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A Novel Approach for Effective Image Retrieval using Color, Texture, Edges and Valleys in Covariance Descriptor

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Abstract

This paper presents a novel system for image retrieval based on integrated mean and covariance matrices of color, texture, edges and valleys information which are estimated from R G and B components of the image, Block variation of local correlation coefficients (BVLC) and Block difference of inverse probabilities (BDIP) on R, G and B components of the image respectively. The BVLC estimates the texture smoothness based on differences among local correlation coefficients and BDIP estimated the edges and valleys by local intensity maxima and local intensity minima respectively. The proposed integrated color, texture, edges and valleys information is categorized by Radial Basis Function Neural Network (RBFNN) to decrease the search space and to increase accuracy of retrieval. Chernoff measure is adopted to estimate the degree of divergence between query and target images. The proposed system has been estimated on Corel- 1k, 5k and 10k databases attained not only significantly better results but also the reasonable computation cost.

Keywords: *BDIP, BVLC, Covariance, RBFNN, Gaussian kernel function, Chernoff distance.*

1. Introduction

Owing to hasty expansion of digital technologies over the decades, people in all domains produce immense image collections. Efficient searching and indexing in such immense image collections is feasible only with promising image retrieval techniques. In recent years, content based image retrieval (CBIR) is receiving more attention for retrieving similar digital images in the field of information retrieval [1-3]. Hence, developing CBIR with elevated accuracy and low storage and time cost has been become a hot research subject in the field of information retrieval.

Earlier CBIR systems were designed for gray scale images. Since the color images are increasing in recent years, researchers computed the color details along with shape and texture details for increasing the performance of image retrieval system. The user's input to CBIR system is query image. The CBIR system computes the feature from the query image then the feature of query image is compared with the feature of images in the repository and the images whose features are more similar with query image are selected to be displayed to the user. Therefore, the core elements of CBIR system are feature extraction and matching. The objective of feature extraction is computing high discriminative features in reasonable time with robustness to deformations such as rotation, translation and scaling. Generally, feature computations falls into global and local techniques. The first one describes the whole image without using any sliding window on pixels, is feasible in time cost and more robust to noise. But, global level features ignores local level information among the adjacent pixels and also sensitive to rotation, illumination and occlusion variations. While the second one describes the image at local levels by using sliding windows on pixels or considering a set of key points or dividing the images into number of patches and thus features computed from local level

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preserves the locality of pixel details. On the other hand, feature matching techniques also plays notable role in CBIR and thus feature matching techniques must be more efficient, robust and suitable for feature descriptor.

Color is an inherent and clearly understandable feature of the image. The global level color features are simple to implement and more robust to deformations like scaling, rotation and translation. Several global level color descriptors have been reported in the literature. For instance, color moments reported in Stricker and Orengo [4] considers mean, variance and skewness for image retrieval, Swain and Ballard [5] introduced color histogram that computes the color distribution in global level but it lacks in spatial information, Cinque et al. [6] presented spatial-chromatic histogram that computes average position of each color and its standard deviation, color autocorrelogram employed in [7] computes spatial correlation between the identical color elements and is a variant of color correlogram [8], chromaticity moments is suggested in [9] for color image retrieval, in HSV and CIELuv color spaces Utenpattanant et al. [10] and Nallaperumal et al. [11] respectively described the wavelet coefficients of color histogram, color difference histogram is reported for image retrieval in [12] and dominant color descriptor described in [13] computes number of dominant colors, percentage, spatial homogeneity and variance of each dominant color.

Local level uniform and non-uniform patterns repeated in the images are coined as texture features [14, 15] and it describes the images more powerfully. Several statistical, structural and spectral based techniques have been presented in the last few decades to compute the texture features like coarseness, regularity, directionality, roughness, etc., from the images. The gray level spatial dependency is measured in Haralick et al. [16] using the Gray level co-occurrence matrix, is a global level feature. Gabor filter, and rotation and scale invariant Gabor filter are reported in [17] and [18] respectively and the main drawback of Gabor approach is its computation cost [19]. SIFT, a 3D- histogram of gradient location and orientation is introduced in [20], SURF described in [21] employed Hessian matrix and Haar wavelet responses for its extraction, local binary pattern (LBP) suggested in [22] is based on local intensity of pixel, histogram of oriented gradients (HOG) presented in [23] counts the gradient orientation's occurrences in sub part of an image, wavelet moments are presented together with color moment, color histogram and co-occurrence matrix in [24] and are clustered using the combination of k-means with particle swarm optimization, various variants of LBP are discussed in [25-32], [33] reported composite moment descriptor for image retrieval, Aggarwal et al. [34] introduced orthogonal Fourier-Mellin moments based feature descriptor for medical image retrieval and trends based correlation among the local level structure is described using multi-trend structure descriptor (MTSD) [35, 36], and the variant of MTSD is described in [37].

Shape also gained much momentum as texture and color features as human distinguish the objects using the shapes. The shape feature descriptors are broadly classified into boundary and region based. Several shape feature descriptors have been reported for image retrieval such as boundary moments [38, 39], Zernike moments [40], Chin code histogram [41], edge histogram [42], Eigen values [43], [44] incorporates Prewitt operator for detecting edgels then it computes co-occurrence of edgels, edge histogram direction (EHD) computes global and local edgels information based on its orientation [45, 46], EHD suggested in [47] computes the edgels information from HSV color space, edge orientation autocorrelogram [48] and its variant [49] for color images, chordiogram image descriptor computes geometric information of predominant edgels is described in [50] and its variants reported in [51] captures texture details along with geometric details.

The classic and few of the recent image retrieval techniques exploit only one kind of features i.e. either color or texture or shape and is not adequate to characterize the image because dissimilar images might have similar or fairly similar color or texture or shape properties. Therefore, in recent years, researchers concentrated on integration of these features to provide a more discriminative feature descriptor [52].

On other side, number efforts have been taken in image retrieval [53-65] using the global feature namely covariance matrix and it significantly performs well in accuracy, storage and time cost, and robust to noise, scaling, translation and rotation invariant, and considerably resilient to uniform luminance variation. In line with this, recently, we introduced a novel image retrieval system based on mean and covariance matrix of BVLC and BDIP [66]. BVLC extracts local probabilities to assess local brightness variat on and results in texture smoothness and BDIP extracts variations of local correlation coefficients to assess edges and valleys [66]. The competence of BDIP and BVLCs and its variants are studied in [67-71]. In [66], BDIP and BVLC are computed from R, G and B components respectively and thus the BVLC and BDIP in covariance descriptor describes the correlation among identified texture, edges and valleys within the individual channel and between the channels respectively. [66] reported that BDIP and BVLC in covariance matrix outperform the state-of-the-art techniques for image retrieval. However, we strongly believe that BDIP and BVLC in covariance matrix alone are not sufficient for retrieving color images where color information also takes part very imperative role and thus, in this paper, we adopted color information in covariance matrix along with BDIP and BVLC in covariance matrix. The color covariance matrix is computed from R, G and B color channels. The number of features in the proposed combined feature vector is drastically less than the state-of-art-techniques for image retrieval.

Further, we employed radial basis function neural network (RBFNN) [7] to classify the images based on the color, BDIP and BVLC in mean and covariance matrix. The combination of classifier and feature similarity matching techniques reduces the matching cost as well it increases the accuracy of retrieval. RBFNN is employed in this paper due to its better classification accuracy against complex and huge image repositories [7]. Though deep learning magnetizes the attention of researchers [72, 73], its computation cost is very high.

The remainder of this paper is discussed as follows. Section 2 illustrates the proposed feature computation and proposed image retrieval system. Section 3 explains the RBFNN and similarity measure. Section 4 deals with experiments and results. Section 5 concludes the paper.

2. Proposed Image Retrieval Technique

This section deals with characterization of images using texture, color, edges and valleys in covariance matrices, classification of images using RBFNN and measure of divergence among images using Chernoff measure [66] based on the proposed covariance matrices. The architecture of the proposed system for retrieving images is depicted in Figure 1.

In this paper, the images in RGB color space are separate out into R, G and B color channels then we computed the BDIP and BVLC as in Eq. (1) and (3) on R, G and B color channels. Afterwards, we estimated the mean of R, G and B and mean of BDIPs and BVLCs on R, G and B as in Eq. (5) – (7). Later on, we estimated the covariance matrices for color, texture, edges and valleys as in Eq. (8) – (9) using R, G and B color channels and BVLCs and BDIPs on R, G and B color channels respectively. Thus, the proposed global features combination consists of texture, color, edges and valleys information and thus it characterizes images more efficiently, estimates the spatial dependencies of textures, color, edges and valleys more effectively, more robust to rotation, scaling and translation deformations, and removes noisy textures, color, edges and valley details. Moreover, the estimation and storage cost of the proposed combination of texture, color, edges and valleys features on covariance matrices is less and too compact respectively, and also comprehensive experiments proved that its competence is far above the state-of-the-art feature descriptors. In this study, the images are classified based on the proposed feature descriptors into number of classes like bus, lion, elephant, ship, Africans, etc., using the RBFNN, which increases the accuracy by defining the degree of importance of texture, color, edges and valleys by assigning weights to each feature, and decreases the time cost of the proposed system by reducing the search space. Further, since the dimension of the proposed merged covariance and mean feature vector is too compact, it reflects in the performance of RBFNN. Moreover, the proposed merged and compact feature vector augmented the generalization and reduces the over fitting in classification phase due to its high discrimination competence and thus RBFNN provides very clear discrimination among the classes. The Chernoff measure for divergence is incorporated in the image matching stage and it estimates the divergence between the input image and the images in the corresponding class. The algorithm of the proposed system is as follows.

Algorithm:

Input: Image *I*
Output: Images related to *I*

1. Separate *I* into R, G and B
2. Compute the mean (μ) for R, G and B images separately
3. Compute the covariance ($\sum$) on R, G and B values
   // *N* and *M* depicts number of rows and columns in image
4. For i=0 to *N* step 2
       For =0 to *M* step 2
           Compute BDIP and BVLC for R, G and B images
       End For
   End For
5. Compute the μ for BDIPs of R, G and B images separately
6. Compute the μ for BVLCs of R, G and B images separately
7. Compute the $\sum$ on BDIPs of R, G and B images
8. Compute the $\sum$ on BVLCs of R, G and B images
9. μ and $\sum$ of color, BDIPs and BVLCs are classified using RBFNN.
10. Compare *I* with the feature vector of images of the corresponding class in image database using Chernoff measure.
11. Retrieve akin images based on finest matches.
12. End.

The estimation of BDIPs, BVLCs and covariance matrix, RBFNN, Chernoff distance and measure of accuracy are explained as follows.

2.1. 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].

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

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.

2.2. 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].

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

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].

$$BVLC^d(l)=\max_{\Delta(k)\in O_4}[\rho^k(l,\Delta(k))] - \min_{\Delta(k)\in O_4}[\rho^k(l,\Delta(k))] \tag{3}$$

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

2.3. Covariance Matrix

Let *I* be a color image in RGB color model. Let $\{K_f\}_{c\,f=1,2,...,n}$ and $\{L_f\}_{c\,f=1,2,...,n}$ be a set of color values / BVLC / BDIP descriptors of each individual color 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 color channel images is defined in Eq.(4).

$$\frac{1}{n}(\sum_{i=1}^{n}(K_f-\overline{K})(L_f-\overline{L}) \tag{4}$$

The mean (μ) value of color values on R, G and B images is as follows:

$$\mu^c=\begin{bmatrix}\mu^c{}_r\\ \mu^c{}_g\\ \mu^c{}_b\end{bmatrix} \tag{5}$$

The mean (μ^{ev}) value of edges and valleys estimated using BDIP on R, G and B images is as follows:

$$\mu^{ev}=\begin{bmatrix}\mu^{ev}{}_r\\ \mu^{ev}{}_g\\ \mu^{ev}{}_b\end{bmatrix} \tag{6}$$

The mean (μ_t) value of texture information estimated using BVLC on R, G and B images is as follows:

$$\mu^t = \begin{bmatrix} \mu^t{}_r \\ \mu^t{}_g \\ \mu^t{}_b \end{bmatrix} \tag{7}$$

The covariance matrix for color information, edges and valleys information estimated using BDIP and texture information estimated using BVLC on R,G and B images is defined as in Eq.(8), (9) and (10) respectively.

$$\Sigma^c = \begin{bmatrix} \sigma^c{}_{rr} & \sigma^c{}_{rg} & \sigma^c{}_{rb} \\ \sigma^c{}_{gr} & \sigma^c{}_{gg} & \sigma^c{}_{gb} \\ \sigma^c{}_{br} & \sigma^c{}_{bg} & \sigma^c{}_{bb} \end{bmatrix} \tag{8}$$

$$\Sigma^{ev} = \begin{bmatrix} \sigma^{ev}{}_{rr} & \sigma^{ev}{}_{rg} & \sigma^{ev}{}_{rb} \\ \sigma^{ev}{}_{gr} & \sigma^{ev}{}_{gg} & \sigma^{ev}{}_{gb} \\ \sigma^{ev}{}_{br} & \sigma^{ev}{}_{bg} & \sigma^{ev}{}_{bb} \end{bmatrix} \tag{9}$$

$$\Sigma^t = \begin{bmatrix} \sigma^t{}_{rr} & \sigma^t{}_{rg} & \sigma^t{}_{rb} \\ \sigma^t{}_{gr} & \sigma^t{}_{gg} & \sigma^t{}_{gb} \\ \sigma^t{}_{br} & \sigma^t{}_{bg} & \sigma^t{}_{bb} \end{bmatrix} \tag{10}$$

Where Σ^c, Σ^{ev} and Σ^t , and σ^c, σ^{ev} and σ^t illustrates spatial relation between color / edges and valleys / texture feature descriptors on R, G and B images and variance among color / edges and valleys / texture feature descriptors on either two of R or G or B images respectively.

2.4. Classification Using RBFNN

In recent years, ANN attracted the researchers owing to its accuracy [7]. In specific, RBFNN is extensively studied in problems like classification, function approximation, system control, time series prediction, interpolation, etc. owing to its accuracy in classification, convergence of optimization is very fast and is a universal approximator [7]. RBFNN is a feed forward approach, has 3 layers namely input, hidden with activation function and output layers. All the inputs are connected with each neuron in the hidden layer without weights. The activation function in hidden layer is Gaussian function and is coined as radial basis function because it is radically symmetric function. In RBFNN, the numbers of neurons in hidden layer is depends on the dimension of input vector. So, when we need fast convergence, the dimension of input vector should be more compact. The neurons in hidden layers are connected with the nodes in output layer with weights. In RBFNN, decision in classification is performed by assigning the input to the output node with the highest score which is computed based on the weighted sum of the activation values of all neurons in hidden layer. Let X and Y be the input and output vectors respectively and are defined as $X = [X_i] \in \Re^n$ and $Y = [Y_o] \in \Re^p$ respectively, where *n* and *p* depicts the dimension of inputs and outputs. We estimated the output Y as in Eq. (11) [7].

$$Y_o = b_0 + \sum_{j=1}^{m} w_{jo} h_j, o = 1,2,...p \tag{11}$$

where b_0 and w_{jo} illustrates bias term and weight of the hidden neuron *j* to output neuron *o*. The weights w_{jo} indicates the relative significance of RBF in response to an external input. Let H be the hidden neuron and is defined as $H = [h_j] \in \Re^m$ where m is number of neurons in hidden layer. The Gaussian activation function i.e., the RBF estimates the distance between input and center and is defined as in Eq. (12) [7].

$$h_j = \exp(\frac{\|X_i - c_j\|}{2\sigma_j^2}, i = 1,2...n, j = 1,2...m \tag{12}$$

Where c_j is the center of the j^{th} hidden neuron and σ_j is the width of the j^{th} hidden neuron. The value of h_j increases while the input is close to the center and the value of h_j decreases quickly to zero as the input's distance from the center increases. In the above equation $\|X_i - c_j\|$ is the Euclidean distance measure and it measures the distance between the centers and input vector and is defined in Eq. (13) as follows

$$\|X_i - c_j\| = \sqrt{(X_1 - c_j)^2 + (X_2 - c_j)^2 + ... + (X_n - c_j)^2} \tag{13}$$

where $\|\cdot\|$ is the norm of $(I_i - c_j)$. Let the weights between the hidden and output layer be W and is defined as $W = [w_{jo}] \in \Re^{jo}$ The W is estimated as in Eq. (14) [7].

$$W = H^+ O = (H^T H)^{-1} H^T O \tag{14}$$

Where is H^T pseudo-inverse of hidden neuron H.

2.5. Measure of Divergence

We employed Chernoff measure for estimating the divergence between two images [66]. The Chernoff measure of divergence is described in Eq.(15) [66].

$$D_{p,q}(s) = \frac{s(1-s)}{2}(\mu_2 - \mu_1)^T [s\Sigma_t + (1-s)\Sigma_2]^{-1}(\mu_2 - \mu_1) + \frac{1}{2}\ln\frac{|s\Sigma_1 + (1-s)\Sigma_2|}{|\Sigma_1||\Sigma_2|^{1-s}} \tag{15}$$

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 covariance's of R, G and B and BDIPs and BVLCs on R, G and B channels individually. Later, we have taken the average of all the three results of Chernoff measure and are used for measuring the degree of divergence between the input image feature vector and target image feature vector.

2.6. Measure of Accuracy

We estimated the competence of the proposed combination of texture, color, edges and valleys on covariance matrix by utilizing most usually used precision (α) [66] and recall (β) [66] and are defined as follows

$$\text{Precision } (\alpha) = \frac{I_N}{N} \tag{16}$$

$$\text{Recall } (\beta) = \frac{I_N}{M} \tag{17}$$

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 precision and recall by using the approach called G-measure [74] and is given by

$$G - Measure = \sqrt{Precision \times Recall} \qquad (18)$$

3. Experiments and Results

3.1. Datasets

The Corel databases [66] of 1k, 5k and 10k was utilized in experiments. The Corel 1k, 5k and 10k databases have 10, 50 and 80 categories of images respectively. The categories are of images are waves, bob, door, flags, balloon, car, butterfly, forests, sunset, waterfall, eagle, fish, fox, deer, iceburg, mountain, cloud, rural, etc. We have given few sample images from Corel 1k, 5k and 10k databases in Figure 2. Each category roughly has 100 or more than 100 images and the images are of 120x80 or 80x120 size.

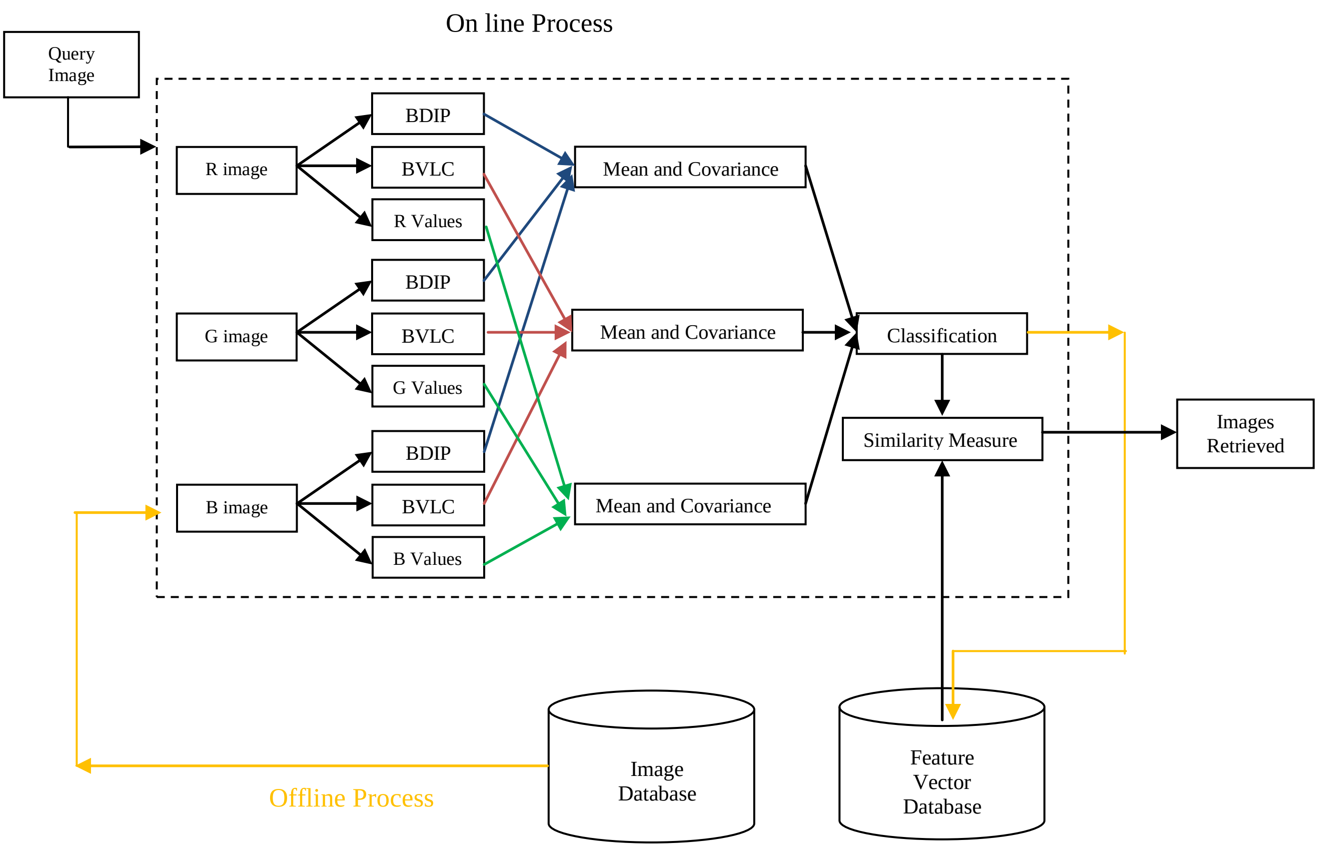

Figure 1. Proposed framework for image retrieval based on the combinations of color, texture based on BVLCs and edges and valleys based on BDIPs in covariance matrices and mean respectively

We divide each Corel database into 5 sets such that four set is taken as the training set and the fifth one is taken as the test set. In this manner, all the five sets are involved in both training and test phase. As mentioned in Section F of II, we assessed the proposed algorithm using Precision-Recall plot and G-measure.

Figure 2. Example images taken from Corel database

3.2. Compared Algorithms

To prove the competence of the proposed algorithm, we compare it with [66] and [75]. The mean and covariance matrices of edges and valleys, and texture information estimated from BDIPs and BVLCs on R, G and B color channels is used in [66]. In [75], the co-occurrences of edges and valleys estimated from BDIPs on RGB image i.e., [75] integrated GLCM and BDIP for extracting spatial dependencies among the edges and valleys. In [66] and [75], Chernoff and Canberra measure respectively is used for measuring the degree of divergence. Due to the ignorance of color information in [66] and both color and texture information in [75], the retrieval competence of [66] and [75] is poor. Further, both the accuracy and time cost of both [66] and [75] is affected due to the ignorance of classifier. By comparing the competence of the proposed algorithm with [66] and [75], we proved the usefulness of combination of texture, color, edges and valleys with RBFNN.

3.3. Algorithm Tuning

There are 5 parameters in RBFNN namely activation function i.e., RBF, center of RBF, spread of RBF, number of neurons in hidden layer and weights between hidden and output layer. Generally, Gaussian function is used as RBF in RBFNN for pattern analysis and recognition. To achieve the best classification rate, we tested four distance measures namely Euclidean, Manhattan, Minkowski and Mahalanobis in Gaussian kernel. The classification result of RBFNN with four distance measures in Gaussian kernel for the proposed approach is illustrated in Table.1.

We tuned the parameters namely connections weights, widths and centers of the hidden layer. k-means clustering is proposed to cluster the training dataset because of its simplicity and ability to produce better results and it identifies subsets of neighbouring data points and uses them to partition the input space. Number of neurons in hidden layer is set to optimum k, which is experimentally determined. The centers of clusters are selected as centers of Gaussian kernel. Setting the spread of Gaussian kernel is critical one because if it is too wide the estimated probability density is over-smoothed and if it is too narrow, there may be over-adaptation to the particular data set. So we set it to the mean of the distances between center and each data points in the corresponding cluster. The weights between hidden and output layer are estimated using pseudo inverse method which does not fall into local minimum and fastest one. By incorporating cross validation, good generalization is achieved in the proposed work.

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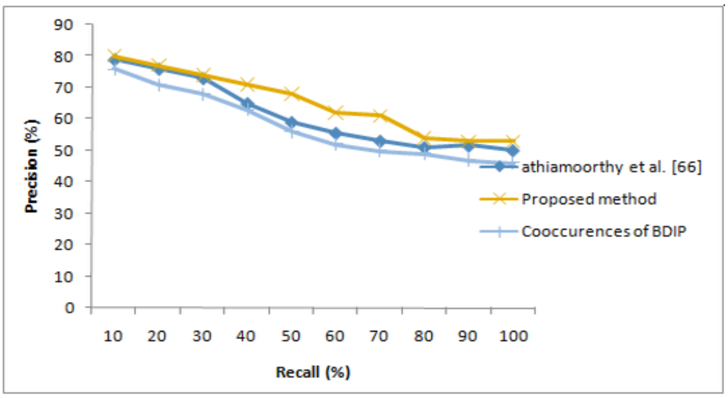

Figure 3. Precision-Recall plot for proposed and existing approaches on Corel 1k database

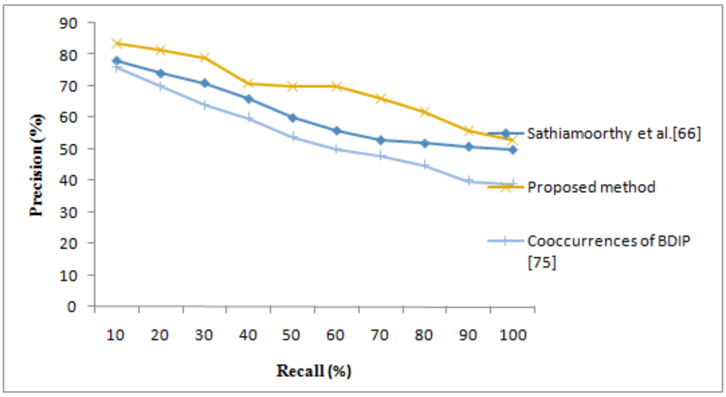

Figure 4. Precision-Recall plot for proposed and existing approaches on Corel 5k database

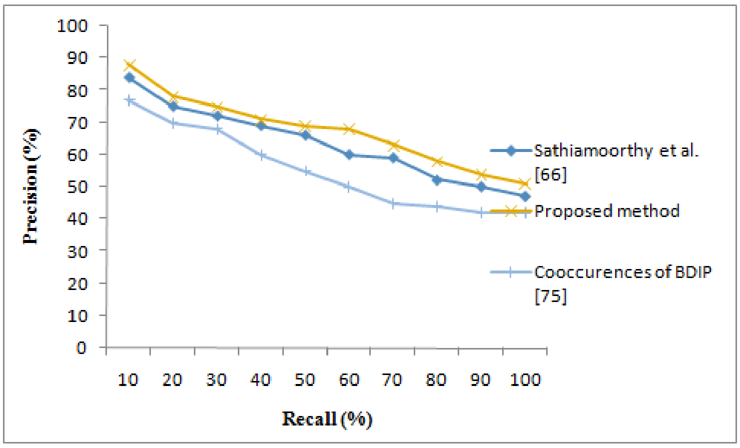

Figure 5. Precision-Recall plot for proposed and existing approaches on Corel 10k database

3.4. Results

We assessed the competence of other methods [66] and [75] with the proposed algorithm by retrieving images using example query images. The Precision-Recall plots for proposed and other methods are shown in Figure 3, 4 and 5 for Corel 1k, 5k and 10k databases, where the sandal, dark blue and light blue plots correspond to proposed, [66] and [75] methods respectively. In Figure 3, 4 and 5, it is seen that the Precision-Recall plots of proposed method is always above the plots of methods [66]

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and [75] i.e., the area under the curve of proposed method is highest than the methods of [66] and [75]. As mentioned above, the reason for better accuracy of proposed method is, it integrates texture, color, edges and valleys information and uses more robust RBFNN classifier to filter the unrelated images in matching stage. Sequentially, to see how deeply the accuracy of retrieval performance affected by the classifier, we performed the experiments with and without classifier for the proposed combined feature vector and the results are illustrated in Table 2. Results in Table 2 clearly indicate that the retrieval results are influenced by the classification that is if the class of query image is identified exactly, high accuracy is achieved. The experimental results clearly depict the superiority of proposed combination of combined feature vector and RBFNN. For instance, we showed the top five retrieval results of proposed method in Figure 6. The G-measure of proposed, [66] and [75] methods are depicted in Table 3. It is obviously seen that the G-measure of proposed one is superior to the methods of [66] and [75]. Thus, the competence of proposed approach is significantly superior to the others approaches [66, 75].

3.5. Comparisons on Efficiency

Lastly, we compare the proposed method with the methods of [66] and [75] from the view of time cost. During the experiments, we estimated the average running time of proposed, [66] and [75] in milliseconds respectively. The dimension and running time cost are shown in Table 4. All the methods are implemented with Matlab and executed in a PC with 2.9 GHz and 8 GB memory. Results depicted in Table 4 shows that proposed one is speediest though its dimension is slightly higher than the [66] due to the inclusion of color details and the reason for less time cost is proposed approach reduces search space by incorporating RBFNN. The method in [75] takes more time than the others and its dimension is equal to proposed and higher than [66].

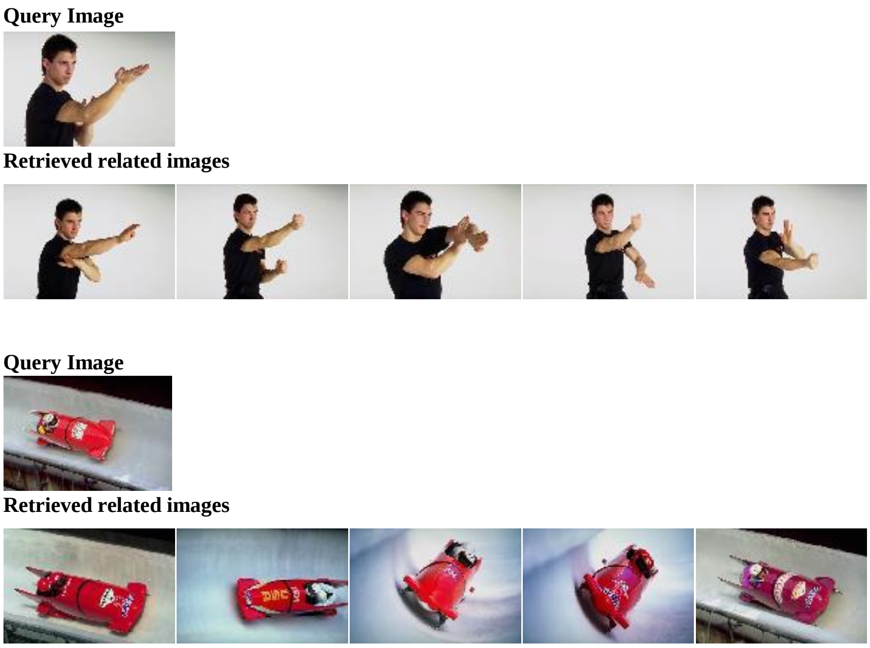

Figure 6. Query image and top 5 similar images retrieved by the proposed system from Corel database

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Table 1. Classification accuracy of RBFNN with various distance measures in RBF for Corel 1k, 5k and 10k databases

Method	Euclidean	Manhaatan	Minkowski	Mahalanobis
Corel 1k	99.01	98.76	98.04	98.09
Corel 5k	98.68	98.21	97.67	97.71
Corel10k	98.02	97.76	96.58	96.65

Table 2. Retrieval accuracy of proposed combined feature vector with and without RBFNN for Corel 1k, 5k and 10k databases

Databases	Proposed Method	Sathiamoorthy et al. [66]	Co-occurrences of BDIP [75]
Corel 1k	76.85	67.23	63.46
Corel 5k	75.23	54.00	61.85
Corel 10k	74.87	62.23	60.77

Table 3. G-measure of proposed and other methods [66, 75] for Corel 1k, 5k and 10k databases

Method	Corel 1k	Corel 5k	Corel 10k
Proposed method	73.21	72.87	72.20
Sathiamoorthy et al. [66]	65.44	53.23	62.10
Co-occurrences of BDIP [75]	62.33	60.57	60.12

Table 4. Dimension and time cost of proposed and other methods [66, 75] for Corel 1k, 5k and 10k databases

Method	Dimension	Time cost (ms)
Proposed method	36	19
Sathiamoorthy et al.[66]	24	24
Co-occurrences of BDIP [75]	36	29

4. Conclusion

This paper presented a novel approach based on mean and covariance matrices for image retrieval. The major contributions are

- Color information on mean and covariance matrices are integrated with texture, edges and valleys information on mean and covariance matrices.
- To narrow down the search space and to increase the accuracy of retrieval, we incorporated RBFNN.

The experimental output on Corel 1k,5k and 10k databases show that proposed method significantly better in accuracy, time and storage cost than the state-of-the-art methods ignoring the texture and color information, and classifier. In future, we plan to increase the competence of proposed approach.

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