[International Journal of Electronics Signals and Systems](https://www.interscience.in/ijess)

Volume 1 | Issue 1 Article 15

2011

Binary Wavelet Transform Based Histogram Feature for Content Based Image Retrieval

Megha Agarwal
Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee, India, meghagarwal29@gmail.com

Rudra Prakash Maheshwari Dr.
Indian Institute of Technology Roorkee, rpmaheshwari@gmail.com

Available online at www.interscience.in

Binary Wavelet Transform Based Histogram Feature for Content Based Image Retrieval

Megha Agarwal, R. P. Maheshwari
Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee, India
E-mail: meghagarwal29@gmail.com, rpmaheshwari@gmail.com

Abstract**—** In this paper a new visual feature, binary wavelet transform based histogram (BWTH) is proposed for content based image retrieval. BWTH is facilitated with the color as well as texture properties. BWTH exhibits the advantages of binary wavelet transform and histogram. The performance of CBIR system with proposed feature is observed on Corel 1000 (DB1) and Corel 2450 (DB2) natural image database in color as well as gray space. The results analysis of DB1 database illustrates the better average precision and average recall of proposed method in RGB space (73.82%, 44.29%) compared to color histogram (70.85%, 42.16%), auto correlogram (66.15%, 39.52%) and discrete wavelet transform (60.83%, 38.25%). In case of gray space also performance of proposed method (66.69%, 40.77%) is better compared to auto correlogram (57.20%, 35.31%), discrete wavelet transform (52.70%, 32.98%) and wavelet correlogram (64.3%, 38.0%). It is verified that in case of DB2 database also average precision, average recall and average retrieval rate of proposed method are significantly better.

***Keywords* -** Binary wavelet transform; content based image retrieval; histogram

I. INTRODUCTION

Digital media is evolving, so digital data archives in art, satellite, scientific, industrial, medical, environmental, educational, entertainment and general collection of photographs. For machine based browsing of images according to user's interest from these large scale image databases it is required to have efficient algorithm. To solve this problem in early 1990 content based image retrieval (CBIR) came into picture [1]. CBIR uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. There exist multiple representations for every content in the image, which characterize visual features from different visual perspectives. So, contents of the images in the database are extracted in the form of features and described as feature vectors. The feature vectors of the database images form a feature database. Similarity comparison is the next step after feature database creation. It finds similarities/ distances between the feature vectors of the query image and database images and then retrieves relevant images in conjunction with an indexing scheme [2]. In an image color is one of the most widely used spatial visual content for image retrieval. Swain *et al.* [3] proposed the idea of color histogram in 1990. Pass *et al.* [4] introduced color coherence vector (CCV) by splitting each histogram bin into two parts, i.e., coherent or incoherent. Huang *et al.* [5] designed a color feature called color correlogram (CC). It characterizes not only the color distributions of pixels, but also the spatial correlation between pairs of colors.

Texture is another salient feature for CBIR. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment [6]. Smith *et al.* [7] calculated mean and variance of the wavelet coefficients for CBIR. Moghaddam *et al.* [8] introduced an algorithm called wavelet correlogram (WC) by combining the concept of color (color correlogram) and texture (wavelet transform) properties. WC first computes the wavelet coefficients then autocorrelation of the quantized coefficients is computed along the direction of wavelet transform. Manjunath *et al.* [9] used Gabor transform for texture image retrieval. Moghaddam *et al.* [10] proposed the Gabor wavelet correlogram for CBIR. Jhanwar et al. [11] introduced motif co-occurrence matrix (MCM) for CBIR. The MCM is defined as a 3D matrix whose (i, j, k) entry denotes the probability of finding a motif *i* at a distance *k* from the motif *j* in the motif transformed image. Murala *et al.* [12] proposed combination of color histogram and Gabor wavelet transform (GWT) for CBIR.

Swanson *et al.* [13] gave the theory of binary wavelet transform (BWT). The binary wavelet transform uses simple modulo-2 operations. It yields an output similar to the thresholded output of a real wavelet transform operating on the binary image. Law *et al.* [14] developed a set of length-independent binary filters for the BWT and applied them to binary image compression. Pan *et al.* [15] proposed a lossless image compression approach using this BWT. Pan *et al.* [16] proposed context-based embedded image compression using BWT. They alleviate the degradation of predictability caused by the BWT. Likewise, BWT has several distinct advantages over the real field wavelet transform, such as no quantization introduced during the transform and computationally efficient since only simple boolean operations are involved.

The paper is organized as follows: section 1 consists of overview of CBIR and related works. In section 2 methodologies for feature extraction are presented. Section 3 explains similarity measurement technique. Section 4 contains the image retrieval process. Section 5 describes experimental results and comparative analysis of proposed method. Finally, in section 6 conclusions are derived.

II. METHEDOLOGY

In this paper feature extraction methodologies are applied on RGB scale as well as gray scale. In case of RGB scale every operation is applied individually on every component of image; R, G and B. In case of gray scale feature vector calculation RGB input image is first converted into gray scale and then same operations are applied on gray image. In this paper performance of proposed BWTH feature is compared with color histogram, auto correlogram, discrete wavelet transform and wavelet correlogram. The methodologies for feature extraction using above techniques are explained below:

A. Proposed Feature (BWTH) Calculation

The primitive step of BWTH calculation is binary wavelet transform (BWT). BWT in 1-D and 2-D are explained in the following section.

1. Binary wavelet transform (BWT): Law *et al.* [14] proposed the in-place implementation of BWT. This reduces memory requirement and arithmetic operations. 1-D BWT is shown in Fig. 1. Odd positions values in 1-D signal give the low pass output while even and odd together with XOR operation give the high pass or band pass output. Thus, low pass output consists only sub sampling operation while the high pass output has XOR operation between two neighboring samples. Low pass output does not create any change apart from sampling.

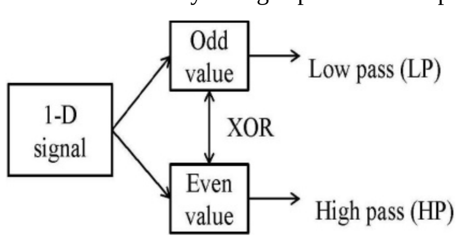

Figure 6. 1-D BWT

Fig. 2 illustrates the 2-D BWT. A separable 2-D BWT can be computed efficiently in discrete space by applying the associated 1-D filter bank to each column of the image, and then applying the filter bank to each row of the resultant coefficients. Fig. 2 shows a one level binary wavelet decomposition of a 2-D image. In the first level of decomposition, one low pass sub image (LL_1) and three orientation selective high pass sub images (LH_1, HL_1, and HH_1) are created. In second level of decomposition, the low pass sub image (LL_1) is further decomposed into one low pass (LL_2) and three high pass sub images (LH_2, HL_2, and HH_2). The process is repeated on the low pass sub image to form higher level of binary wavelet decomposition. In other words, BWT decomposes an image in to a pyramid structure of the sub images with various resolutions corresponding to the different scales. Thus, three scale BWT decomposition of an image will create three low pass subbands and nine (three each in horizontal, vertical, and diagonal direction) high pass directional subband.

2. Binary wavelet transform based histogram (BWTH):

This paper proposes BWTH feature vector for image representation. Algorithm of proposed feature calculation for RGB/Gray image is described as follows:

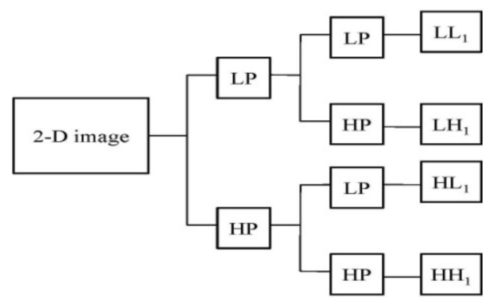

Figure 7. 2-D BWT

1. Input RGB/Gray image
2. Repeat a to d steps for i. *(i=1 to 3)* for RGB image and *(i=1)* for Gray image
   a. Convert i^{th} component image into 8-bit binary image
   b. On each bit image individually apply binary wavelet transform up to 3 scales
   c. Convert 8 bit subbands into gray scale back
   d. Now, for each subband calculate histogram
3. These histograms give the final feature vector for the given image

Fig. 3 illustrates the process of BWTH feature vector calculation in case of RGB image. In implementation, low pass subband is divided into 32 equally spaced histogram bins while high pass subband is divided into 35 histogram bins with varying width.

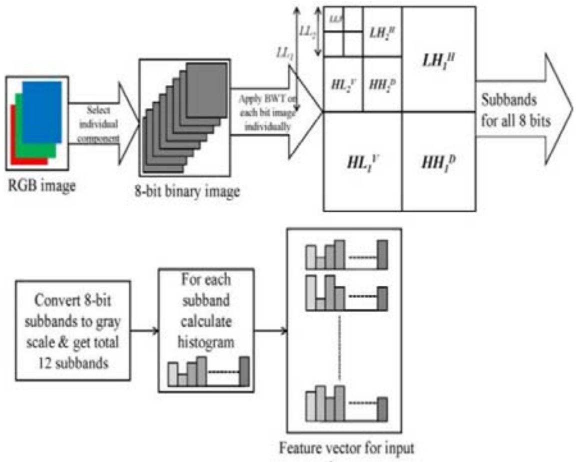

Figure 8. BWTH feature vector calculation for RGB image

B. Color Histogram

In 1991 Swain *et al.* [3] proposed a method for color indexing with the help of color histogram. The color histogram represents the count of each color in the image. Histogram is robust to translation, rotation and scale. A color histogram feature *H* for a given image is defined as:

$$H = \{H[0], H[1], ..., H[i], ...H[N]\} \tag{1}$$

Where, *i* represent the color in color histogram, *H*[i] represent the number of pixels with color *i* in the image and *N* is the number of bins used in color histogram. In implementation $N=32$ is used. For RGB implementation, histogram of each color channel is calculated.

For comparing the histogram of different sizes, color histogram should be normalized. The normalized color histogram is given as

$$H' = \frac{H}{p}$$

Where, *p* is the total number of pixels in the image.

C. Auto Correlogram

The color correlogram (or color co-occurrence matrix) is proposed by Huang *et al.* [5]. In implementation input image intensity values are quantized into 32 levels and then auto correlogram is calculated. A color correlogram is a table indexed by color pairs, where the k^{th} entry for *(i, j)* specifies the probability of finding a pixel of color j at a distance *k* from a pixel of color *i* in the image. Let *I* represents the entire set of image pixels and $I_{c(i)}$ represent the set of pixels whose colors are *c(i)*. Then, the color correlogram feature is defined by eq. (2).

$$\gamma_{i,j}^{(k)} = \Pr_{p_1 \in I_{c(i)},\, p_2 \in I}\left[p_2 \in I_{c(j)} \,\middle\|\, |p_1 - p_2| = k \right] \tag{2}$$

$i = j$ *for autocorrelogram*

D. Discrete Wavelet Transform (DWT)

Smith *et al.* [7] used the mean and variance of the wavelet coefficients as texture features for CBIR. The 2-D DWT decomposes an image $f(x,y) = L^2(R^2)$ in terms of a set of shifted and dilated wavelet functions $\left\{\psi^{0^0}, \psi^{90^0}, \psi^{\pm 45^0}\right\}$ and scaling function $\varphi(x,y)$ as given by eq. (3).

$$f(x,y) = \sum_{k \in Z^2} s_{j_o,k}\varphi_{j_o,k}(x,y) + \sum_{b\in\theta}\sum_{j \geq j_0}\sum_{k \in Z^2} w^b_{j,k}\psi^b_{j,k}(x,y) \tag{3}$$

Where, $\varphi_{j_0,k}(x,y) = 2^{\frac{j_0}{2}}\varphi(2^{j_0}(x,y) - k),$

$$\psi^b_{j,k}(x,y) = 2^{\frac{j}{2}}\psi^b(2^j(x,y) - k)$$

and $b \in \theta = \left\{0^0, 90^0, \pm 45^0\right\}$. *b* denotes the subbands of the wavelet decomposition with information in $0^0, 90^0$ *and* $\pm 45^0$. The computation of the wavelet transforms of a 2D signal involves recursive filtering and sub-sampling. At first level, the signal is decomposed into four frequency sub-bands, LL (G_{11}), LH (G_{12}), HL (G_{13}) and HH (G_{14}) where L denotes low frequency filtering and H denotes high frequency filtering. In further levels DWT recursively decomposes the LL band. DWT is applied for scale *(M) =3* and orientation *(N) =4*. It generates array of 12 sub-bands *(G_{11}, G_{12}, … ,G_{mn}, ... ,G_{MN})*.

To represent homogenous texture feature of the region the mean μ_{mn} and standard deviation σ_{mn} are calculated by using eq. (4) and (5) respectively on the magnitude of the transformed coefficients [12].

$$\mu_{mn} = \sum_x\sum_y G_{mn}(x,y) \tag{4}$$

$$\sigma_{mn} = \sqrt{\sum_x\sum_y (|G_{mn}(x,y)| - \mu_{mn})^2} \tag{5}$$

Where, $m = 1,2,3$ and $n = 1,...,4$. Final wavelet transform feature vectors are extracted using μ_{mn} and σ_{mn} as the feature components for each subband. The feature vector array *f* is represented by eq. (6).

$$f = (\mu_{11}, \mu_{12}, ...\mu_{34}, \sigma_{11}, \sigma_{12}, ...\sigma_{34}). \tag{6}$$

E. Wavelet Correlogram

In case of gray scale only, wavelet correlogram is calculated. It is not applied in RGB space because it will increase complexity in RGB space. Moghaddam *et al.*

[8] introduced an algorithm called wavelet correlogram (WC) by combining the concept of color (color correlogram) and texture (wavelet transform) properties. Tarzjan *et al.* [6] applied wavelet correlogram with optimized quantization threshold on Corel database.

III. SIMILARITY MEASUREMENT

To find similarity among query and database images, a query image is taken from image database. Query image and database images are processed to compute features. Distance measure given by eq. (7) is used to compute the difference between query image and database image features.

$$D(Q,T)=\sum_{i=1}^{\Gamma}\frac{|Q_i-T_i|^2}{|1+Q_i+T_i|^2} \tag{7}$$

Where, Q_i is feature vector of query image, T_i is feature vector of database images and Γ is the feature vector length. Database image having small *D (Q, T)* value is more relevant to query image.

IV. IMAGE RETRIEVAL

The block diagram of CBIR system with proposed feature is shown in Fig. 4 and algorithm of CBIR system is given as follows:

1. Input query image (RGB/Gray)
2. Calculate BWTH features for query image and all database images.
3. Apply similarity measurement to calculate dissimilarity among query and database image features.
4. Database images getting less dissimilarity values will be considered as more relevant to query.
5. Retrieval result is a list of relevant images in the database.

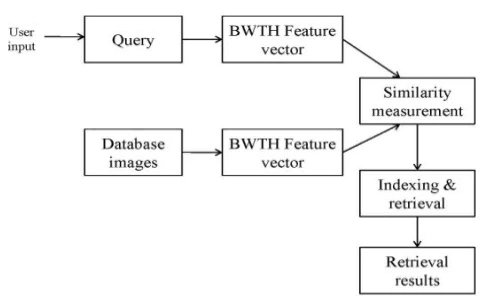

Figure 9. Schematic diagram of image retrieval system with proposed feature

V. EXPERIMENTS RESULTS

All the experiments are performed on the Corel 1000 (DB1) and Corel 2450 (DB2) natural image databases [17]. Both databases consists of images with two different sizes (either 256×384 or 384×256). All images are in jpg format. Database DB1 consists of 10 groups and each group contains 100 images of the same type. Database DB2 are categorized into 19 groups. Each category contains 50 to 600 images. For performance evaluation various performance measures like average precision (*AP %*) and average recall (*AR %*) and average retrieval rate (*ARR %*) are calculated by using eq. (10), (13) and (14) respectively. Precision is defined in terms of number of relevant images retrieved out of total number of retrieved images considered. Precision tends to decrease as the total number of retrieved images increases. In case of recall number of retrieved images is always considered as maximum number of relevant images in database. It is typical to have a high numeric value for both precision and recall. In ideal case both precision and recall should achieve 100 %. It can be obtained when all the retrieved images belong to the query image group only i.e. all retrieved images should be relevant.

$$Precision(P_i)=\frac{No.of\ relevant\ images\ retrieved}{Total\ no.of\ retrieved\ images\ considered\ (T)} \tag{8}$$

$$Group\ precision\,(GP)=\frac{1}{N}\sum_{i=1}^{N}P_i \tag{9}$$

$$Average\ precision\,(AP)=\frac{1}{\Gamma}\sum_{i=1}^{\Gamma}GP_i \tag{10}$$

$$Recall\,(R)=\frac{No.of\ relevant\ images\ retrieved}{Total\ no.of\ relevant\ images\ in\ database} \tag{11}$$

$$Group\ Recall\,(GR)=\frac{1}{N}\sum_{i=1}^{N}R_i \tag{12}$$

$$Average\ Recall\,(AR)=\frac{1}{\Gamma}\sum_{i=1}^{\Gamma}GR_i \tag{13}$$

$$Average\ Retrieval\ Rate\,(ARR_T)=\frac{1}{DB}\sum_{j=1}^{DB}R_j\Big|_{T\le100} \tag{14}$$

Where, N is number of relevant images in database, Γ is number of groups and DB is number of database images. The retrieval result is not a single image but it's a list of images depending upon relevancy. *T* gives the total number of retrieved images considered $(e.g. 10, 20, \ldots\ldots, 100)$. Value of *T* is selected by user.

Table 1 illustrates the retrieval performance measure i. e. average precision and average recall comparison of proposed method with autocorrelogram, wavelet transform and wavelet correlogram in gray space. It is verified that of average precision and average recall of proposed method (66.69%, 40.77%) is better compared to auto correlogram (57.20%, 35.31%), wavelet transform (52.70%, 32.98%) and wavelet correlogram (64.3%, 38.0%). It is evident form Table 2 that in RGB space proposed method average precision and average recall (73.82%, 44.29%) is more compared to color histogram (70.85%, 42.16%), auto correlogram (66.15%, 39.52%) and wavelet transform (60.83%, 38.25%). Table 3 illustrates the average precision comparison of proposed method with Jhanwar *et al.* [17] in case of 20 retrieved image considered. It is observed that the proposed method gives 66.57 % while Jhanwar *et al.* [17] result is 52.64%. Table 1, Table 2 and Table 3 results are obtained for database DB1. Table 4 comprises the results of proposed method, wavelet transform, auto correlogram and wavelet correlogram in gray scale for DB2 database. Table 5 illustrates comparison between proposed method and color histogram, wavelet transform, auto correlogram for DB2 database in color scale. It is clear from Table 4 and Table 5 that performance of proposed method is far better than other method for different number of retrieved image considered.

Fig 5 and Fig 6 show the average retrieval rate (*ARR %*) of proposed method and comparison with other method in case of gray and color scale for database DB1 respectively. Fig 7 and Fig 8 describe the *ARR %* comparison among proposed method and various methods in gray and color scale for database DB2 respectively. It is verified from Fig. 5 and Fig. 7 that *ARR %* of proposed method (40.773, 33.67) is always higher than auto correlogram (35.31 and 29.52), wavelet transform (32.98, 23.77) and wavelet correlogram (38, 32.14) for 100 retrieved images. Similarly from Fig. 6 and Fig. 8 it is evident that proposed method always shows better performance in case of different number of retrieved images.

VI. CONCLUSION

This paper proposed a new visual feature BWTH; it exhibits the qualities of binary wavelet transform as well as histogram. In the primitive step of proposed algorithm binary wavelet transform is applied to calculated different subbands. Then, histogram is calculated on each subband to extract the proposed feature BWTH. The experimental results show that the proposed feature provides useful information to represent images in gray as well as in color scale. Results on database DB1 and DB2 verify that the proposed method outperform color histogram, auto correlogram, discrete wavelet transform in RGB space and auto correlogram, discrete wavelet transform, wavelet correlogram in gray space.

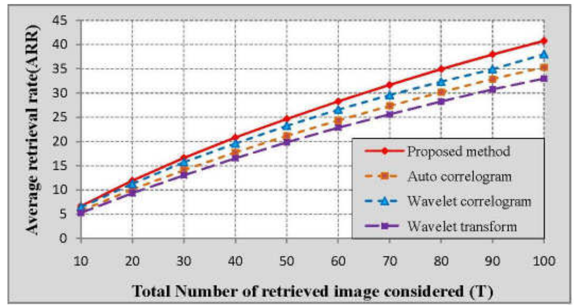

Figure 10. *ARR (%)* for database DB1 with gray scale

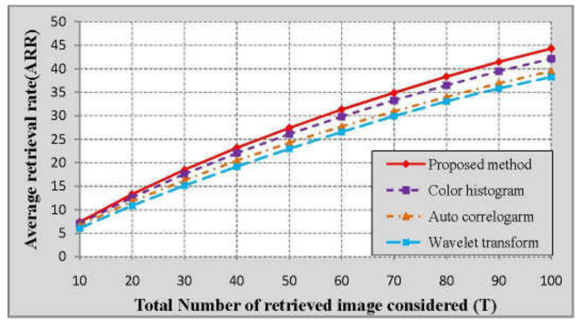

Figure 11. *ARR (%)* for database DB1 with color scale

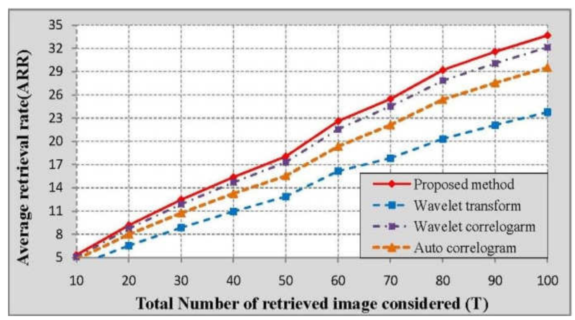

Figure 12. *ARR (%)* for database DB2 with gray scale

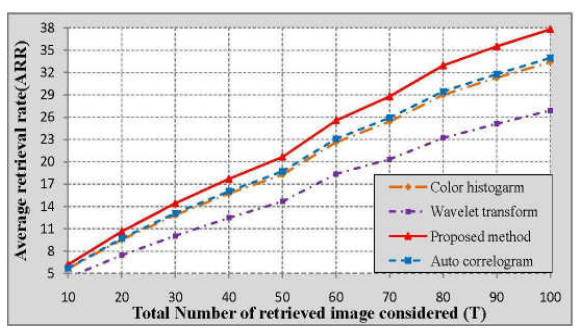

Figure 13. *ARR (%)* for database DB2 with color scale

REFERENCES

[1] Y. Rui, T. S. Huang, S. F. Chang, "Image Retrieval: Current Techniques, Promising Directions and Open Issues", Elsevier J. Visual Communication and Image Representation, vol. 10, no. 1, Mar . 1999, pp. 39–62.

[2] R. Datta, D. Joshi, J. Li and J. Z. Wang, ``Image Retrieval: Ideas, Influences, and Trends of the New Age," ACM Computing Surveys, vol. 40, no. 2, article 5, 2008, pp. 1-60.

[3] M. J. Swain, D. H. Ballard, "Indexing via color histograms", Proc. IEEE 3rd International Conference Computer Vision, Osaka, Japan, 1990, pp. 390–393.

[4] G. Pass, R. Zabih, J. Miller, "Comparing images using color coherence vectors", Proc. 4th ACM Multimedia Conference, Boston, Massachusetts, US, 1996, pp. 65–73.

[5] J. Huang, S. R. Kumar, M. Mitra, W.-J. Zhu, R. Zabih, "Image indexing using color correlograms", Proc. IEEE Computer Vision and Pattern Recognition, San Juan., 1997, pp. 762-768.

[6] M. S. –Tarzjan, H. A. Moghaddam, "A Novel Evolutionary Approach for Optimizing Content Based Image Retrieval", IEEE Trans. Systems, Man, and Cybernetics, vol. 37, no. 1, 2007, pp. 139-153.

[7] J. R. Smith and S. -F. Chang, "Automated Binary Texture Feature Sets for Image Retrieval", Proc. IEEE International Conf. Acoustics, Speech and Signal Processing, vol. 4, Atlanta, GA, 1996, pp. 2239–2242.

[8] H. A. Moghaddam, T. T. Khajoie and A. H. Rouhi, "A New Algorithm for Image Indexing and Retrieval Using Wavelet Correlogram", Proc. IEEE International Conference Image Processing, vol. 3, Barcelona, Spain, Sept. 2003, pp. 497–500.

[9] B. S. Manjunath and W. Y. Ma, "Texture Features for Browsing and Retrieval of Image Data", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 18, no. 8, Aug. 1996, pp. 837–842.

[10] H. A. Moghaddam, M. S. -Tarzjan, "Gabor wavelet Correlogram Algorithm for Image Indexing and Retrieval", Proc. 18th International Conference Pattern Recognition, Hong Kong, 2006, pp. 925-928.

[11] N. Jhanwar, S. Chaudhurib, G. Seetharamanc, B. Zavidovique, "Content based image retrieval using motif co-occurrence matrix", Elsevier J. Image and Vision Computing, vol. 22, 2004, pp. 1211–1220.

[12] S. Murala, A. B. Gonde, R. P. Maheshwari, "Color and Texture Features for Image Indexing and Retrieval", Proc. IEEE International Advance Computing Conference, Patiala, 2009, pp.1411−1416.

[13] M. D. Swanson, A. H. Tewfik, "A Binary Wavelet Decomposition of Binary Images", IEEE Trans. Image Processing, vol.5**,** no. 12, Dec. 1996, pp. 1637- 1650.

[14] N.F. Law, W.C. Siu, "A filter design strategy for binary field wavelet transform using the perpendicular constraint", Elsevier J. Signal Processing, vol. 87, 2007, pp. 2850–2858.

[15] H. Pan, W.-C. Siu, N.-F. Law, "Lossless image compression using binary wavelet transform", IET Image Processing, vol. 1, no. 4, 2007, pp. 353–362.

[16] H. Pan, L. Jin, X. Yuan, S. Xia, L. Xia, "Context-based embedded image compression using binary wavelet transform", Elsevier J. Image and Vision Computing, vol. 28, 2010, pp. 991–1002.

[17] Corel 1000 and Corel 10000 image database. [Online]. Available 2011: http://wang.ist.psu.edu/docs/related/

TABLE I. RETRIEVAL PERFORMANCE COMPARISON FOR DATABASE DB1 WITH GRAY SCALE

Group Name	Proposed Method		Auto Correlogram		Wavelet transform		Wavelet correlogram	
	P% *(T=10)*	R% *(T=100)*	P% *(T=10)*	R% *(T=100)*	P% *(T=10)*	R% *(T=100)*	P% *(T=10)*	R% *(T=100)*
Africans	76.20	38.38	74.50	48.47	39.00	20.02	57.7	31.1
Beaches	42.90	22.91	29.10	15.21	37.10	22.77	49.3	28.6
Buildings	46.00	26.47	38.70	18.75	29.70	19.45	50.9	30.5
Buses	73.30	48.80	35.80	19.01	56.40	34.38	87.1	64.0
Dinosaurs	99.90	94.70	100.00	96.27	95.60	62.25	74.6	28.8
Elephants	66.20	34.57	58.10	32.44	48.50	27.83	55.7	30.7
Flowers	93.90	65.51	85.40	47.14	90.60	71.17	84.3	65.3
Horses	74.50	28.58	73.50	34.35	57.10	30.81	78.9	39.9
Mountains	29.90	16.52	21.90	12.13	32.80	18.26	47.2	25.1
Foods	64.10	31.29	55.00	29.41	40.20	22.82	57.1	36.4
Average	**66.69**	**40.77**	**57.20**	**35.31**	**52.70**	**32.98**	**64.3**	**38.0**

TABLE- II : RETRIEVAL PERFORMANCE COMPARISON FOR DATABASE DB1 WITH COLOR SCALE

Group Name	Proposed Method		Color histogram		Auto Correlogram		Wavelet transform	
	P% *(T=10)*	R% *(T=100)*	P% *(T=10)*	R% *(T=100)*	P% *(T=10)*	R% *(T=100)*	P% *(T=10)*	R% *(T=100)*
Africans	82.80	41.76	83.10	49.34	84.80	55.22	45.70	24.25
Beaches	52.80	26.76	52.40	24.64	43.70	22.50	48.00	26.90
Buildings	58.90	29.76	54.50	27.35	51.20	22.35	36.20	21.45
Buses	80.30	55.00	62.10	41.98	38.90	24.76	59.00	38.35
Dinosaurs	99.90	95.05	100	96.90	100.00	96.42	97.80	70.00
Elephants	71.30	34.50	67.10	34.82	65.90	35.04	58.00	31.32
Flowers	93.00	67.53	84.30	50.57	81.60	44.64	91.30	74.75
Horses	84.70	36.90	90.50	42.60	89.20	42.71	78.00	44.06
Mountains	39.20	20.20	38.20	18.98	35.80	17.90	43.30	23.22
Foods	75.30	35.44	76.30	34.43	70.40	33.74	51.00	28.15
Average	**73.82**	**44.29**	**70.85**	**42.16**	**66.15**	**39.52**	**60.83**	**38.25**

TABLE- III. AVERAGE PRECISION (%) COMPARISON FOR DATABASE DB1 WITH GRAY SCALE (*T=20*)

Group number	1	2	3	4	5	6	7	8	9	10	Average
Proposed method	74.80	45.20	50.70	75.95	99.55	61.75	89.85	73.30	30.85	63.75	66.57
Jhanwar *et al.* [11]	45.25	39.75	37.35	74.10	91.45	30.40	85.15	56.80	29.25	36.95	52.64

TABLE – IV. AVERAGE PRECISION (%) COMPARISON FOR DATABASE DB2 WITH GRAY SCALE

No of retrieved images (T)	10	20	30	40	50	60	70	80	90	100
Proposed method	53.27	45.81	41.54	38.45	36.10	37.68	36.38	36.49	35.08	33.67
Wavelet transform	39.60	32.70	29.49	27.35	25.75	26.92	25.48	25.40	24.55	23.77
Auto correlogram	47.77	39.89	35.79	33.15	31.07	32.24	31.59	31.74	30.60	29.52
Wavelet correlogram	50.54	43.61	39.61	36.73	34.59	35.92	35.03	34.78	33.40	32.14

TABLE – V. AVERAGE PRECISION (%) COMPARISON FOR DATABASE DB2 WITH COLOR SCALE

No of retrieved images (T)	10	20	30	40	50	60	70	80	90	100
Proposed method	61.80	53.16	48.12	44.27	41.31	42.58	41.13	41.19	39.46	37.80
Color histogram	56.63	47.69	42.84	39.33	36.59	37.70	36.29	36.25	34.79	33.39
Wavelet transform	44.67	37.26	33.57	31.18	29.34	30.62	29.06	29.00	27.91	26.90
Auto correlogram	57.23	48.56	43.67	40.11	37.43	38.47	37.03	36.82	35.32	33.97