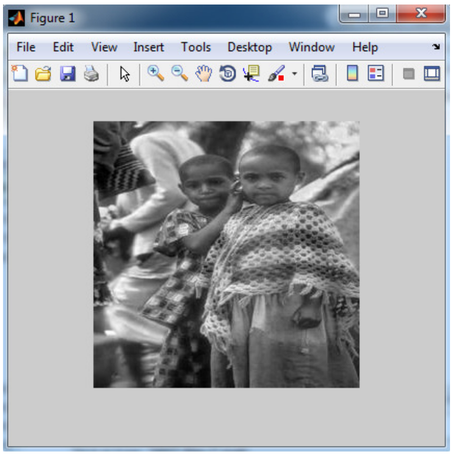


Fig.1. RGB to Gray level Image

This is the input image (RGB to Gray level Image structures) for our propose work process in CBIR.

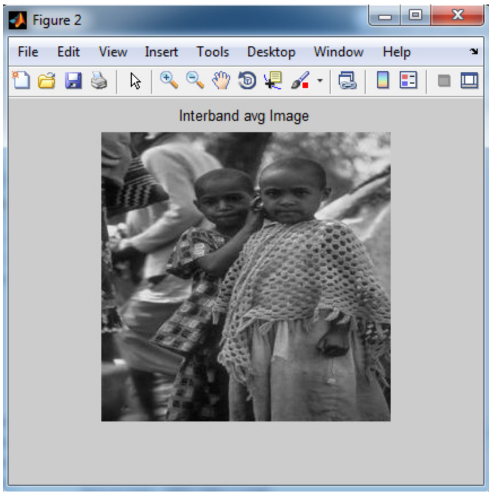


Fig.2. Inter-band Average Image

This is inter-band average image from our query image

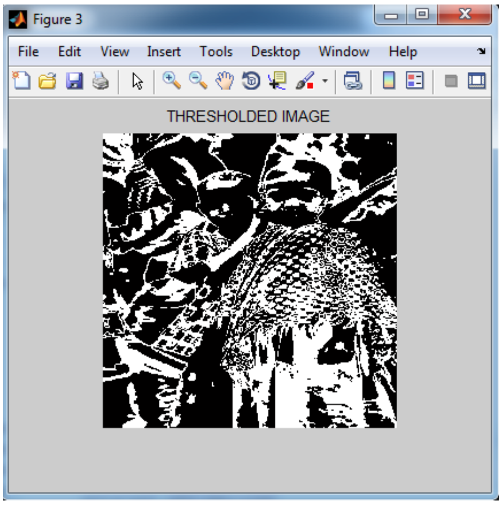
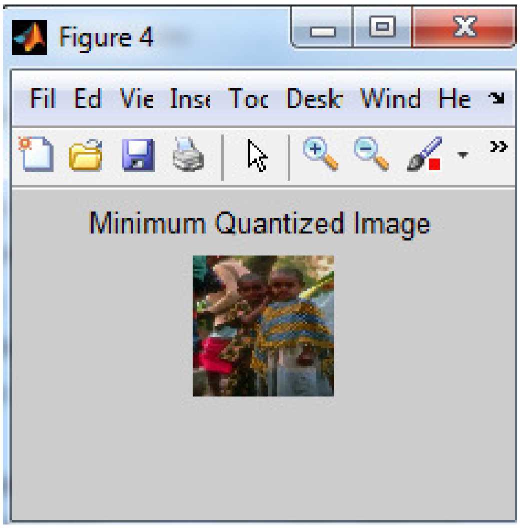


Fig. 3. Threshold Image

Threshold Image from Query Image



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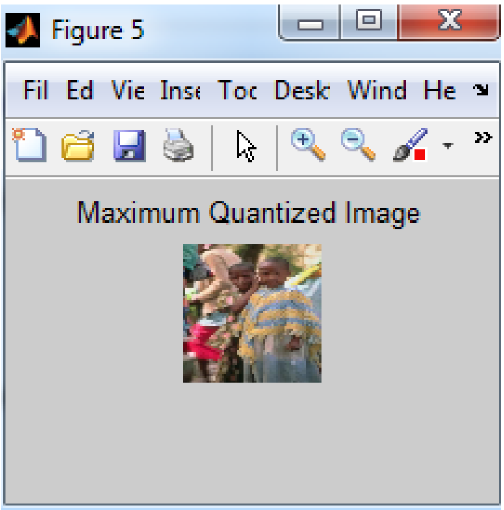

Fig.4&5 . Minimum And Maximum Quantizer

Minumum and Maximum Quantized image from RGB Query Image Structures

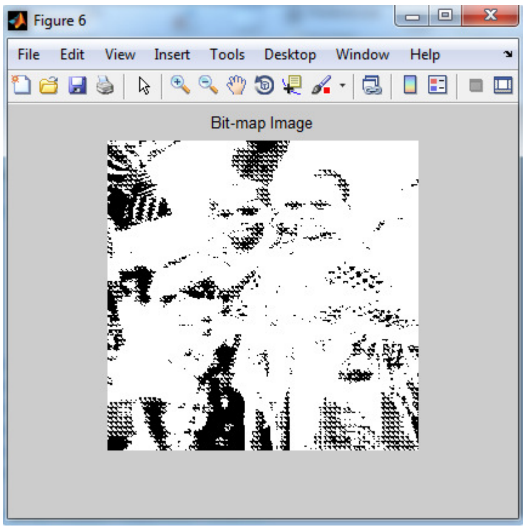

Fig.6. Bit map Image

Bit map image from our Query Image

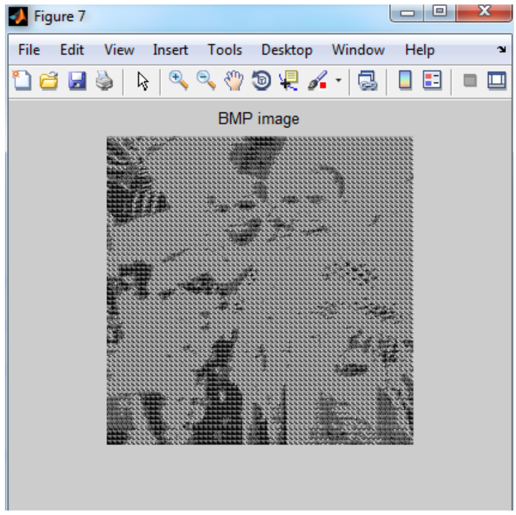

Fig.7. BMP image
BMP image from query image

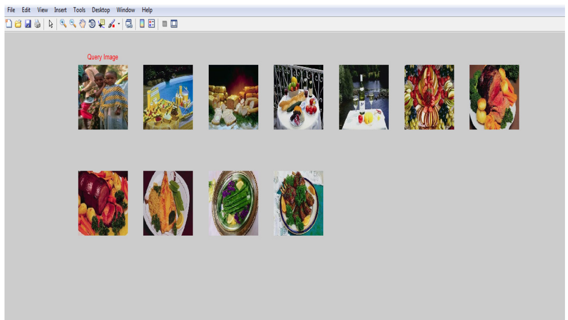

Fig.8. Image Retrieval
Image Retrieval from our query image

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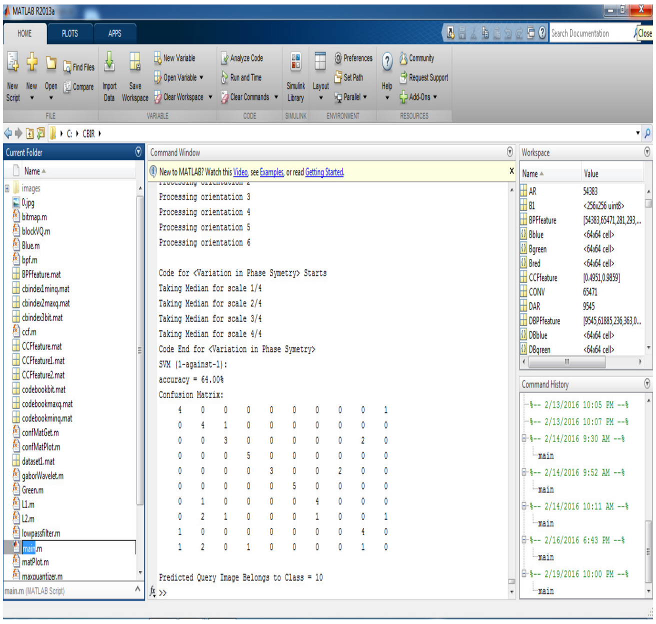

Fig.9.SVM Classification

SVM Classification from query image and accuracy

V CONCLUSION

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. As documented in the experimental results, the proposed scheme can provide the best average precision rate 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.

For the further studies, the proposed image retrieval scheme can be applied to video retrieval. The video can be treated as sequence of image in which the proposed ODBTC indexing can be applied directly in this image sequence. The ODBTC indexing scheme can also be extended to another color space as opposed to the RGB triple space. Another feature can be added by extracting the ODBTC data stream, not only CCF and BPF, to enhance the retrieval performance. In the future possibilities, the system shall be able to bridge the gap between explicit knowledge semantic, image content, and also the subjective criteria in a framework for human-oriented testing and assessment.

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