

Effective Image Retrieval Using Combined Features of Dot Diffused Block Truncation Coding and SIFT Keypoint Features

Asha. S , PG Student. Syama. R, Assistant Professor, Department of Electronics and Communication Engineering, College of Engineering Kidangoor, Kottayam

Abstract—Image being an idea of visual representation produced on a surface, have been technologized these days with digital images. This approach proposes a visual content based image retrieval from large scale image database in accordance with the user interests. Feature extraction from Dot-Diffused Block Truncation Coding (DDBTC) and Scale Invariant Feature Transform (SIFT) combined are used for compressing image data stream and used for retrieving images effectively. A feature descriptor is extracted from the Bit Pattern Feature (BPF) and SIFTS Keypoint Feature for this index color imaging technique. The image attributes BPF and SIFTS Keypoint Features, characterizing textural and edge information with prominent features, scaling parameters and restoration of potential keypoints at scale respectively. The degree of similarity of images influences performance accuracy which is measured by similarity distance scored between descriptors, smaller the distance provide higher accuracy. Experimental result substantiates effective feature extraction for image retrieval and classification.

Index Terms—Dot Diffusion Block Truncation Coding (DDBTC), Bit Pattern Feature (BPF), Scale Invariant Feature Transform (SIFT), image retrieval, image classification

I.INTRODUCTION

The flexibility of digital color imaging is increasing accordingly with the rapid advancement in the technologies, for the management of digital images. Internet being a global system is an interconnected network which has a very large amount of data collection. Due to the open access on internet there are different sources of contribution in the fields of images, videos and other information. This causes technical challenges in the storing and management of data, resulting in difficulty of accessibility. Thus the management of these data are mandatory.

In the area of images, storage and transmission issues occur which are solved by compression/coding. For the ease of searching, browsing and retrieval in digital images from a large database. Traditionally the used method was Annotation which included keywords, tags and description as input. For images this can be applied on applications like Google Search Engine. The searches traditionally relayed purely on metadata are dependent on annotation quality and completeness. Thus the text based image processing may consume time, may not capture description for obtaining desired image and also it may obtain only largely unsolved images. And also manual annotation will not be possibly available always for obtaining an accurate output.

The more efficient and opposed method used to overcome these flaws is Content Based Image Retrieval

(CBIR). This application of computer vision technique for bringing back digital images is a search analysis based on content of the image rather than the metadata search. Content refers basically to the color, shape and texture from the images. Other information of images can also be derived with detailed techniques such as integrating pixel cluster indexing, histogram intersection and discrete wavelet besides the content. Thus it is also known as Content Based Visual Information Retrieval (CBVIR) or Query by Image Content (QBIC). The scheme has multimedia images already in a compressed data form stocked in the storage devices for the sake of reduction in computational time. Content Based Image Retrieval avoids the flaws of the former method by giving a picture as an input from where the color layout, histogram, edges, regions etc are extracted directly and forwarded for calculating similarities of images from the database to retrieve corresponding image. The similarity measurement depends on elements of Euclidean distance, intersections, shape comparison, mutual information of regions etc. The appropriate image segmentation and involvement of each potential region can be engaged finally by proceeding with linear ordering and projection for the visualization. CBIR thus being the effective index color imaging has been illustrated in the Fig: 1 elaborating the feature extractions in image retrieval providing easy accessibility for users.

Data compression to a new domain is executed for reducing the space needed for the storage and transmission of a particular data. This is known as quantization where large sets of input is converted to reduced or smaller output sets, with the difference between input and quantized value mentioned as quantization error. Rounding and truncation are examples for quantisation. Image compression concerned to the visual perception follows lossy image compression technique as it is relevant to natural images with a negligible rate of bit reduction causing lossless visual effect.

Block Truncation Coding (BTC) is a lossy image compression technique. The original image converted into grayscale is segmented into number of non-overlapping blocks or the original image is replaced by simple set of representative vectors, where each block is processed independently. The original and compressed image have blocks with same mean and standard values. Thus BTC is used as the encoding data in the Content Based Image Retrieval.

Truncation Coding and Scale Invariant Feature Transform Keypoint features.

II. LITERATURE SURVEY

A. BTC (Block Truncation Coding)

Image coding/compression algorithm where the image coding histogram executes in lesser time than former annotation method with lesser complexity and higher efficiency. The latest technologies like Joint Photographic Experts Group (JPEG) have coding gains, but demands complexity than BTC. The input image of BTC is being sub divided into non- overlapping blocks and each block is thresholded. This enables representation of a block by two quantizers i.e. high and low mean and a bitmap image using mean value of the particular block, resulting in reconstruction of image with the same information as in input image and providing real time implementation effectively.

B. EDBTC (Error Diffusion Block Truncation Coding)

BTC although having effective outcomes, encounters complications like lesser compression ratio, false contour problems, blocking effect and less satisfaction for human perception longing for EDBTC. The scheme is similar to BTC representation but in bitmap image, the quantized error is being diffused to the neighboring unprocessed pixels during encoding by employing the fundamental Error Kernel algorithm. The output serves a deficient visual quality of images desiring for an improved version.

C. DDBTC (Dot Diffusion Block Truncation Coding)

This scheme is an improved comprehension of BTC, designed for improving visual quality of images for human satisfactory perception. In DDBTC each block is processed parallel and independently. The algorithm is similar to BTC with only two differences, one being the replacement of high and low mean by local minimum and maximum in a particular block and second being the replacement of bitmap generation by dot-diffusion. Quantized error is diffused to current unprocessed neighboring blocks as shown in Fig 2, by means of class and diffused matrix simultaneously for generating bitmap image where high compression is carried out with restoring all the prominent features of the image.

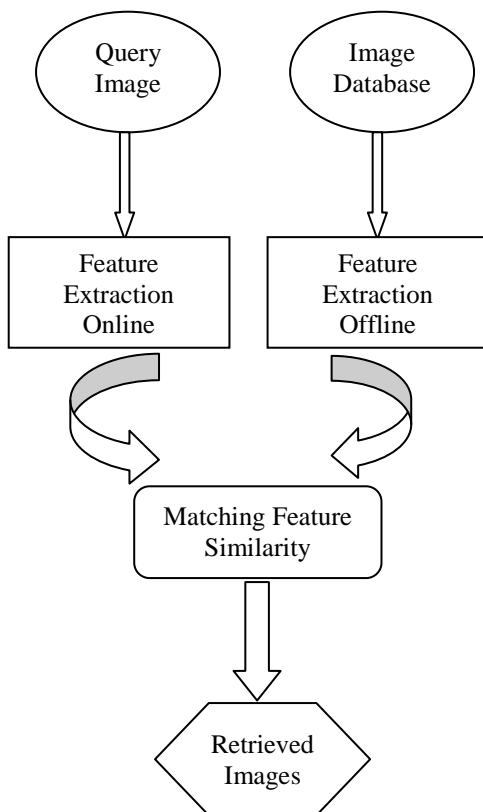


Figure 1: Schematic diagram for CBIR

In this paper, the scheme outperforms area of image retrieval and classification using Dot Diffusion Block

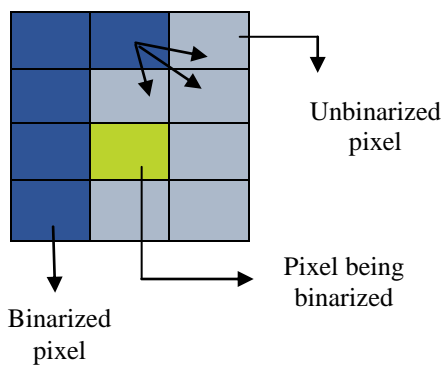


Figure 2: Diffusion of pixels

III. PROPOSED METHOD

The proposed technique has a perspective of image retrieval from a large data base on the basis of a new feature extracted from bit pattern and SIFT features derived from the techniques of DDBTC and SIFT Keypoint as shown in Fig 3.

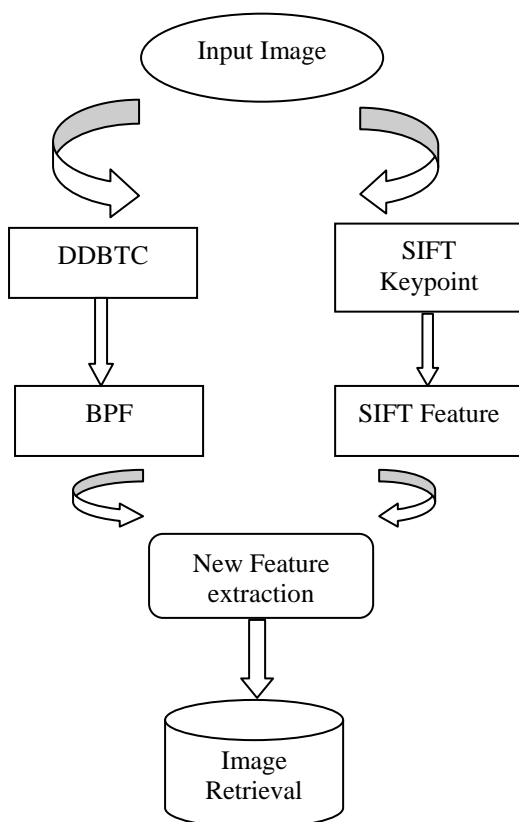


Figure 3: Feature extraction from DDBTC and SIFT Features

Considering the input image being given, the image is read and the size is calculated (rows, columns and number of bands) which is then converted to grayscale and

proceeded further dividing the image into blocks. The image is sub divided into non- overlapping blocks, each blocks are processed with parallel mechanism and independently. The quantized error formed from the quantized blocks is now being diffused to the unprocessed neighboring blocks in the image. Class matrix and diffused matrix are used simultaneously for generating bitmap image. For each block, maximum and minimum values are calculated with two representations which helps in quantizing. In the color images minimum and maximum values have information of the red, blue and green bands whereas in grayscale images have only two gray levels (black and white).The values in an image should always be known for which the class matrix are used. Class matrix help in finding the starting point/pixel as shown in Fig 4 for processing the blocks. Blocks are processed according to the values in ascending order generating bit map image. Every block's starting position is saved and concurrently is processed in each block. Processing every block with thresholding generates a diffused weight of pixels which is diffused to unprocessed neighboring pixels as shown in the Fig: 2 describing binarized, unbinarized and being binarized pixels.

The two extreme quantizers (minimum and maximum values) for the image block as

$$q_{min}(i, j) = \{ \min_{x,y} f_R(x, y), \min_{x,y} f_G(x, y), \min_{x,y} f_B(x, y) \} \quad (1)$$

$$q_{max}(i, j) = \{ \max_{x,y} f_R(x, y), \max_{x,y} f_G(x, y), \max_{x,y} f_B(x, y) \} \quad (2)$$

The color image converted to inter-band value as,

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

Considering the image block $f(i, j)$, with position (i, j) with mean value computed as,

$$\bar{f}(i, j) = \frac{1}{m \times n} \sum_{x=1}^m \sum_{y=1}^n \bar{f}(x, y) \quad (4)$$

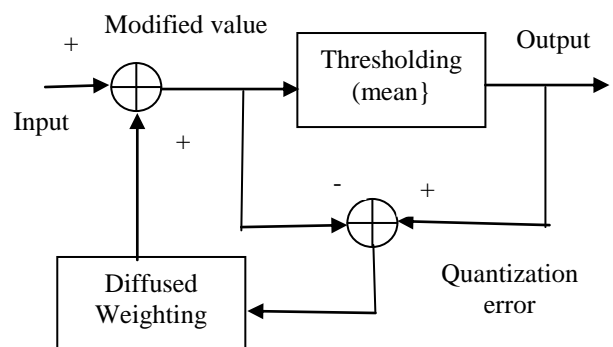


Figure 4: Pixel processing in DDBTC method

The input is modified into $v(x, y)$ and quantization error is related as,

$$v(x, y) = \bar{f}(x, y) + s(x, y) \quad (5)$$

Where $s(x, y)$ is the diffused weighting defined as,

$$s(x, y) = \sum_{p, q \in \mathbb{R}} \frac{\varepsilon(x+p, y+q) \times w(p, q)}{\text{sum}}$$

$$\varepsilon(x, y) = v(x, y) - t(x, y) \quad (6)$$

$$t(x, y) = \begin{cases} \bar{f}_{\max}(i, j), & \text{if } v(x, y) \geq \bar{f}(i, j) \\ \bar{f}_{\min}(i, j), & \text{if } v(x, y) < \bar{f}(i, j) \end{cases}$$

The input image does not have a diffused weight at the initial step of modifying input, thus input block value equals modified value. The next value when processed has the previous diffused weight (quantized error) of the processed pixel to get a modified value. The value now passes through thresholding to get a thresholded output as given in Fig: 4, this continues until the last value of every block is processed simultaneously.

SIFT Keypoint extracts distinctive invariant features where it gives peer concentration on features to ease the match of images to other. Image generally has a lot of features including the distribution of intensity, thus elaborating even the smaller objects. Recognizing the matching of two objects each feature is being computed and matched to another. Similar features from both images are matched via SIFT featuring. Thus relating features of different parts in different images. Even though when the images appear different, the SIFT feature analyses some part to be similar.

The extraction of keypoint involves some basic stages as mentioned below:

1. Scale-space peak selection: it is the identification of peak locations in the scale space (different soothing versions of image).
2. Keypoint Localization: to know where the real location of feature is and eliminating unstable location.
3. Orientation assignment: each of the interest points will have orientation and constructs a conical view.
4. Keypoint Descriptor: builds local image descriptor for every keypoint.

The algorithm describes features of every local point in the image having real time applications like 3D modelling, object and gesture recognition, match moving

etc. Using the feature descriptor, the higher quality and locality images are matched.

This scheme is a modified index color imaging with accurate and high quality images, followed by information of prominent features and scaling parameters restoring the potential keypoints. Thus the new merged feature extracted from both Dot Diffusion Based Block Truncation Coding and SIFT Keypoint provide efficient index imaging along with maximum capability of image compression and feature restoration within less computational time.

IV. PROPOSED ALGORITHM

The joint features of Dot Diffusion Block Truncation Coding and SIFT Keypoint contributes an image retrieval with dynamic outcomes. The input given image is read and its size is calculated with information including number of rows, columns and bands. Image passes through the different stages:

1. Input image converted to grayscale image
2. Image sub-divided into non overlapping blocks
3. Through thresholding pixel weights are diffused to neighboring unprocessed pixel
4. DDBTC of all blocks
5. Initialize pool of code book
6. Compare all blocks with code book to choose the closest of them
7. BPF feature extraction
8. Compare BPF feature with database of train features
9. Simultaneously stages of extraction of Keypoints are followed
10. Features related to locality, quality and efficiency are diagnosed and identical images are retrieved.

V. SIMULATION RESULTS

This section reports the effective demonstration of combined features of DDBTC and SIFT features extracted which is relevant for image retrieval and classification. This technique extracts feature descriptor from all the images in database and compares it with the input image subjected. The similarity of images within two different images are identified by feature descriptor comparison.

The smaller difference between features denote higher similarity.

When an input of Lena image is given, it is initially converted to grayscale image as given in the fig: 5 (a). And DDBTC coding with earned minimum and minimum values and also coding with 0 and 1 are shown in (b). Finally Fig: (c) Shows the significant potential points of Lena to be restored.

Another input cat is given with different features, where it is also converted to grayscale image. Then coding with minimum and maximum values and with 0s and 1s are executed as shown in Fig: 6, as accomplished for image Lena. Here the potential points help in recovering the cat image features particularly.



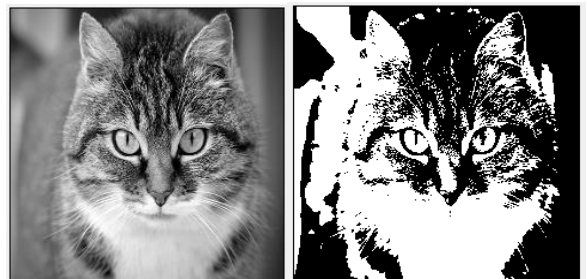
Figure: 5
(a) Input Lena image and Grayscale image



Figure: 6
(a) Input Cat image and Grayscale image



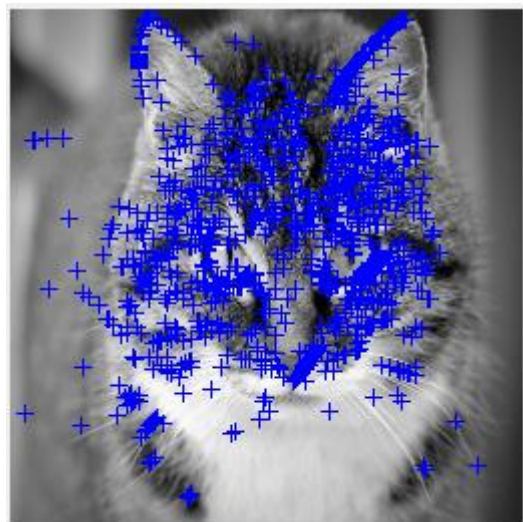
(b) DDBTC coding with minimum and maximum values and with 0s and 1s



(b) DDBTC coding with minimum and maximum values and with 0s and 1s



(c) Identifying potential points in image



(c) Identifying potential points in image

Finally for all the input images given are provided with similar featured output images from the large database. The sample BPF and SIFT features which are derived from DDBTC and SIFT Keypoint are shown in Fig: 7 and Fig: 8 respectively.

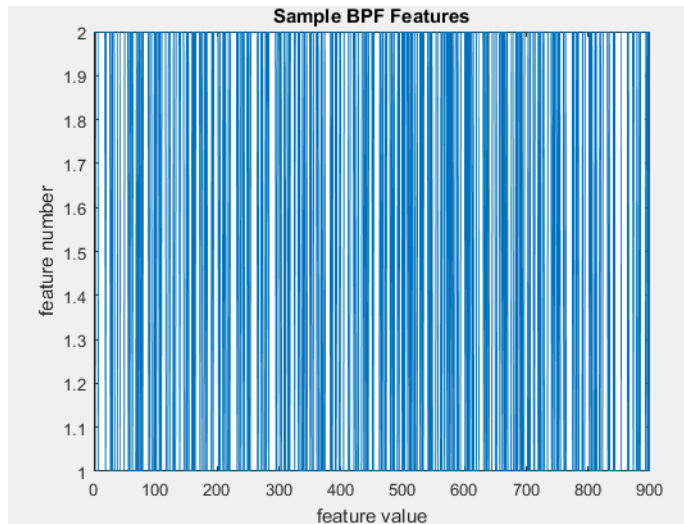


Fig :7 BPF Feature Extracted

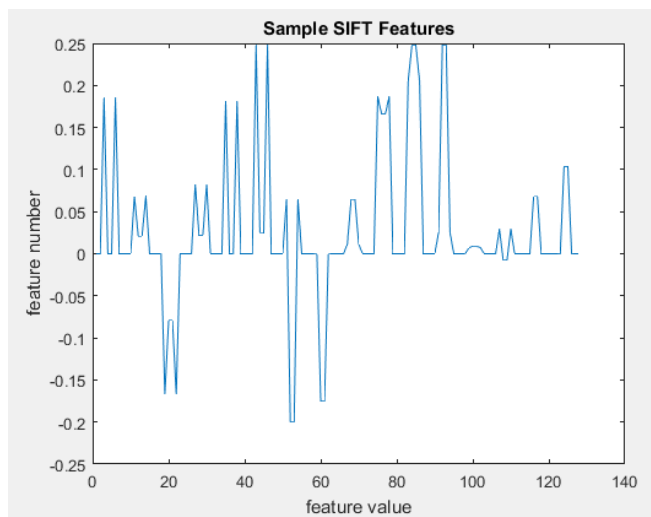


Fig 8: SIFT Keypoint Featue Extraction

The retrieved images of certain inputs (Lena and Cat) through the matched similar features particularly are shown finally in Fig: 9 with higher quality and restoring all potential points.

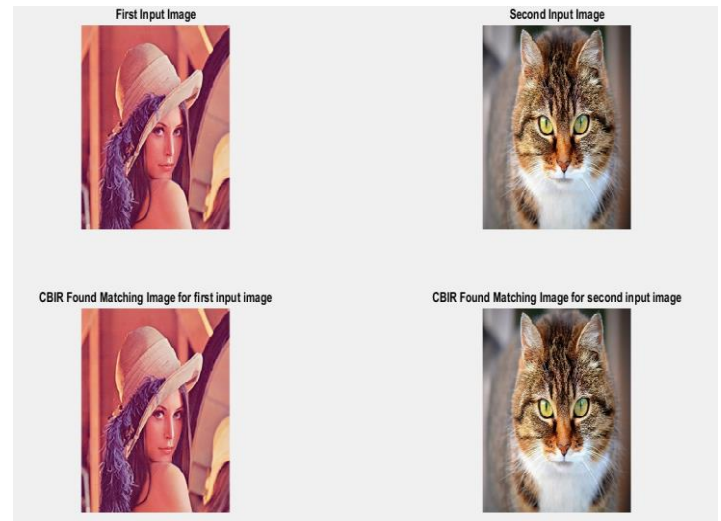


Fig: 9 Image Retrieval with accurate feature restoration

VI CONCLUSION

This paper in the image system proposes an efficient index color imaging by exploiting Dot-Diffusion Block Truncation Coding and SIFT Keypoint Features. This strategy overcomes the less satisfactory outcomes as in the traditional methods by providing higher quality, higher compression ratio and by restoration of all specific potential points in less computational time without any complexity. It is the replacement of former method BTC, based on image indexing. Thus this technique can be considered as accomplishing image retrieval at desirable satisfaction in human perception.

ACKNOWLEDGEMENT

We would like to acknowledge the funding provided from the TEQIP Phase 2 of College of Engineering Kidangoor to publish this work.

REFERENCES

- [1] Jing-Ming Guo, Senior Member, IEEE, Heri Prasetyo, and Nai-Jian Wang, "Effective Image Retrieval System Using Dot-Diffused Block Truncation Coding Features," IEEE TRANSACTION OF MULTIMEDIA, VOL-17, NO.9, SEPTEMBER 2015
- [2] E. J. Delp and O. R. Mitchell,"Image Compression Using Block Truncation Coding", IEEE Trans. Commun, Vol. 27, no. 9, pp.135-1342, Sep.1979

- [3] Y. G. Wu and S. C Tai “An Efficient BTC Image Compression Technique”, IEEE Trans. Consum, Electron., Vol. 44, no.2,pp.317-325
- [4] J.M. Guo, “Improved Block Truncation Coding Using Modified Error Diffusion”, Electron. Lett., Vol.44 no.7, March 2008. Pp.462-464
- [5] Y.F. Liu, J. M. Guo, and J.D. Lee, “Inverse halftoning based on the Bayesian Theorem ”, IEEE Trans. Image Process.,Vol. 20,no.4, pp1077-1084, April 2011
- [6] Jing-Ming Guo, Senior Member, IEEE, Heri Prasetyo, and Jen- Ho Chen, “Content Based Image Retrieval Using Error Diffusion Block Truncation Coding Features”, IEEE Transaction on Circuits and Systems afor Video Technology, Vol. 25, No. 3 March 2015.
- [7] A. Magadan, Member IEEE, I. Martin,C. Conde and E. Cabello, “Evaluation of Keypoint Descriptors Applied in the Pedestrian Detection in Low Quality Images”IEEE LATIN AMERICA TRANSACTIONS, VOL. 14, NO. 3,2016.
- [8] Ru Zhou, Sang Woo Sin, Dongju Li, Tsuyoshi Isshiki and Hiroaki Kunieda, Department of Communications and Integrated Systems, Tokyo Institute of Technologies, “Adaptive SIFT-Based Algorithm for Specific Fingerprint Verification”
- [9] Bartzack ,P Zwirzeikowaski, “SIFT- The Scale Invariant Feature Transform” Distinctive image features from scale-invariant keypoints. David. G. Lowe, International Journal of Computer Vision, 60, 2 (2004)
- [10] Miguel Lourenco, Joao P. Barreto, and Francisco Vasconcelos, “sRD-SIFT:Keypoint Detection And Matching in Images With Radial Distortion” IEEE Transactions on Robotics, Vol. 28, No. 3, JUNE 2012
- [11] T. Lindeberg, “ Scale Space Theory: A basic tool for analyzing structures at different scales ” ,Journal of Applied Statistics, 21(2): 224-270.1994
- [12] R. Cappelli, “Synthetic Fingerprint Generation”, in Handbook of Fingerprint Generation (Second Edition),, Springer (London), 2009
- [13] David G. Lowe, “Object Recognition from local scale-invariant Features”,International Conference on Computer Vision, Corfu, Greece,pp. 1150-1157, 1999