International Journal of Future Generation Communication and Networking
Vol. 13, No. 1, (2020), pp. 01-14

A Framework for Medical and Stock Image Retrieval in Wavelet Domain using Color, BDIPs and BVLC in Covariance

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Abstract

In the present scenario, content based image retrieval (CBIR) for diverse image collection is fascinating and essential task. Many researchers have worked and presented diverse feature descriptors. However, most of them are limited in discriminative power. In this work, we increased the retrieval rate of CBIR by integrating the multi resolution domain based color, BDIP (Block difference of inverse probabilities) and BVLC (Block variation of local correlation coefficients) in mean and covariance matrix. The multi resolution domain has been exploited using the Discrete Wavelet Transform (DWT) on R, G and B images respectively. The coefficients of DWT are used to estimate the proposed integrated feature vector. The BDIP computes edges and valleys details using local intensity maxima and minima respectively and BVLC computes texture smoothness details using the differences between local correlation coefficients The presented approach is tested on six benchmark databases namely Corel 1k, 5k and 10k, Holiday, Caltech 101 and Histopathology image databases. The proposed integration of multiresolution feature descriptor is compared with previous approaches and results in terms of precision, recall and G-measure are clearly shown that proposed approach is superior in performance for diverse image collections.

Keywords: *BDIPs, BVLCs, Chernoff Measure, Discrete Wavelet Transform, Covariance Matrix.*

1. Introduction

Content based image retrieval (CBIR) retrieves pertinent images from massive image dataset for a given query image by performing image matching and image matching is done on feature matching. The commonly used image features are shape, color and texture. In the present scenario, computing the discriminative image features is tougher task because images of different categories have different kinds of features. Most of the features proposed in the past are stick to specific kinds of images. Accordingly, still there is a scarcity for effective and versatile image feature which is more beneficial when the dataset consists of different kinds of images. Wide-ranging reviews for CBIR have been discussed in [1-3].

Though many systems for retrieval of images have been described by researchers, most of the systems considers either mathematical or statistical or geometrical based image features and for example, Haralick [4] computed the co-occurrence of every two pixels in the image and coined it as Gray level co-occurrence matrix (GLCM) then Haralick computed the low and high order statistical details from GLCM as texture information, Zhang et al., [5] used Prewitt operator to find edges then co-occurrence of every edgels in the image is computed which in turn used to calculate low and high order statistics and are described as shape and texture information of an image, color moment presented by Stricker and Orengo [6] includes mean, variance and skewness, the color histogram which exploits the distribution of color at global level is suggested in [7], Paschos et al. [8] introduced chromaticity moments, Hung el al., [9] presented color correlogram and it exploits local and global level spatial correlation among colors, Chang and Krumm [10] described color co-occurrence histogram, Color autocorrelogram reported by Chun et al.,[11] exploits global and local level spatial correlation among identical colors, [12, 13] defined area, circularity, convexity, eccentricity, etc for describing shape information, [14**,** 15] introduced boundary moments, eigen values reported in [16], local and global level details of edgels based on orientation is reported in [17, 18] and is coined as edge histogram descriptor and its variant is reported in [19, 20], global and local level spatial correlation among identical edgels based on orientation is described in [21] and its variant is reported in [22] for medical image retrieval, color histogram for k-mean intended for color detail and difference between pixels of scan pattern for texture and color information is presented in [23], third order local statistics in the image is extracted by motif co-occurrence matrix [24] and its enhanced variant called modified color motif co-occurrence is introduced by Murala et al., [25] in which relationship among color spaces that is red, green and blue is utilized, [26] combines texton histogram with motif matrix in HSV color model, Local binary pattern (LBP) is presented for computing local information of each point of interest based on its neighbors [27], LBP with rotation invariant capability is suggested in [28], various variants of LBP has been reported in [29-35], in [36], biomedical image indexing and retrieval is performed using directional binary wavelet pattern, SIFT which is a distribution of directions of key points is suggested in [37], SURF is introduced in [38], distributions of directions of gradients is reported in [39] and termed as histogram of orientation gradients (HOG), fusion of LBP and histogram of gradient is used by Wang et al., [40] for INRIA dataset, Rahman et al., presented heterogeneous medical image retrieval using color, Gabor and Tamura moments, GLCM, SIFT, LBPP, LBP-I, EHD, CEDD, FCTH, CLD, edge frequency, primitive length, autocorrelation coefficients together with "Bag of words" containing title, problem, modality, region of interest, organ of images etc., in [41], edge co-operative maps are computed by performing phase congruency task in L*a*b* color channel and is combined with SIFT to drive key points which are quantized to construct a codebook in [42], in [43 - 45], CT image retrieval is performed using local bit-plane decoded pattern, local diagonal extrema pattern and local wavelet pattern, CT and MRI image retrieval using Directional local ternary quantized extrema pattern (DLTerQEP) is described in [46] which exploits more structure and spatial details by incorporating ternary patterns from vertical, horizontal, diagonal, anti-diagonal structure of directional local extrema values of an image, Saravanan et al., [47] combined chordiogram image descriptor (CID) with color autocorrelogram for image retrieval which results in better retrieval rate due to mixture of shape and geometric details. The variants of CID is suggested in [48] and in [49] correlation based CID is integrated with color autocorrelogram for retrieval of images. [50 - 52] exploited color, shape and texture details using multi-trend structure descriptor, features based on the variant of multi-trend structure descriptor is reported in [53] for stock and medical image retrieval. In recent years, number of systems has been developed for image retrieval using BDIP and BVLC [54 –60] and they emerge as one of the prominent shape and texture features respectively. In [61], we presented mean and covariance matrices of BDIPs and BVLCs for retrieving images and in [62], we introduced the co-occurrences of BDIPs for image retrieval. Though the variants of BDIP and BVLC and the combinations of BDIP and BVLC with other feature descriptors increased the competence of retrieval systems, still the accuracy of retrieval systems for images based on contents suffers in accuracy. Though, features reported in [61] and [62] is significantly discriminative one, those features are exploited from single resolution of image. Literature reports that image contains varying levels of information and single resolution is not sufficient to decide the varying levels of information within the image. But, this drawback is addressed by multiresolution analysis which performs image analysis at more than one resolution and thus information that are unobserved at one level acquire consideration at another level. Thus, in this paper, we introduce a system for retrieving images using color, shape and texture information where color, shape and texture information are exploited from more than one resolution of the image and we implemented the multiresolution analysis using DWT method. The color information is encoded as mean and covariance matrices of approximation coefficients of R, G and B component images in multiresolution domain, texture and shape information are encoded as mean and covariance matrices of BVLCs and BDIPs computed from the details coefficients of R, G and B images in multiresolution domain respectively. Comprehensive experiments done on benchmark datasets exposed that proposed integration of multiresolution features in mean and covariance matrix is outperforming for image retrieval. The rest of the article is organized as: proposed multiresolution features computation and background of wavelets are described in Section 2, Section 3 discuss about experiments and finally section 4 deals with conclusion.

2. Proposed Method for Image Retrieval

Generally, images are complex in structure and contain varying level of details. Therefore, to extract information from all these levels, in this paper, we decompose the image into multiple resolutions and thus proposed system able to encode the proposed features at different orientations. In the proposed system, images are in RGB color format. Therefore, we separate out RGB into R, G and B than each component image is decomposed into level 3 using DWT. At each level of decomposition of R or G or B, one approximation and three details coefficients (horizontal, vertical and diagonal details) are produced. The proposed color information in mean and covariances is extracted from the approximation coefficients of R, G and B components image in multiresolution domain and texture and shape information are encoded as mean and covariance matrices of BVLCs and BDIPs computed from details coefficients of R, G and B images in multiresolution domain. The proposed color and texture, edges and valley information in mean and covariance's are computed from the approximation and details coefficients of level 1 to finest level of multi resolution domain respectively and are integrated to retrieve similar images. Experimentally we determined the finest level and it is 3. The proposed multiresolution features encodes color information with spatial dependencies of color, texture, edges and valley with directional information along with the spatial dependencies of texture, edges and valley respectively and thus, the proposed integration of multiresolution features performs considerably well in accuracy. The structure of proposed system is depicted in Figure1.

2.1. Wavelets

In recent years, wavelets come out as more popular basis for image retrieval. Image representation in wavelet domain provides a detail of the image in various resolutions at different scales that is images analysis and representation is performed at multiple resolutions. As mentioned in Section I, the features that are not detected at one resolution is acquired at another one is the beneficial of wavelet domain. In multiresolution domain, the minute details in low contrast are detected in high resolution whereas other details are detected in low resolution.

2.1.1. Discrete Wavelet Transform

In DWT, images are represented as a sum of wavelet functions with different locations and scales. Since the implementation of DWT [63] is easy and provides adequate information for image analysis, we incorporated DWT in the proposed system. DWT decomposes images into 4 sub-bands namely LL, HL, LH, and HH, encompassing approximation, vertical, horizontal and diagonal details respectively. From 2nd level onwards, HH sub-band (approximation details) is decomposed into 4 sub-bands.

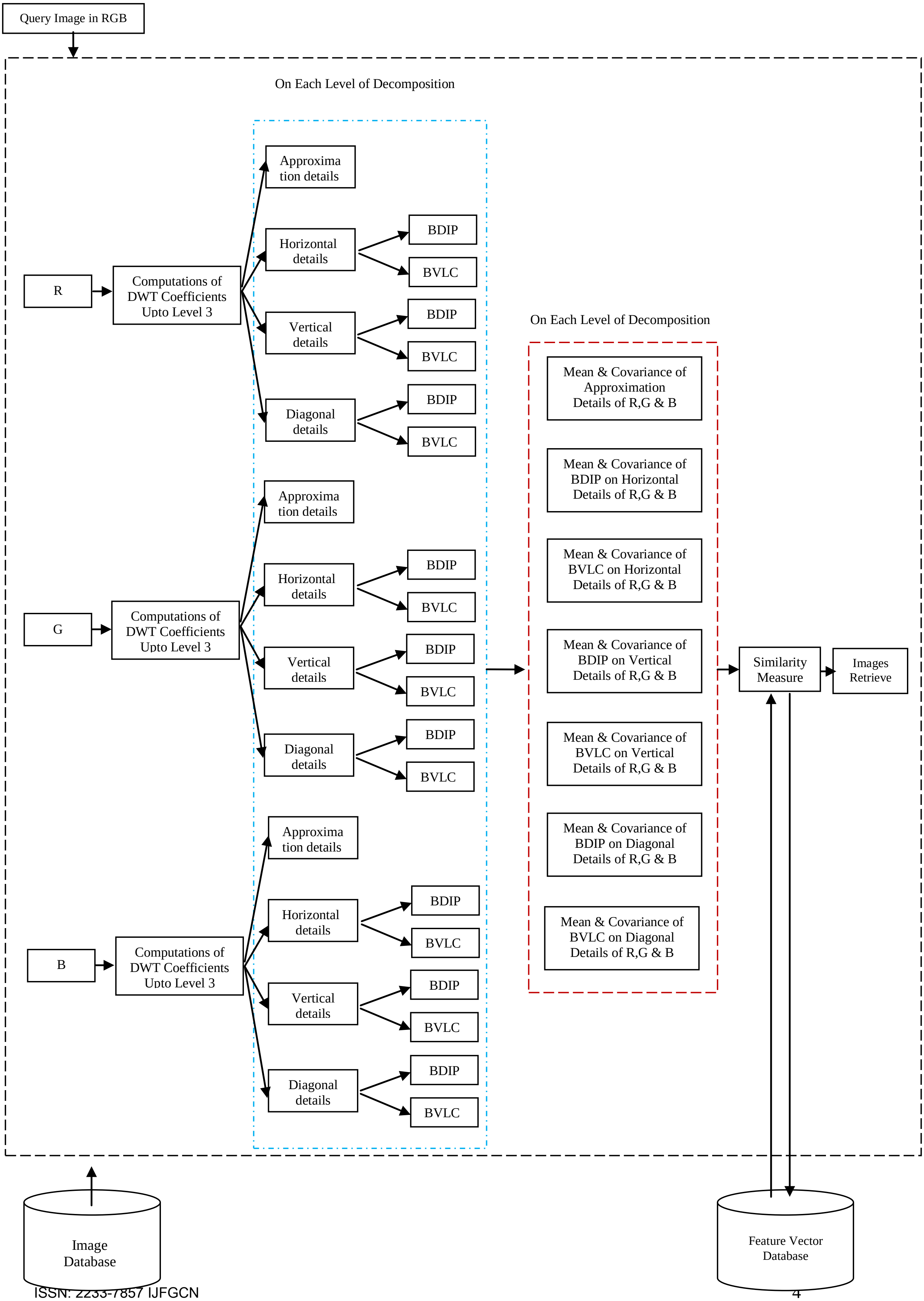
Query Image in RGB
On Each Level of Decomposition
R
Computations of DWT Coefficients Upto Level 3
G
Computations of DWT Coefficients Upto Level 3
B
Computations of DWT Coefficients Upto Level 3
Approxima tion details
Horizontal details
Vertical details
Diagonal details
BDIP
BVLC
On Each Level of Decomposition
Mean & Covariance of Approximation Details of R,G & B
Mean & Covariance of BDIP on Horizontal Details of R,G & B
Mean & Covariance of BVLC on Horizontal Details of R,G & B
Mean & Covariance of BDIP on Vertical Details of R,G & B
Mean & Covariance of BVLC on Vertical Details of R,G & B
Mean & Covariance of BDIP on Diagonal Details of R,G & B
Mean & Covariance of BVLC on Diagonal Details of R,G & B
Similarity Measure
Images Retrieve
Image Database
Feature Vector Database

Figure 1. Proposed image matching technique using DWT based BVLCs and BDIPs in mean and covariance.

Generally, more level of decomposition results in loss of details and thus, we found level 3 is apt for the proposed system on aforementioned databases and we determined the level 3 based on experiments.

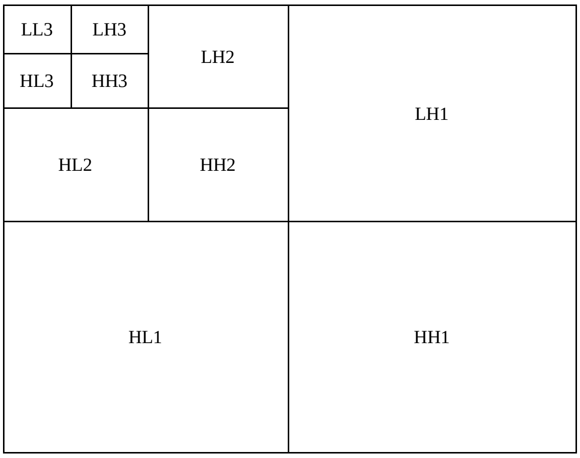

Figure 2. Image decomposition at level 3 using DWT

2.1.1.1. 1D DWT

Let $f(t) = L^2(R)$ be a signal. The signal is decomposed by 1D DWT in terms of shifted and dilated mother wavelet $\psi(t)$ and scaling function $\varphi(t)$.

$$f(t) = \sum_{l \in Z} S_{j_o}, \varphi_{j_o,l}(t) + \sum_{j \geq j_0} \sum_{I \in Z} w_{j,l} \psi_{j,l}(t) \tag{1}$$

where

$$\varphi_{j_o,l}(t) = 2^{\frac{j_0}{2}} \varphi(2^{j_o} t - l)$$

$$\psi_{j,l}(t) = 2^{\frac{j}{2}} \varphi(2^{j} t - l)$$

When $\{\varphi_{j_o,l}, \psi_{j,l}, j \geq j_0, l \in Z\}$ form an orthonormal basis of $L^2(R)$, the scaling coefficient $S_{j_o,l}$ and wavelet coefficient $w_{j,l}$ is computed by standard L^2 inner product: $S_{j_o,l} = \langle f, \varphi_{j_o,l} \rangle$ and $W_{j,l} = \langle f, \psi_{j,l} \rangle$.

2.1.1.2. 2D DWT

By applying the 1D filter bank to every column of an image then by applying the 1D filter bank to every of resultant coefficients, 2D DWT is calculated in discrete space. Figure 2 depicts 3 level decomposition of image $I = f(x, y)$ of size MxN pixels using DWT where LL1, HL1, LH1; HH1, and LL2, HL2, LH2, and HH2; and LL3, HL3, LH3, and HH3 are the approximation, vertical, horizontal and diagonal details of image at level 1, 2 and 3 decomposition respectively. Therefore, 3 level decomposition formed 3 low pass (approximation) images and 9 high pass (vertical, horizontal and diagonal details) sub images. The approximation is the low resolution of image and details provides changes in brightness in corresponding directions respectively

2.2. BDIP

BDIP [66], a sketch descriptor describes edges by local intensity maxima and describes valleys by local intensity minima, and described as in Eq. (1) [66].

$$BDIP^{d}(l) = \frac{\frac{1}{B_l^d} \Sigma(x,y) \in B_l^d (\max_{(x,y)\in B_l^d} f(x,y) - f(x,y))}{\max_{(x,y)\in B_l^d} f(x,y)} \tag{2}$$

where f(x, y) illustrates intensity of pixel at position (x, y) in block B_l^k of dimension (k+l) x (k+l), k illustrates utmost distance among pixels pairs and l illustrates place index. Therefore, $B_l^k = (k+1)^2$. In Eq. (1), numerator and denominator describes maximum intensity variation and representative value in a block of dimension (k+l) x (k+l) respectively.

2.3. BVLC

BVLC [66], characterizes texture smoothness based on differences among local correlation coefficients corresponding to $0^\circ, 90^\circ, 45^\circ, -45^\circ$ orientations, and described as in Eq. (2) [66].

$$\rho(k,l) = \frac{\frac{1}{M^2} \sum_{(x,y)\in B} f(x,y) f(x+k, y+l) - \mu_{0,0}\mu_{k,l}}{\sigma_{0,0}\sigma_{k,l}} \tag{3}$$

where B illustrates block of dimension $M \times M$ and $\mu_{0,0}, \mu_{k,l}$ and $\sigma_{0,0}$, $\sigma_{k,l}$ are local mean and standard deviation. The (k, l) illustrates a pair of horizontal and vertical shift connected with orientations $0^\circ, 90^\circ, 45^\circ, -45^\circ$ .Consequent to shifting of $M \times M$ window in each of 4 directions, *p(0,1), p(1,0), p(1,1), p(1,-1)* is estimated then BVLC is estimated in Eq. (3) [66].

$$BVLC^{d}(l) = \max_{\Delta(k)\in O_4} [\rho^k(l, \Delta(k))] - \min_{\Delta(k)\in O_4} [\rho^k(l, \Delta(k))] \tag{4}$$

Where $\Delta(k) = (\Delta_x(k), \Delta_y(k))$ illustrates shift in one four directions and $O_4 = \{(-k,0), (0,-k), (0, k), (k,0)\}$

2.4. Covariance Matrix

Let I be the image in RGB space. Let $\{K_f\}_{c\, f=1,2,\ldots,n}$ and $\{L_f\}_{c\, f=1,2,\ldots,n}$ be a set of color values / BVLC / BDIP descriptors of R / G / B channel images respectively, $\overline{K}$ and $\overline{L}$ are corresponding mean vectors, *c* is either R or G or B image then variance [66] between color values / BVLC / BDIP descriptors of two individual channel images is defined in Eq.(4).

$$\frac{1}{n}\left(\sum_{i=1}^{n}(K_f - \overline{K})(L_f - \overline{L})\right) \tag{5}$$

The mean (μ^C) value of color information in approximation coefficients of R, G and B images is as follows [62]:

$$\mu^C = \begin{bmatrix} \mu^C{}_R \\ \mu^C{}_G \\ \mu^C{}_B \end{bmatrix} \tag{6}$$

The mean (μ^T) value of BVLC in details coefficients of R, G and B images is as follows [62]:

$$\mu^T = \begin{bmatrix} \mu^T{}_R \\ \mu^T{}_G \\ \mu^T{}_B \end{bmatrix} \tag{7}$$

The mean (μ^{EV}) value of BDIP details coefficients of R, G and B images is as follows [62]:

$$\mu^{EV} = \begin{bmatrix} \mu^{EV}{}_R \\ \mu^{EV}{}_G \\ \mu^{EV}{}_B \end{bmatrix} \tag{8}$$

The covariance matrix for color information from approximation coefficients of R, G and B images and covariance matrix of BVLC and BDIP from details coefficients (horizontal / vertical / diagonal details) of R, G and B images are defined as in Eq.(9) to (11) respectively [62].

$$\Sigma^C = \begin{bmatrix} \sigma^C{}_{RR} & \sigma^C{}_{RG} & \sigma^C{}_{RB} \\ \sigma^C{}_{GR} & \sigma^C{}_{GG} & \sigma^C{}_{GB} \\ \sigma^C{}_{BR} & \sigma^C{}_{BG} & \sigma^C{}_{BB} \end{bmatrix} \tag{9}$$

$$\Sigma^T = \begin{bmatrix} \sigma^T{}_{RR} & \sigma^T{}_{RG} & \sigma^T{}_{RB} \\ \sigma^T{}_{GR} & \sigma^T{}_{GG} & \sigma^T{}_{GB} \\ \sigma^T{}_{BR} & \sigma^T{}_{BG} & \sigma^T{}_{BB} \end{bmatrix} \tag{10}$$

$$\Sigma^{EV} = \begin{bmatrix} \sigma^{EV}{}_{RR} & \sigma^{EV}{}_{RG} & \sigma^{EV}{}_{RB} \\ \sigma^{EV}{}_{GR} & \sigma^{EV}{}_{GG} & \sigma^{EV}{}_{GB} \\ \sigma^{EV}{}_{BR} & \sigma^{EV}{}_{BG} & \sigma^{EV}{}_{BB} \end{bmatrix} \tag{11}$$

where Σ^C illustrates the spatial relation between color details, $\sum^T$ and $\sum^{EV}$ illustrates the spatial relation between texture, edges and valleys descriptors on details coefficients (horizontal / vertical / diagonal details) of R, G and B images respectively and σ^C illustrates the variance among color details, σ^T and σ^{EV} illustrates the variance among texture, edges and valleys descriptors on details coefficients (horizontal / vertical / diagonal details) of R, G and B images respectively.

3. Experimental results

We used benchmark datasets namely Corel 1k, 5k and 10k [64], Holiday [65], Caltech 101[66] and Histopathology image [51, 52] databases to validate the competence of proposed retrieval system. In Figure 3, we have given sample images from the benchmark databases. The feature descriptors of [62] and [54] is compared with proposed one. The proposed DWT based mean and covariance feature descriptors are extracted from all the 3 levels of approximation and details coefficients and are integrated and stored separately in the database and we named it as feature descriptor database. To assess the competence of proposed integration of multiresolution feature vector, we randomly selected query images from each database. To measure the divergence among query and database images, most frequently used Chernoff dissimilarity measure [64] is employed in the proposed DWT based retrieval and is defined as follows [62]

$$D_{p,q}(s) = \frac{s(1-s)}{2}(\mu_2 - \mu_1)^T [s\Sigma_t + (1-s)\Sigma_2]^{-1}(\mu_2 - \mu_1)$$
$$+\frac{1}{2}\ln\frac{|s\Sigma_1 + (1-s)\Sigma_2|}{|\Sigma_1||\Sigma_2|^{1-s}} \quad (12)$$

where $D_{p,q}(s)$ signifies Chernoff measure of divergence, μ_t , μ_q , Σ_t and Σ_q signifies mean and covariance's of target image and input image respectively, and finest s provides maximum value for Chernoff measure of divergence and is achieved by using various s and it lies in range $0 \le s \le 1$. In this study, we estimated the Chernoff measure for the mean and covariances of color, texture and shape information on approximation and details coefficients for all the levels (i.e upto 3) respectively and individually. Later, we have taken the average of all the results of Chernoff measure and are used for measuring the degree of divergence between the input image feature vector and target image feature vector.

We measured the competence of proposed DWT based retrieval system using the most commonly used precision (α) [62] and recall (β) [62] and are defined as follows

$$\text{Precision } (\alpha) = \frac{I_N}{N} \quad (13)$$

$$\text{Recall } (\beta) = \frac{I_N}{M} \quad (14)$$

where N and M indicates number of retrieved images and number of images in database akin to query image. We also combined the results of α and β by the approach called G-measure [62] and is given by

$$G-Measure = \sqrt{\Pr ecision \times \text{Re}\,call} \quad (15)$$

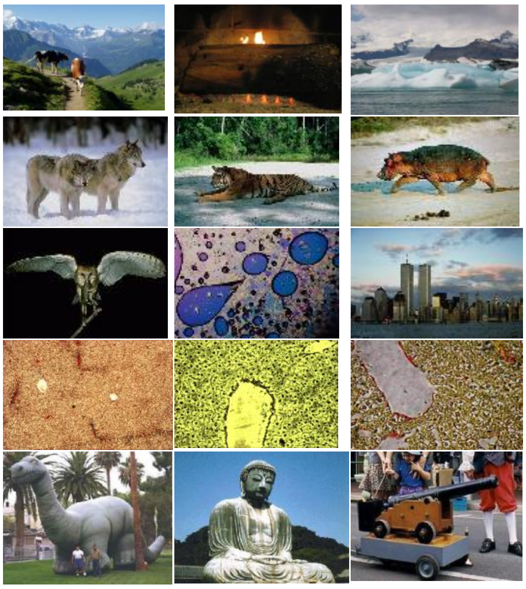

Figure 3. Sample images from benchmark databases

Experimental results obviously shown that for all the benchmark databases least performer is [54] and moderate performer is the approach proposed in [62] and proposed DWT based integration of mean and covariance matrices of color in approximation coefficients, texture and shape in vertical, horizontal and diagonal coefficients of level 1 to finest level is superior performer and is evident from its α and β plots. The finest level is 3 in our case. For each level of decomposition, image size is reduces to half of the image in preceding level. For instance, if image size is 512x512, its size reduces to 256x256, 128×128, 64×64 in levels 1 - 3 respectively. Since proposed multiresolution feature descriptor extracts spatial dependencies of color and spatial dependencies of textures and edges and valleys with directional information from different scale at different resolution, it is highly discriminative one and highly resilient to rotation, translation and scaling, and eradicate noisy color, texture and shape details. Therefore, proposed integrated multiresolution feature vector is highly efficient and overpowers the existing approaches [54, 62]. Figure 4 to 9 illustrates the α and β plots for the benchmark databases used in the experiments respectively. Though the computation cost of proposed multiresolution feature descriptor is significantly greater than [54, 62], its accuracy is highly satisfactory and thus we ignored its higher dimension.

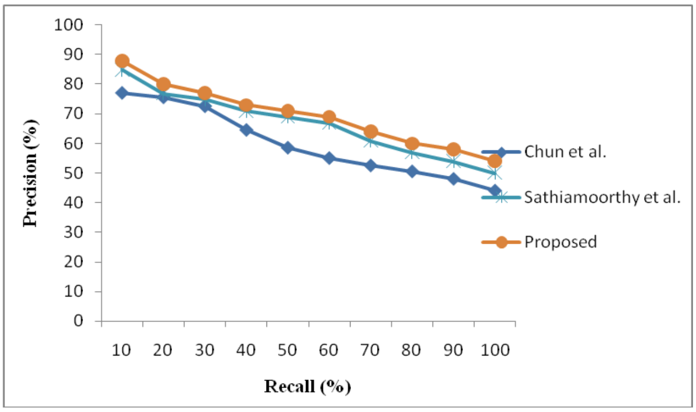

Figure 4. Precision-Recall plot for proposed multiresolution and existing feature descriptors for Corel 1k database

Table 1 represents the G-measure for proposed fusion of multiresolution feature vectors and existing approach [54, 62]. We also tested proposed fusion of multiresolution feature vector against scaling and rotation. The results revealed that proposed approach is well against rotation and scaling. The sample visual results of proposed integrated multiresolution features for query image with top 5 matches in ascending order of divergence among query and database images is shown in Figure 10.

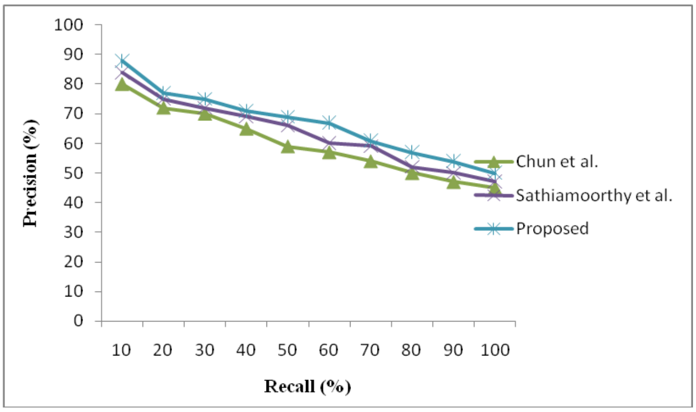

Figure 5. Precision-Recall plot for proposed multiresolution and existing feature descriptors for Corel 5k database

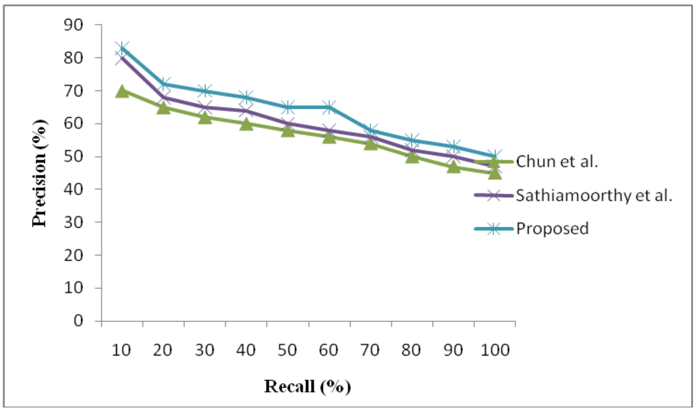

Figure 6. Precision-Recall plot for proposed multiresolution and existing feature descriptors for Corel 10k database

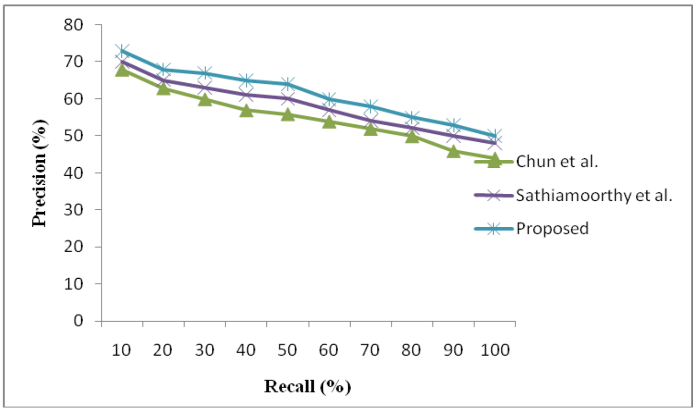

Figure 7. Precision-Recall plot for proposed multiresolution and existing feature descriptors for Caltech 101 database

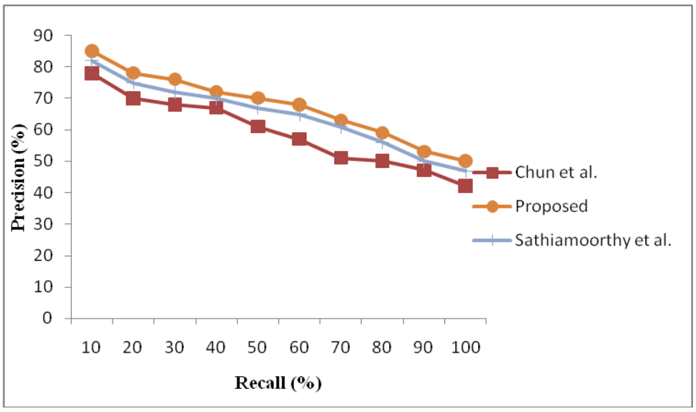

Figure 8. Precision-Recall plot for proposed multiresolution and existing feature descriptors for holiday database

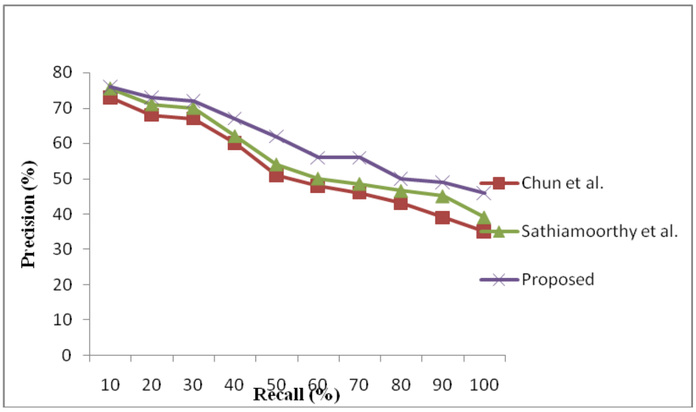

Figure 9. Precision-Recall plot for proposed multiresolution and existing feature descriptors for histology database

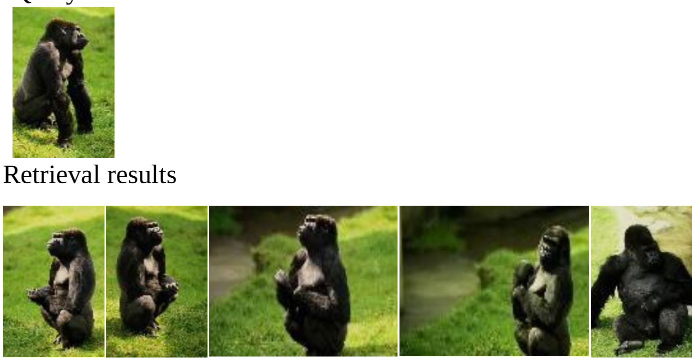

Figure 10. Sample query image and its top five retrieval results for proposed approach

Table 1. G-measure for proposed multiresolution based and existing retrieval systems for benchmark databases

Database	Proposed	Sathiamoorthy et al. [62]	Chun et al [54]
Corel 1k	82.70	70.41	66.30
Corel 5k	80.63	65.67	56.11
Corel 10k	79.43	68.92	61.12
Holiday	84.10	72.44	70.78
Caltech 101	81.89	69.25	65.62
Histology database	79.23	68.23	60.89

4. Conclusion

A novel feature fusion is proposed for general and medical image retrieval which includes color, texture, edges and valleys on mean and covariance matrices which are computed at varies resolutions at different scales using DWT. The BVLC computes texture and BDIP computes edges and valleys on multiresoltion domain. The BVLCs and BDIPs are computed from the details coefficients of R, G and B component images of wavelet domain. Whereas color information is computed from the approximation coefficients of R, G and B component image of wavelet domain. The covariance matrix of color, texture, edges and values exploits spatial correlation among color, texture and shape details respectively. The integration of color, texture and shape information of twelve sub-bands of R, G and B components respectively is applied on various benchmark databases and its performance is compared with existing approaches. The results are explained using Precision-Recall plots and the results obviously evident that proposed approach outperforms significantly.

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