Content-Based Image Retrieval Using Direct Binary Search Block Truncation Coding Features

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Abstract— **This paper presents a new image feature descriptor derived from the Direct Binary Search Block Truncation Coding (DBSBTC) data-stream without requiring the decoding process. Three image feature descriptors, namely Color Autocorrellogram Feature (CAF), Legendre Chromaticity Moment Feature (LCMF), and Local Halftoning Pattern Feature (LHPF), are simply constructed from the DBSBTC min quantizer, max quantizer, and its corresponding bitmap image, respectively. The similarity between two images can be measured using these descriptors under specific distance metric. The proposed method yields better image retrieval performance compared to the former Block Truncation Coding (BTC) and existing schemes under the natural and textural image database in the grayscale and color space. The DBSBTC performs well for image compression, at the same time, it gives an effective discriminative feature in the image retrieval task.**

I. INTRODUCTION

An image retrieval system gives a convenient way to browse, access, and retrieve a set of similar images on a big image database. An effective image feature descriptor is required for achieving a good performance on image retrieval and classification system. Some methods have been proposed to develop and improve the efficiency of image feature descriptor for describing the image content. Most of methods extract the image descriptor directly from an original input image [2, 4-6, 8-15], while some existing schemes derive the image feature from the compressed data stream [3, 7]. As reported in the literature, an image feature descriptor deriving from the compressed data stream offers comparable performance compared to the image feature from the original input image in the image retrieval application. The feature descriptor from the compressed data stream also yields almost similar performance compared to that of an uncompressed image in the image retrieval domain.

The image feature descriptor can also be generated from the Block Truncation Coding (BTC) compressed data stream. The BTC is simple image compression technique which decomposes an original input image into two color quantizers (low and high extreme quantizer) and the bitmap image at encoding step. The BTC simply replaces the bitmap image with two color quantizers based on its binary value, i.e. replace 0 with low extreme quantizer and vice versa, at the end of decoding process. The halftoning-based BTC, namely Direct Binary Search BTC (DBSBTC), has been proposed in [1] to further improve the BTC reconstructed image quality by replacing the BTC bitmap image with the efficient Direct Binary Search (DBS) halftoning pattern image [1]. The two color quantizers in DBSBTC are simply obtained from the minimum and maximum value found on each image block. Using these strategies, the image reconstructed from DBSBTC is better than the BTC decompressed image.

The rest of this paper is organized as follows. The DBSBTC is briefly introduced and generalized for color images in Section II to facilitate the understanding of the prospective readers. Section III elaborates the proposed image retrieval system for the color and grayscale images. Extensive experimental results are reported in Section IV. Finally, the conclusion is drawn in Section V.

II. DIRECT BINARY SEARCH BLOCK TRUNCATION CODING FOR COLOR IMAGE

This section delivers the Direct Binary Search Block Truncation Coding (DBSBTC) compression for color image. Given a color image, the DBSBTC decomposes this image to yield the two color quantizers (namely min and max quantizer) and single bitmap image. Fig. 1 depicts the schematic diagram of DBSBTC color image compression.

Let $\mathrm{f(x,y)}$ be an image of size $\mathrm{M \times N}$. This image is firstly partitioned into multiple non-overlapping image patches of size $\mathrm{m \times n}$. The min and quantizer of DBSBTC can be simply obtained as follow

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

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

for $x = 1,2,\dots,m$ and $y = 1,2,\dots,n$. And image block position $i = 1,2,\dots,\frac{M}{m}$ and $j = 1,2,\dots,\frac{N}{n}$. While $f_R(x,y)$, $f_G(x,y)$, and $f_B(x,y)$ be the pixel value on red, green, and blue color space. The inter-average-band image of the original input image is needed for obtaining the bitmap image and can be simply computed as follow

$$\mathrm{g(x,y)} = \frac{1}{3}\left(\mathrm{f_R(x,y)} + \mathrm{f_G(x,y)} + \mathrm{f_B(x,y)}\right). \quad (3)$$

The DBSBTC performs the direct binary search thresholding [1] for this inter-average-band image to obtain the bitmap image. Fig. 2 shows the example of DBSBTC reconstructed image which give smooth decoded image.

III. Proposed DBSBTC Image Retrieval

This section explains the DBSBTC image retrieval system in detail. Three image features are incorporated for the proposed method. Fig. 3 illustrates the schematic diagram of the proposed image retrieval system.

A. Color Autocorrelogram Feature (CAF)

The color autocorrelogram characterizes the pixel color distribution as well as spatial correlation between color pair. It describes the probability of a pixel with the specific color and another pixel with the same color under predetermined distance. The CAF grabs the spatial correlation between identical color over two adjacent pixels. For computing the CAF, the min quantizer is firstly indexed using the color codebook $\mathrm{C}_{\min} = \{\mathrm{c}_1, \mathrm{c}_2, \dots, \mathrm{c}_{\mathrm{N_c}}\}$ of size N_c. This color codebook can be generated using the Vector Quantization (VQ) algorithm using several images as training set. The color indexing of min quantizer can be formally described as follow

$$\tilde{\imath}_{min}(i,j) = \underset{k=1,2,\dots,N_c}{argmin} \left\| q_{min}(i,j), c_k^{min} \right\|_2^2. \tag{4}$$

Subsequent, the CAF can be simply computed as

$$CAF(k) = \Pr\{\tilde{\imath}_{\min}(\mathrm{i},\mathrm{j}) = k | \tilde{\imath}_{\min}(\mathrm{i}+\emptyset, \mathrm{j}+\emptyset) = k\}, \tag{5}$$

for $k = 1,2,\dots,N_c$. Where $\emptyset$ denotes distance between two adjacent pixels. The feature dimensionality of CAF is simply identical with the color codebook size used in the color indexing process, i.e. N_c.

B. Legendre Chromaticity Moment Feature (LCMF)

Another color feature, namely Legendre Chromaticity Moment Feature (LCMF) [2], is simply derived from the DBSBCT max quantizer. It represents the color content and captures the chromaticity aspect of an image. For computing the LCMF, the max quantizer in RGB color space should be firstly converted into its chromaticity color. The LCMF is then formally defined as follow

$$LCMF(M,N) = \frac{(2M+1)(2N+1)}{mn} \sum_{k=0}^{mn-1} P_M(rg(k)) P_N(yb(k)), \tag{6}$$

where $P_n(x)$ denotes the n-th order Legendre polynomial as given bellow

$$P_n(x) = \frac{1}{2^n n!} \frac{d^n}{dx^n} (x^2-1)^n . \tag{7}$$

The $rg(k)$ and $yb(k)$ are the transformed opponent chromaticity of max quantizer. The feature dimensionality of LCMF is $P(P+3)/2$, where P denotes the Legendre order.

C. Local Halftoning Pattern Feature (LHPF)

The third image descriptor, namely Local Halftoning Pattern Feature (LHPF), captures the textural information of an image. It describes the textural, edge, line, and several image content of an image. This feature can be directly constructed from the DBSBTC bitmap image $bm(i,j)$ on image block position (i,j) consisting two values, i.e. $\{0,1\}$. Let g_c and g_p be center binary pixel and its neighboring binary pixel, respectively, on bitmap image $bm(i,j)$. The Local Halftoning Pattern (LHP) code for the current binary pixel and its neighboring can be computed as

$$LHP(x,y) = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p, \tag{8}$$

for $x = 1,2,\dots,m$ and $y = 1,2,\dots,n$. And

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}. \tag{9}$$

The LHP encode the binary pattern of current pixel and its neighboring pixel into the real-code value. Then, the LHPF of bitmap image $bm(i,j)$ can be simply computed as

$$LHPF(z) = \sum_{x=1}^{\frac{M}{m}} \sum_{y=1}^{\frac{N}{n}} h(LHP(x,y), z), \tag{10}$$

for $z \in [0,\dots,Z]$. The symbol Z represents the maximum value of LHP code. By setting the number of neighboring pixel as 8, the feature dimensionality of LHPF is 59.

D. Similarity Measurement

The similarity degree between two images (query image and target image stored in database) can be measured using a specific similarity distance. The similarity distance plays an important in the image retrieval and classification system. A good choice of similarity distance yields a good result in the retrieved images. The similarity distance between the query image and target image stored in database is formally defined as

$$\delta = \alpha_1 \sum_{k=1}^{N_c} \frac{|CAF^{query}(k) - CAF^{target}(k)|}{CAF^{query}(k) + CAF^{target}(k) + \varepsilon} + \alpha_2 \sum_{p=1}^{P} \frac{|LCMF^{query}(t) - LCMF^{target}(t)|}{LCMF^{query}(t) + LCMF^{target}(t) + \varepsilon} + \alpha_3 \sum_{z=1}^{Z} \frac{|LHPF^{query}(z) - LHPF^{target}(z)|}{LHPF^{query}(z) + LHPF^{target}(z) + \varepsilon}, \tag{11}$$

where $\{\alpha_1, \alpha_2, \alpha_3\}$ denotes the similarity weighting constants controlling the percentage distribution of each feature descriptor on the similarity distance computation. For avoiding computation error caused by zero-division, a small number ε is added in the similarity distance computation.

IV. Experimental Results

Some extensive experiments were conducted for investigating the usability and superiority of the proposed image retrieval system. The image retrieval system firstly decomposes all images in database using DBSBTC and extracts the image features from the compressed DBSBTC data-stream. In this paper, several experiments were conducted over various image databases including the natural and textural images in the grayscale and color space.

A. Performance Evaluation

The superiority of the proposed method against the former schemes is investigated using the Precision and Average Retrieval Rate (ARR) measurements. The proposed method utilizes the Nearest Neighbor (NN) classification in order to retrieve a set of similar images in database. Let q be query image, and $n_q(L)$ denotes the number of correctly retrieved images among L retrieved images returned by NN classifier given a query image q. Suppose there are N_t images in database. Then, the Precision $(P(q))$ and ARR value are formally defined as

$$P(q) = \frac{1}{N_t L} \sum_{q=1}^{N_t} n_q(L), \tag{12}$$

$$ARR = \frac{1}{N_t N_R} \sum_{q=1}^{N_t} n_q(N_R). \tag{13}$$

where N_R denotes the number of relevant images for each class in the database. As similar to the Precision score, higher value of ARR shows the better performance on the image retrieval system.

B. Image Retrieval Performance

Several experiments were conducted to further investigate the proposed method superiority compared to the former schemes in the image retrieval system. Herein, the DBSBTC image block size and color codebook size are set at 4×4 and $N_c = 64$, respectively. The Legendre order is set at 6 producing 27 feature dimensionality. The uniformity constraint is utilized in the LHPF in the proposed method yielding 59 feature dimensionality. Thus, the dimensionality of the proposed feature descriptor is 64+27+59=150.

Table I shows the precision comparison between the proposed method and former schemes using the Corel image database with the number of retrieved images $L = 20$. As it can be seen from this table, the proposed method outperforms the former existing schemes in the Corel image database with the low feature dimensionality.

An additional experiment were carried out to further investigate the superiority of the proposed scheme in the textural image retrieval system. The performance of the proposed method is examined using three different textural image database, i.e. Brodatz, Vistex-640, and ALOT image databases. The ARR score is utilized for compared the proposed method performance with the former schemes. Table II shows the ARR comparison between the proposed method and former schemes under the Brodatz and Vistex-640 image databases. The proposed method outperforms the former existing schemes under these image databases with the lower feature dimensionality. Table III report the ARR score between the proposed method and former schemes using the ALOT image database. Herein, the proposed method employs the Rotation Invariant Uniform (RIU) constraint to further reduce the LHPF feature dimensionality. As this table shown, the proposed method yields the best ARR value compared to the former scheme in the ALOT image database. However, the feature dimensionality of the proposed method is slightly higher than the former schemes.

V. Conclusions

A new image feature descriptor for image retrieval and classification has been presented in this paper. The image descriptor is directly derived from the DBSBTC compressed data-stream without performing the decoding process. Three feature descriptors, namely ACF, LCMF, and LHPF, are simply constructed from the DBSBTC min quantizer, max quantizer, and the corresponding bitmap image, respectively. The experimental result demonstrates the effectiveness and successfulness of the proposed feature descriptor in the image retrieval task. The proposed method gives a promising result compared to the former schemes for this problem.

References

[1] J. M. Guo, and C. C. Su, “Improved block truncation coding using extreme mean value scaling and block-based high speed direct binary search,” *IEEE Signal Process. Lett.*, vol. 18, no. 11, pp. 694-697, 2011.

[2] P. T. Yap, and R. Paramesran, “Content-based image retrieval using Legendre chromatic distribution moments,” *IEE Vis. Image Signal Process.*, vol. 153, no. 1, pp. 17-24, 2006.

[3] J. M. Guo, and H. Prasetyo, “Content-based image retrieval using features extracted from halftoning-based block truncation coding,” *IEEE Trans. Image Process.*, vol. 24, no. 3, pp. 1010-1024, 2015.

[4] T. C. Lu, and C. C. Chang, “Color image retrieval technique based on color features and image bitmap,” *Inf. Process. Manage.*, vol. 43, no. 2, pp. 461-472, Mar. 2007.

[5] F.X. Yu, H. Luo, and Z.M. Lu, “Colour image retrieval using pattern co-occurrence matrices based on BTC and VQ,” *Electronics Letters*, 20th, vol. 47, no. 2, Jan. 2011.

[6] C. H. Lin, R. T. Chen, and Y. K. Chan, “A smart content-based image retrieval system based on color and texture feature,” *Image and Vision Computing*, vol. 27, no. 6, pp. 658–665, May 2009.

[7] P. Poursistani, H. Nezamabadi-pour, R. A. Moghadam, and M. Saeed, “Image indexing and retrieval in JPEG compressed domain based on vector quantization,” *Math. and Comp. Modeling*, 2011, http://dx.doi.org/10.1016/j.mcm.2011.11.064.

[8] T. Ojala, M. Pietikainen, and D, Harwood, “A comparative study of texture measures with classification based on feature distributions,” *Pattern Recognition*, vol. 29, no. 1, pp. 51-59, 1996.

[9] X. Tan, and B. Triggs, “Enhanced local texture feature sets for face recognition under difficult lighting conditions,” *IEEE. Trans. Image Proc.*, vol. 19, no. 6, pp. 1635-1650, 2010.

[10] M. Subrahmanyam, R. P. Maheswari, and R. Balasubramanian, “Local maximum edge binary patterns: A new descriptor for image retrieval and object tracking,” *Signal Processing*, vol. 92, pp. 1467-1479, 2012.

[11] B. Zhang, Y. Gao, S. Zhao, and J. Liu, “Local derivative pattern versus local binary pattern: face recognition with high-order local pattern descriptor,” *IEEE Trans. Image Process.*, vol. 19, no. 2, pp. 533-544, 2010.

[12] S. Murala, R. P. Maheshwari, and R. Balasubramanian, “Local tetra patterns: a new feature descriptor for content-based image retrieval,” *IEEE Trans. Image Process.*, vol. 21, no. 5, pp. 2874-2886, May 2012.

[13] R. Kwitt, and A. Uhl, “Lightweight probabilistic texture retrieval,” *IEEE Trans. Image Process.*, vol. 19, no. 1, pp. 241-253, Jan. 2010.

[14] R. Kwitt, and A. Uhl, “Image similarity measurement by Kullback-Leibler divergences between complex wavelet subband statistics for texture retrieval,” in *Proc. 15th IEEE ICIP*, pp. 933-936, Oct. 2008.

[15] N. E. Lasmar, and Y. Berthoumieu, “Gaussian copula multivariate modeling for texture image retrieval using wavelet transforms,” *IEEE Trans. Image Process.*, vol. 23, no. 5, pp. 2246-2261, May. 2014.

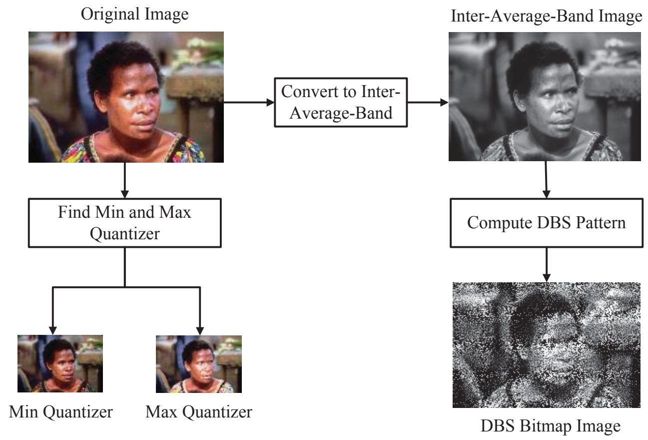

Fig. 1. Schematic diagram of DBSBTC for color image.

Fig. 2. Example of DBSBTC reconstructed image (second column). The original image is shown at first column.

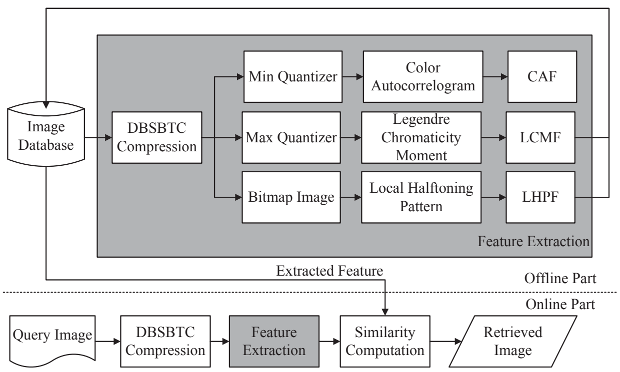

Fig. 3. Schematic diagram of the proposed image retrieval system.

TABLE I. COMPARISONS AMONG THE PROPOSED SCHEME AND THE FORMER SCHEMES IN TERMS OF AVERAGE PRECISION RATE FOR COREL IMAGE DATABASE

Method	Average
Lu [4]	0.665
Yu [5]	0.717
Lin [6]	0.727
Poursistani [7]	0.743
ODBTC-IR [3], 64+256=320	0.779
Proposed Scheme, 64+27+59=150	**0.788**

TABLE II. COMPARISONS AMONG THE PROPOSED SCHEME AND THE FORMER SCHEMES IN TERMS OF ARR FOR BRODATZ AND VISTEX-640 IMAGE DATABASES

Method	Feature Dimension	Brodatz	Vistex-640
LBP [8]	59	79.97	82.23
LTP [10]	2x59=118	82.51	87.52
LDP [11]	4x59=236	79.91	87.27
LTrP [12]	13x59=767	85.3	90.02
ODBTC-IR [3]	128+128=256	85.80	90.67
Proposed Scheme	128+27+59=214	**87.11**	**92.11**

TABLE III. COMPARISONS AMONG THE PROPOSED SCHEME AND THE FORMER SCHEMES IN TERMS OF ARR FOR ALOT IMAGE DATABASE

Methods	Feature Dimensionality	ALOT
Wbl-DT-CWT-1 scale [13]	3x2=6	23.28
Wbl-DT-CWT-2 scale [13]	6x2=12	33.56
Wbl-DT-CWT-3 scale [13]	9x2=18	40.01
GG-DT-CWT-1 scale [13]	3x2=6	23.86
GG-DT-CWT-2 scale [13]	6x2=12	33.38
GG-DT-CWT-3 scale [13]	9x2=18	39.33
GC-MWbl-DT-CWT-1 scale [13, 14]	1+1+4x4=18	27.69
GC-MWbl-DT-CWT-2 scale [13, 14]	1+1+4x4=18	37.68
GC-MWbl-DT-CWT-3 scale [13, 14]	1+1+4x4=18	43.25
GC-MGG-DT-CWT-1 scale [15]	1+1+4x4=18	30.58
GC-MGG-DT-CWT-2 scale [15]	1+1+4x4=18	38.20
GC-MGG-DT-CWT-3 scale [15]	1+1+4x4=18	43.06
ODBTC-IR [3]	8+8=16	43.62
Proposed Scheme-RIU	8+5+9=22	**44.78**