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A Novel Similarity Measure for Content Based Image Retrieval in Discrete Cosine Transform Domain

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Abstract. Content-based image retrieval (CBIR) scheme has gained popularity in the field of information retrieval for retrieving some relevant images from the image database based on the visual descriptors such as color, texture and/or shape of a given query image. In this paper, color features have been exploited from each color component of an RGB color image by using multi-resolution approach since most of the information of an image is undetected at one resolution level while some other undetectable information is visualized in other multi-resolution levels. Initially, Gaussian image pyramid is employed on each color component of the color image and subsequent DCT is computed directly on the obtained multi-resolution image planes. Then some significant DCT coefficients are selected according to the zigzag scanning order. For formation of the feature vector, we have derived some statistical values from AC coefficients and all other DC coefficients are included entirely. Finally, a similarity measure is suggested during image retrieval process and it is found that the overall computation overhead is reduced due to consideration of the proposed similarity measure. The proposed CBIR scheme is validated on a two standard Corel-1K and GHIM-10K image databases and satisfactory results are achieved in terms of precision, recall and F-score. The retrieved results show that the proposed scheme outperforms significantly over other related CBIR schemes.

Keywords: Content Based Image Retrieval, DCT, Feature Extraction, Gaussian Image Pyramid, Similarity Measure

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1. Introduction

In recent years, the rapid advancement of Internet and information technology have made drastic changes in digital communication systems. The multimedia based web applications are becoming popular due to the availability of high speed Internet technology and advanced image acquisition devices such as digital cameras, scanners, smart phones etc. Some multimedia based web applications are like live video streaming, multimedia data sharing through social networking sites, video/audio conferencing, resources like education, geographical, cultural heritage, entertainment, etc. are quite popular among users, so as a result the volume of these multimedia libraries are increasing day-by-day. The searching and retrieving the relevant multimedia data like audio, image and video from these large volume libraries is a tedious task. In general, several search engines are used to retrieve the relevant textual information through the text based query, but they are not suitable to search appropriate multimedia data. Since text query based multimedia searching is done based on their textual information where the multimedia data are manually annotated by a tag value like some unique sequence number or text descriptive keywords. These systems are known as text based multimedia data retrieval systems. Sometimes, these traditional method of multimedia data retrieval has proven to be insufficient due to the improper human visual perception. The descriptive queries are limited in text based image retrieval process and sometimes retrieved results are not accurate and perfect. Several multimedia data retrieving schemes based on the visual/audio contents [1, 2] of query have been developed to overcome the limitation of the text based multimedia data retrieval systems. Therefore, the proficient image retrieval schemes are required for retrieving desired image data from digital image libraries/databases based on the visual descriptors of the given query image. This field is known as content based image retrieval (CBIR) [3, 4] which overcomes the problem of the textual based image retrieval schemes. The visual descriptors of image data such as color [5, 6], texture [7, 8] and/or shape [9, 10] are used for devising an effective and efficient CBIR schemes. The main challenges for developing an efficient CBIR scheme is that the organization and management of huge amount of multimedia data/files should be automatically and the retrieval outcomes from these multimedia data are very close to the human visual perception. The performance of general CBIR scheme rely on the appropriate feature extraction techniques for deriving the significant low dimensional features/contents from high dimensional image data set. The extracted significant contents of the query image is compared with the other significant contents of the database images using appropriate similarity measure. Hence the combination of feature extraction techniques and similarity measure are effectively produced the desired outcomes during image retrieval. It has been found in literature review that the color features are most commonly used descriptors for the classification of images in CBIR schemes since it is one of the most powerful low level visual contents of images and it has the rotation, scaling invariant characteristics and it is also invariant for other spatial transformation of the images. So here, we have shown our interest on color features of the images for devising the efficient CBIR schemes. Since RGB color image is consist of red, blue and green color components so we have considered each color component as same priority during image retrieval process. In this paper our objective is to find out significant multi-resolution features from each color component since most of the information is not visualized at a particular resolution level. Several multi resolution schemes are available for analysis of images at different resolutions. One of the popular approach for extracting image features

at the multi-resolution is known as Gaussian image pyramid [11] which is very simple and straightforward approach. So in this paper, we have applied Gaussian image pyramid approach on each color component. Subsequently, multi-resolution images obtained from each color component are further exploited by a suitable transformation tool. It has been observed that the transformation tools like DCT which can be efficiently classify the data as significant and insignificant features. So in this proposed research work, we have employed DCT transformation at each multi-resolution image to extract/select the significant coefficients into a zigzag scanning fashion. The selected coefficients are the DC and AC values of DCT transformed image where AC values are divided into several numbers of uniform groups since the local information of AC coefficients carry much more information as compared to the global information of AC coefficients. An each uniform group has the same number of AC coefficients. From each uniform group, we have computed some statistical values and include DC value for forming the image feature vector. Afterwards, a suitable similarity measure like Euclidean distance, Mahalanobis distance, Minkowski distance, quadratic distance, square chord distance, chi-square distance etc. is computed between the feature vector of query image and database images. The top relevant images based on their minimal distances have been retrieved. The computation overhead during these similarity measures is enormously high due to the large dimensional feature vector and huge image databases sizes. Several researchers have adopted hierarchical approach [12, 13] during image retrieval process for reducing the similarity measure cost. In this paper we have suggested a novel similarity measure which is straightforward and have less computation overhead than other distances. So our main contribution is two folded in first case we have proposed an image feature extraction approach and in second case a novel similarity measure is incorporated to make the CBIR scheme more effective and efficient in terms of retrieval performance and computation overhead.
The rest of the paper is organized as follows: Section 2 presents the review of the related works; In Section 3, the general outline of CBIR, basic concepts of discrete cosine transformation (DCT), Gaussian image pyramid and statistical parameters have been described in briefly. The proposed CBIR scheme is elaborated in Section 4. The experimental results and discussions are presented in Section 5. Finally, Section 6 concludes the paper.

2. Related Works

In literature, several researchers suggested CBIR schemes based on primitive/low level visual features such as color, texture and/or shape. These visual features are exploited in both the spatial and transform domains. A number of CBIR [14, 15, 16, 17] schemes have been developed in the spatial domain. Swain et al. [18] has exploited the color features using color histograms of the multi-colored objects for formation of image feature vector. For similarity measure, they have used histogram intersection matching approach. Li et al. [19] suggested a CBIR scheme where they have divided an image into several number of blocks for extracting the color region information. The different weights have been assigned to the blocks and the similarity matrix between the objects of images have been used in the retrieval process. Lu et al. [5] have computed globally color features by calculating mean and standard deviation of an image while the local color features have been represented by the bitmap feature extraction technique. The combination of local and global features of an image have considered as an image feature vector. Yang et al. [20] also developed a CBIR scheme based on a color quantization for dominant color extraction using a linear block algorithm (LBA) and it has been observed that LBA is a proficient algorithm for color quantization and computation. Wang et al. [6] suggested a CBIR scheme based on the color histogram of the local feature regions. In their scheme, an RGB color image is converted into YCbCr color space and the multi-scale Harris-Laplace detector was applied for extracting color feature points of an image. The local feature regions (LFRs) have been extracted from quantized image. Finally the histogram of the LFRs has adopted as an image feature vector. Liu et al. [15] have considered color difference histogram(CDH) features as an image feature vector. In their scheme, L*a*b color space have been used and CDH features of image have been extracted through the edge orientation detection technique. Imran et al. [21] divided an RGB color image into fixed number of sub-images and converted each sub-image into a HSV sub-image. The image feature descriptor have been calculated by combining the statistical values of the sub-images. Liu et al. [22] proposed a CBIR scheme based on the chroma texture features. They have adopted the chroma information of the quantized a and b color components of L*a*b color space for calculating the texture features and comparison among many texture feature extraction techniques like GLCM features, Tamura features, wavelet textures have been performed and found that the wavelet textures have generated the better results among all. Several transform domain based CBIR [23, 24, 25, 26] schemes are also found in literature review where authors had achieved that the extracted image features in the transform domain are more robust than the extracted image features in the spatial domain. Some transformation tools like DCT, DWT, PCA, SVD etc. are widely used in devising various CBIR schemes. Malik et al. [27] have also suggested image retrieval scheme based on block level DCT transform, where They have decomposed gray scale image into fixed number of non-overlapping 8×8 blocks and constructed the four different histograms of DC AC_1, AC_2 and AC_3 coefficients individually and subsequently they have quantized each histogram into several number of bins. Thereafter, they have computed statistical parameters like mean, standard deviation, skewness, kurtosis and smoothness from each quantized bin of histograms for formation of feature vector. They observed that the 32 bins of the histogram gives the best retrieval results. In their scheme, choosing the desire of bin number requires several analysis i.e which one is best among 32, 16, 8, 4 bins during construction of feature vector. Hence it is computationally high. Huang et al. [28] presented a CBIR scheme based on two novel visual features where the first visual feature has been extracted by using composite sub-band gradient vector while the other feature have been computed by energy distribution pattern string technique. These two novel features have been generated from the sub-images of wavelet domain. Alamin et al. [29] have converted color image from RGB color space into HSV color space and divide each color component of HSV color space into 8×8 non-overlapping blocks. After that SVD have been applied on all blocks of each color component i.e. Hue, Saturation and Value. The selected singular values of each SVD block have formed the feature vector. Another SVD based CBIR scheme developed by Varish et al. [30], where they have applied SVD transform on entire color components of RGB color image except applying block level and they have constructed the approximate images for different color components using eigen images. Further, they have extracted the visual features by computing some statistical parameters from approximate images of each color component and retrieved the desired images based on the Euclidean distance. To improve the retrieval accuracy, several CBIR [31, 32, 33, 34] schemes have been developed together with the spatial and transform domain features. Singh et al. [32] proposed CBIR scheme based on two methods where first method was purely based on color histogram in spatial domain while the second method is based on wavelet domain. The color features were extracted from histogram of quantized color images and histograms of sub-images of discrete wavelet transform. Another CBIR scheme was developed by Rahimi et al. [31] based on the distribution of Color Ton (DCTon) and texture features of an image where the DCTon component was determines how the pixel values with the color components, i.e. (Ri, Gi, Bi) appeared in the spatial relationship. They have extracted the texture visual features by applying a Dual tree complex wavelet transform (DT-CWT) multi-resolution approach and SVD on the segmented image regions. The segmentation of the image was done on the basis of human visual perception. Varish et al. [12] suggested a hierarchical CBIR scheme based on color and texture visual descriptors where color visual descriptor has been extracted by computing the statistical parameters from the non-uniform bins of color histograms of HSV color space while the texture visual descriptors have been computed by using DT-CWT and rotational invariant principal texture direction technique. Their image retrieval scheme is based rotational invariant property of the image. From above discussed existing works, it has been observed that use of transformation tools along with other schemes provides the satisfactory retrieval results but most of transformations were applied on block level. In this paper, authors have applied DCT on entire color plane rather than applying block level. The DCT are applied on entire color planes of RGB color image for extracting visual features where each color component has been analyzed by image Gaussian pyramid. Thereafter, significant DCT coefficients have been selected in a zigzag scanning order and divided AC coefficients into uniform group where each group contain same number AC coefficients. For formation of feature vector, some statistical parameters are directly computed from the each uniform AC group. The combination of DC value and the computed statistical values of AC coefficients form the feature vector and it represents the image into the compact form. For searching and retrieval phase, several similarity measures like Euclidean distance, Minkowski distance, square chord distance chi-square distance etc. were used for matching in the many existing CBIR schemes where it has been found that searching and retrieval time are high. So in this work, a novel similarity measure is suggested to reduce the computational overhead.

3. Basic Concepts

In this section, we have presented relevance preliminaries for understanding of the proposed CBIR scheme.

3.1. Content Based Image Retrieval

Content Based Image Retrieval(CBIR) is a technique for searching and retrieving most relevant images from large scale digital repositories/libraries based on the primitive visual features (or low level visual features) of the given query image. Hence the retrieval performance of any image retrieval scheme rely on the selection of the appropriate low level visual features and suitable similarity measurement methods. In general, CBIR system performs in two steps; Feature extraction from the images and similarity measurement between the query image and target images of database based on the extracted significant visual contents/features. The effective CBIR system requires suitable feature extraction techniques and appropriate similarity measurement methods. Feature extraction techniques are used for computing the significant visual features from images and set of significant visual features form the feature vectors/descriptors of images. These feature descriptors or vectors represent the prominent details of an images in a compact form. The main objective of the feature extraction technique is for extracting the suitable and important information of an image and the dimension of the feature descriptors should be minimum with low computational cost and retrieved results of the CBIR system should be satisfactory for the users. In similarity measurement, the distance between the feature descriptor of the query image and the other feature descriptors of the database images are computed. The top most relevant images are retrieved based on the minimum similarity distance criteria. The block diagram of general CBIR system is depicted in Fig. 1.

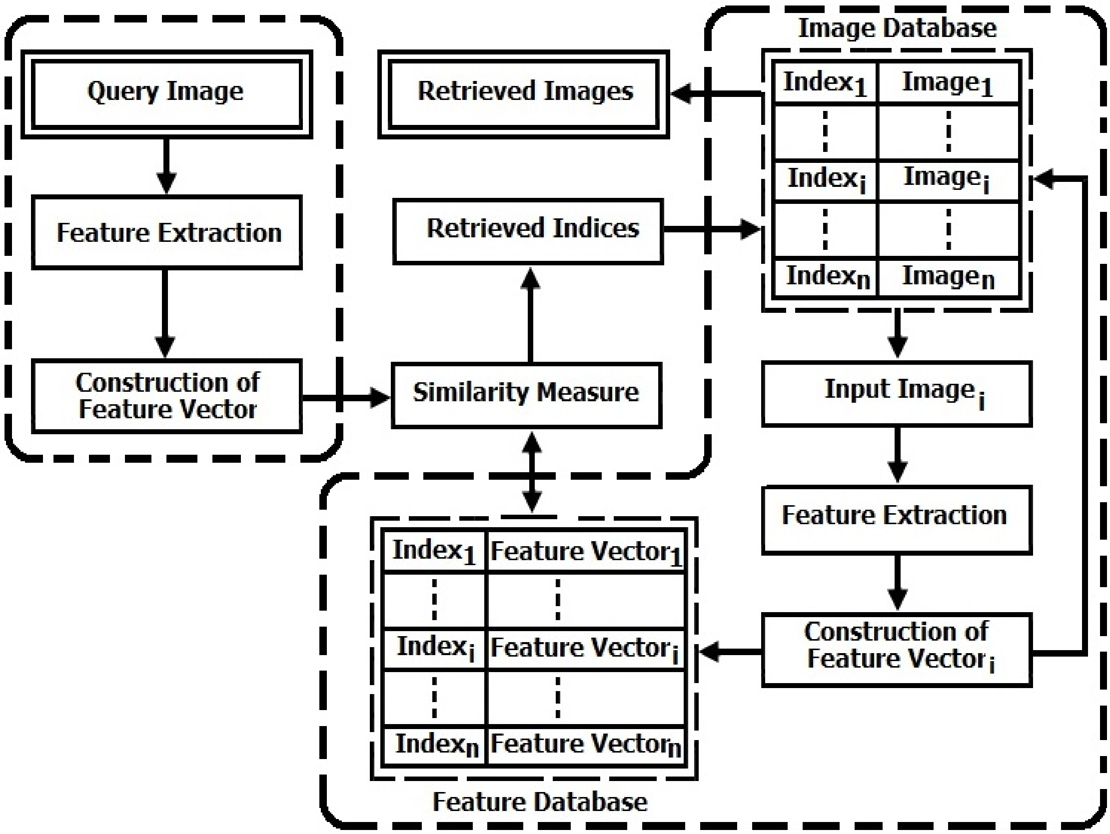


Figure 1. Schematic block diagram of general CBIR scheme

3.2. Gaussian Image Pyramid

Multi-resolution techniques are widely used for extracting the significant image features at different resolution levels which are very difficult to extract from the original image directly. There are several multi-resolution techniques are available,from where Gaussian image pyramid [35] has been selected

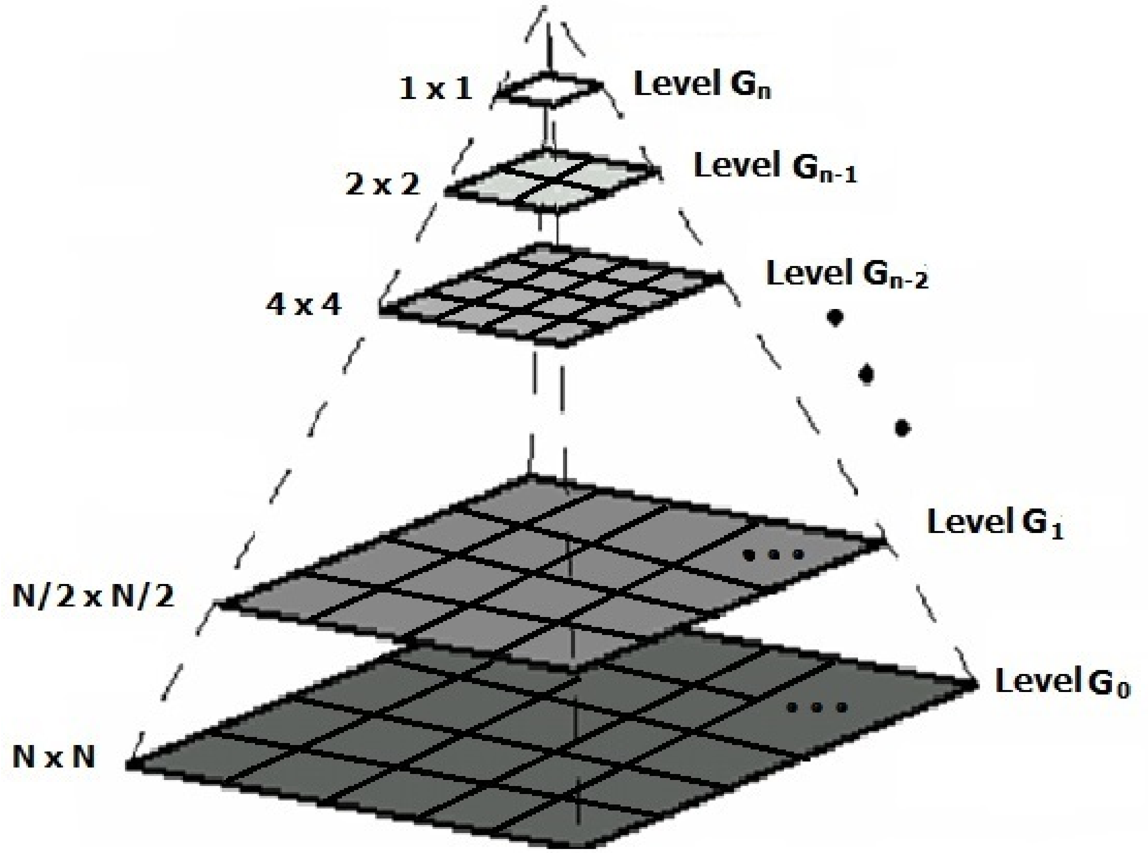


Figure 2. Image pyramid of a grayscale image

here because it is easy to implement and it needs low computational efforts. An image pyramid is useful for representing images at different resolutions [36] and widely used for charactering the texture property of the image due smoothing and down-sampling at different scales [37] since images in nature are not similar. An image pyramid is a sequence of sub-images of original image at different resolutions and as we move from from the highest level to the lowest level, both the resolution image and size are decreases. Lowest(base) level image has high resolution while the highest(apex) level image has low resolution which means that lower level images have more significant and fine details than higher level images. The Gaussian image pyramid is performed in two steps: one is averaging filter/smoothing operation and down-sampling where original image I_0 convolved with Gaussian kernel function i.e low pass filter and down sampled to produce next level image I_1. Similarly I_2 has produced by convolving I_1 with low pass filter and down-sampling. This process is iteratively repeated G_n times for G_n level image pyramid. The mathematical formula for Gaussian image pyramid [38] of original image $I(x,y)$ is given as

$$\begin{aligned} I_0(x,y) &= I(x,y) \\ I_l(x,y) &= \sum_{m=-2}^{2}\sum_{n=-2}^{2} w(x,y) I_{l-1}(2x+m, 2y+n), \\ &\quad \forall\ 0 \le l \le G_n \end{aligned} \tag{1}$$

where $w(x,y)$ is a low pass filter (weighing function) and it is also known as generating kernels. These weighting functions are constants, separable and symmetric for all decomposition levels. The hierarchical representation of image of size $N \times N$ with decreased resolution and size from higher level to lower level is shown in Fig. 2. The 3-level Gaussian image pyramid on individual color components of Lena image of size 512×512 is depicted in Fig. 3.

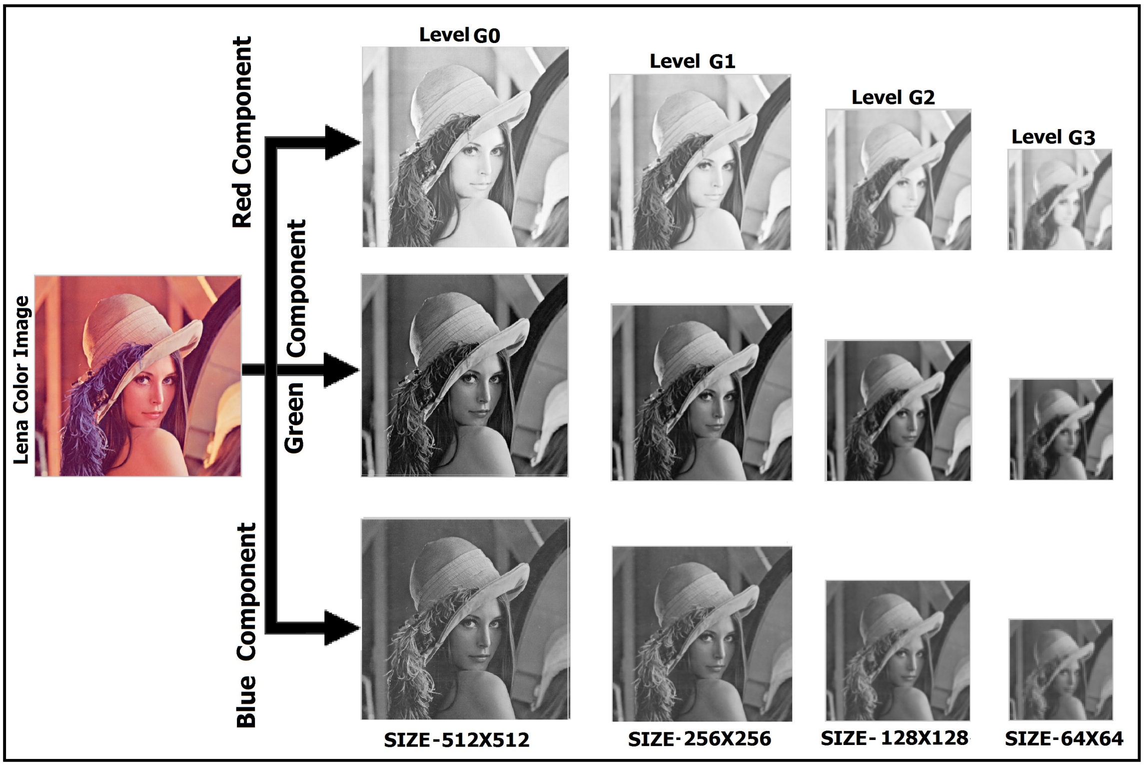


Figure 3. Three level Gaussian image pyramid of color components of RGB Lena color image

3.3. Discrete Cosine Transformation

Discrete cosine transformation (DCT) has widely used in various applications of digital image processing like image compression, feature extraction and selection, CBIR etc. This transformation tool has the de-correlation and high energy compaction properties which means that it de-correlate the pixel values with each other and preserves the energies of the images. The DCT tool transforms the image from pixel domain to the transform/frequency domain where the transformed image has DC and AC coefficients. The few coefficients has capability to represent the whole image efficiently into a compact form. The most of the significant information of transformed image lies on the upper top left corner. The 2-D DCT transformation of an image of size $N \times N$ can be defined as

$$F(u,v) = \frac{2}{N} c(u)\, c(v) \sum_{x=1}^{N} \sum_{y=1}^{N} f(x,y) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \times cos\left[\frac{(2y+1)u\pi}{2N}\right],$$
$$c(u) = c(v) = \left\{ \begin{array}{cc} \frac{1}{\sqrt{2}} & if\, u = v = 0 \\ 1 & if\, u, v > 0 \end{array} \right\} \tag{2}$$

where $F(u,v)$ and $f(x,y)$ are the values of transformed and original image respectively. The top upper left DCT coefficient i.e. $F(0,0) = DC$ represents the average intensity or energy of the image. The rest of coefficients of transformed image are known as AC coefficients. As we moves from DC coefficient to AC coefficients deeper in zigzag scanning order, the significant information of the image decreases. Therefore few AC coefficients including DC coefficient are sufficient to represent the approximate image. In other words, when we move from top left corner to bottom right corner of the transformed image into a zigzag scanning fashion, then significant information is decreases ino a some extent. Hence, few coefficients are sufficient to represent the whole image with little bit distortion. Therefore, in the presented work some significant coefficients have been taken in a zigzag scanning order for formation of the feature vector. In Fig. 4, zigzag scanning process, selecting significant coefficients and discarding insignificant coefficients of 8×8 DCT block is depicted.

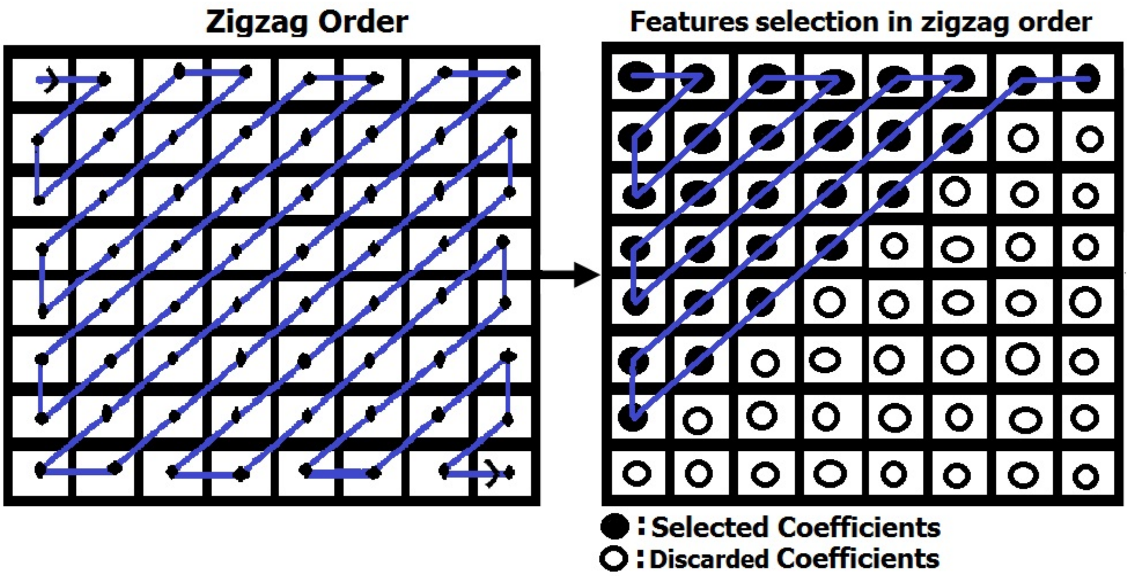


Figure 4. DCT coefficients of $N \times N$ image in Zigzag scanning order

3.4. Statistical Parameters

In digital image processing, some statistical parameters are used to describe the visual contents of the images significantly. The statistical parameters like mean, standard deviations, skewness, kurtosis and smoothness are most commonly used for classifying the images. These parameters become popular in CBIR schemes because they are invariant to size, position and orientations. In the presented work, some statistical parameters are directly computed from the AC coefficients of the DCT domain. In the presented scheme, the authors have selected some significant and essential AC coefficients from DCT image. The selected AC coefficients are divided into several numbers of uniform groups since the computed statistical values from small uniform groups carry much information as compared to the calculated statistical values of whole AC coefficients directly. In our work, we have various multi-resolution image planes for red, green and blue components. Hence, the statistical values of various groups at different levels for each color plane are computed as follows: The mean (μ_{lCj}) for each group of the AC coefficients (X_r) in the range $[LB, UB]$ is defined as

$$\mu_{lCj} = \sum_{r=LB}^{UB} X_r P(X_r) \tag{3}$$

where $P(X_r)$ is the corresponding probability of AC coefficients (X_r) ; LB and UB represent the lower and upper bound of the groups of AC coefficients. The standard deviation (σ_{lCj}), skewness (γ_{lCj}) and kurtosis (κ_{lCj}) for each group of the AC coefficient (X_r) in the range $[LB, UB]$ are obtained as follows:

$$\sigma_{lCj} = \sqrt{\sum_{r=LB}^{UB} (X_r - \mu)^2 P(X_r)} \tag{4}$$

$$\gamma_{lCj} = \frac{1}{\sigma^3} \sum_{r=LB}^{UB} (X_r - \mu)^3 P(X_r) \tag{5}$$

$$\kappa_{lCj} = \frac{1}{\sigma^4} \sum_{r=UB}^{UB} (X_r - \mu)^4 P(X_r) \tag{6}$$

$$SM_{lCj} = 1 - \frac{1}{1+\sigma^2} \tag{7}$$

where image pyramid level $l = 1, 2, .., k$, color plane C=Red(R), Green(G), Blue(B) and groups $j = 1, 2, ..., q$. The mean is the average intensity values of the image which represents the brightness of the image. The standard deviation is the scattering/distribution of the intensity values of the image about its mean and it also represents the contrast of the image. If the values of standard deviation of the group is less than the other group it means that the first group has high contrast. The skewness represent how the intensity values of the image are skewed to the left or right about its mean. If the value of skewness is negative then most of gray scale values or AC values lies on right side of its mean and if skewness is positive then intensity values skewed to the left of the mean. If value of the skewness is zero then data of the AC values are symmetric about its mean. Kurtosis is the fourth statistical moment of the image which represents the peakness or flatness of AC values or intensity values about its mean. The high value of kurtosis means the data has the sharp peak about the mean and generate the flat and long tail and vice-versa. The smoothness measures the surface property of the image. It is computed by the variance of the AC values of group.

4. Proposed CBIR Scheme

In this section, the proposed feature extraction technique and similarity measurement method is presented where the feature extarction technque uses DCT and multi-resolution approach for computing visual features of the image and novel similarity measure is used in the matching during retrieval process. It reduces the computational cost and searching time.

4.1. Feature Extraction

The accuracy of any traditional CBIR scheme rely on the computation of the appropriate visual contents or features from the images using optimum feature extraction techniques and selection of the suitable similarity matching methods. The CBIR will efficient and effective if the feature descriptor of image has low dimension and contains most significant image contents. Therefore, the computation of significant contents of the image and selection of the suitable dimension of the feature descriptor of the image is one of the important issue in CBIR. Hence in the presented scheme, the multi-resolution approach and DCT tool are adopted to compute the visual features of the images where we achieved that the dimension of the feature descriptor is low as compared to the original size of the images and produces the satisfactory retrieval results. From the previous works we found that in most of the cases, DCT based CBIR schemes have been developed in block level operations. So the computation overhead is not negligible. In this paper, authors have computed DCT coefficients from an entire image data in the different multi-resolutions so that the computational processing cost and searching time will be reduced. Initially, the color image is decomposed into its three color components and performed the multi-resolution approach on each color component to obtain the color planes (i.e. red plane, green plane and blue plane). The DCT is employed on each obtained reduced size color plane. The significant DCT coefficients are selected according to zigzag scanning order. The DC components are kept intact while some statistical parameters like mean, standard deviation, skewness, kurtortis and smoothness are computed directly from the selected significant AC coefficients. We have selected p number of AC coefficients (p is small as much as possible) and divide p number of AC coefficients into different q number of groups at each decomposition level. Each group has n number of AC coefficients. Let variable X contains p number of AC coefficients and it is divided into q number of groups. All the statistical parameters from each group are computed by using equations (3-7) and stored as a feature vector forms i.e. mean feature vector, skewness feature vector, kurtosis feature vector and smoothness feature vector. Hence, the statistical feature vectors for red plane at level l are computed as:

$$\left.\begin{array}{l} \mu_{lR}=\left\{\mu_{lR1},\,\mu_{Rl2},\ldots,\mu_{lRq}\right\} \\ \sigma_{lR}=\left\{\sigma_{lR1},\,\sigma_{lR2},\ldots,\,\sigma_{lRq}\right\} \\ \gamma_{lR}=\ \left\{\gamma_{lR1},\,\gamma_{lR2},\,\ldots,\,\gamma_{lRq}\right\} \\ \kappa_{lR}=\ \left\{\kappa_{lR1},\,\kappa_{lR2},\,\ldots,\kappa_{lRq}\right\} \\ SM_{lR}=\left\{SM_{lR1},SM_{lR2},\,\ldots,SM_{lRq}\right\} \end{array}\right\} \tag{8}$$

where the statistical feature vectors μ_{lR}, σ_{lR}, γ_{lR}, κ_{lR} and SM_{lR} are the collection of the computed mean, skewness, kurtosis and smoothness of different groups of AC coefficients at level l. The feature vector for each plane at level l is constructed by considering the DC and the statistical parameters of the AC coefficients of DCT domain.
Therefore feature vector of the red plane at level l is computed as

$$F_{lR}=\{DC_{lR},\mu_{lR},\,\sigma_{lR},\,\gamma_{lR},\,\kappa_{lR},\,SM_{lR}\} \tag{9}$$

Similarly feature vectors for green (G) and blue (B) planes are calculated as

$$F_{lG}=\{DC_{lG},\mu_{lG},\,\sigma_{lG},\,\gamma_{lG},\,\kappa_{lG},\,SM_{lG}\} \tag{10}$$

$$F_{lB}=\{DC_{lB},\mu_{lB},\,\sigma_{lB},\,\gamma_{lB},\,\kappa_{lB},\,SM_{lB}\} \tag{11}$$

Therefore, the single feature vector of the image plane at level l can be obtained by combining the feature vectors of red, green and blue components by using equations (9-11). It is obtained as:

$$FV_l=\{F_{lR},F_{lG},F_{lB}\} \tag{12}$$

We have employed image pyramid to the each color plane up to three levels because more than 3 levels do not change the retrieval results in the presented CBIR.
Let FV_1, FV_2 and FV_3 are the feature vectors at image pyramid level 1, 2 and 3 respectively. So the final feature vector of image for three decomposition levels is given as:

$$FV=[FV_1,FV_2,FV_3] \tag{13}$$

The whole feature extraction process of image for constructing the feature vector is shown in Fig 5.

4.2. Novel Similarity Measure

In this section, the proposed novel similarity measure will be described in brief. Let $FV_Q=[q_1,q_2,\ldots,q_n]$ be the feature vector of a query image, $FV_t=[t_1,t_2,\ldots,t_n]$ be the feature vector of the target images in the database; then combined feature vector (CFV) can be computed as

$$CFV=\left[\frac{t_1-q_1}{q_1},\frac{t_2-q_2}{q_2},\ldots,\frac{t_n-q_n}{q_n}\right] \tag{14}$$

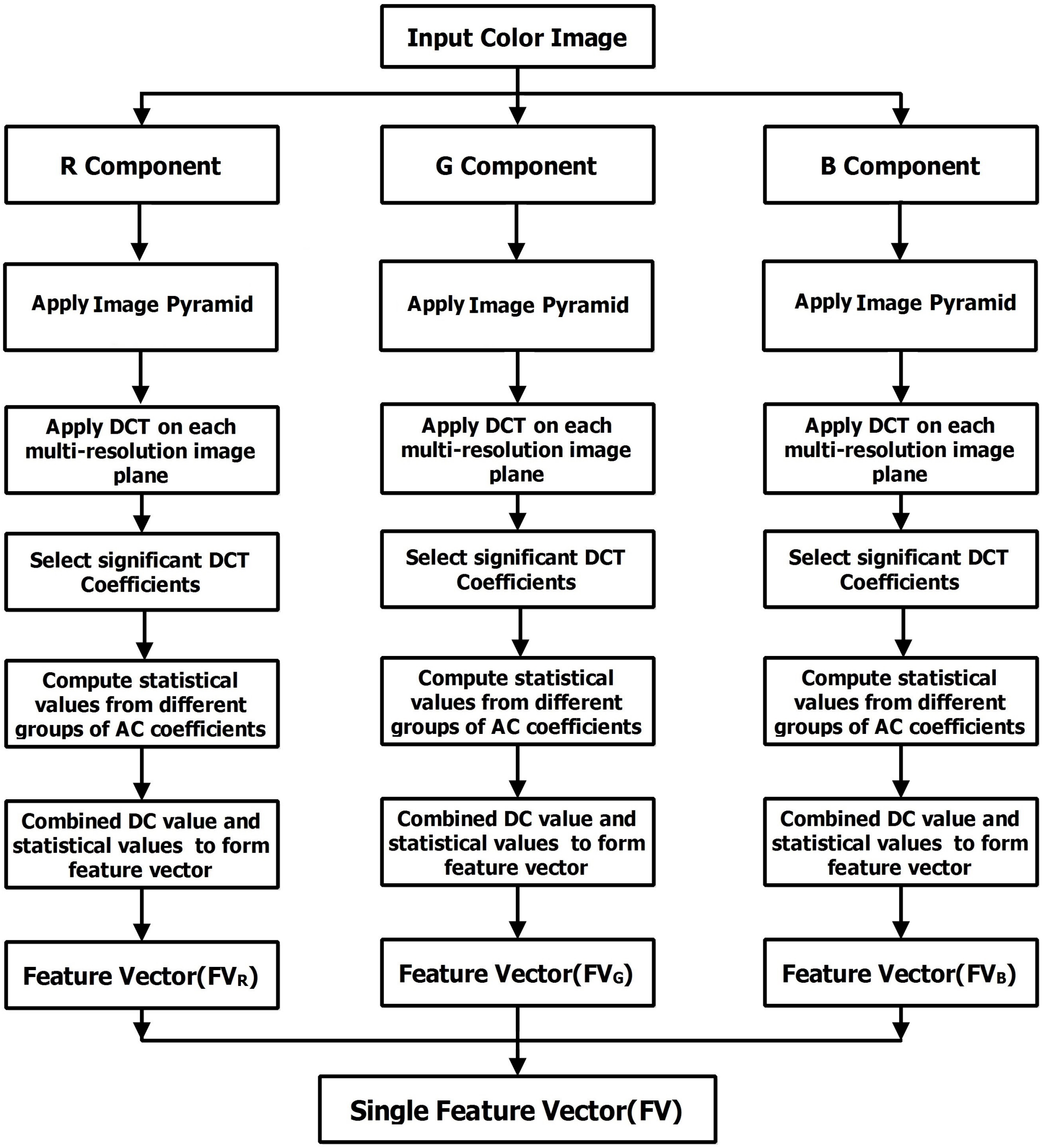


Figure 5. Feature Extraction Process

The new feature vector based on the predefined threshold is obtained as

$$FV_B = [B_1, B_2, ..., B_n]$$
$$\text{where}\,\mathrm{B}_i = \begin{cases} 1 & \text{if} \left|\frac{t_i - q_i}{q_i}\right| \leq \alpha \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

where α is any constant/threshold. The vector FV_B consists of binary values i.e. zeros and/or ones. It requires only 2-bit to store these values in the memory space because it contains only 0 and 1 values. The binary feature vectors are computed between the database images and query image. In the presented similarity distance, the authors have counted the number of ones for each feature vector FV_B and stored the counted values into the distance variable D. The maximum number of ones in the binary feature vector returns most identical image while the minimum number of ones returns the dissimilar image. Hence, we sorted the values of D into descending order and select the top most images those having the maximum number of ones. The whole process for computation of D is illustrated by a given example, let us consider the feature vector of target image $FV_t = [2, 29, 32, 8]$ in the database and the feature vector of a query image $FV_Q = [10, 31, 23, 5]$. These feature vectors requires 5-bit to store the values in the memory, hence we will reduce it into 2-bit by using the following operation. Let $\alpha = 10\%$ then the values of binary feature vector are defined as

$$B_1 = \left|\frac{2-10}{10}\right| \leq 0.10 = \left|\frac{-8}{10}\right| \leq 0.10 = 0.8 \leq 0.10 \\ = 0 \tag{16}$$

Similarly B_2, B_3 and B_4 will be computed, Therefore the binary feature vector is obtained as $FV_B = [0, 1, 0, 0]$, Here $D = 1$. Hence the proposed distance has the number of ones only and we sort these distances D into the descending order and select top L number of images. These L number of images are most relevant to the query image which is our desired output. The schematic diagram of proposed CBIR scheme is depicted in Fig. 6.

4.3. Image Retrieval

The major algorithmic steps of the presented CBIR scheme are as follows:

Algorithm : Input: Query image; **Output**: Retrieved images

Step 1. Upload RGB color image as a query and decompose it into its three color components i.e. Red(R), Green (G) and Blue (B) respectively.

Step 2. Employed Gaussian image pyramid on each color plane up-to three levels and simultaneously operate 2D-DCT on each color plane.

Step 3. Take DC coefficients and p number of AC coefficients from each color plane at l^{th} decomposition level.

Step 4. Divide the AC coefficients into several number of uniform groups where each group contains the same number of AC coefficients. Compute the statistical parameters from each group and intact DC coefficient as it is at each decomposition level.

Step 5. Combine the DC coefficients and the statistical parameters of AC coefficients for formation of the feature vector.

Step 6. Construct the feature vector of an query image and feature vectors of target images of database using steps from **1** to **5**.

Step 7. Compute the novel distance between feature vector of the query image and the feature vectors of the database images for the similarity measurement.

Step 8. Sort the computed distances into decreasing order and select top L number of images those having the maximum number of ones.

The proposed feature extraction technique is also tested for the euclidean distance where the feature descriptor/vectors of the query image and database images have been constructed by using equation (13) and euclidean distance between them have been also constructed. The computed euclidean have been sorted in increasing order and top L number of images have been selected from database those having the minimum distances. We have also compared the results of both euclidean distance and proposed novel similarity measure/distance in the experiments for two standard databases and we found that the retrieval results are better than the proposed distance but it takes more time than the proposed novel distance.

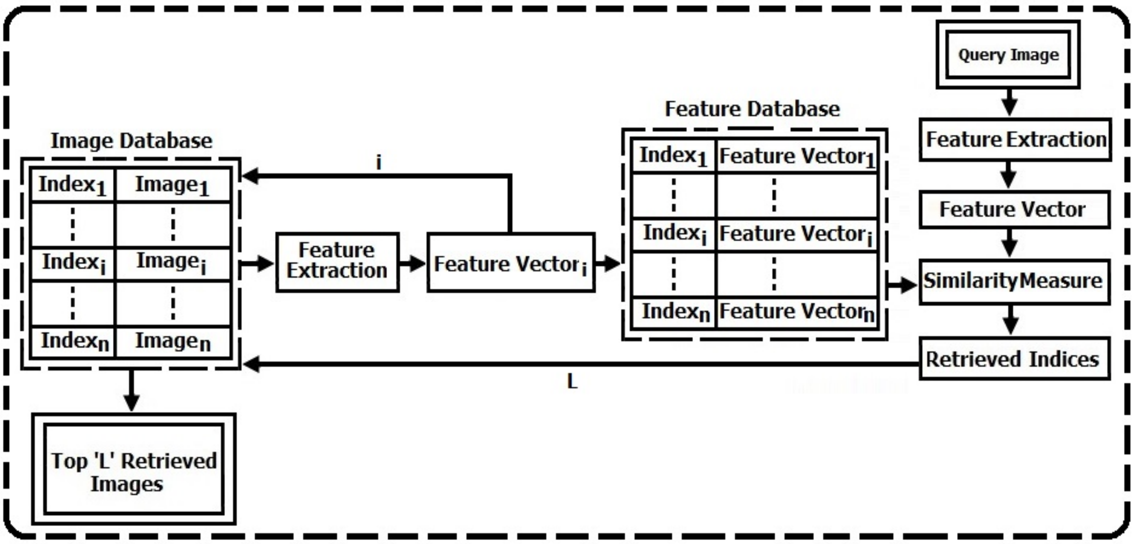


Figure 6. Proposed CBIR diagram

5. Experimental Results and Discussions

The experimental results are carried out by using Matlab R2011b on the platform Intel Core i5-2365 CPU @ 1.65 GHz, 6 GB RAM, 32 bit, Microsoft Windows 7 OS. The performance of the proposed CBIR system is evaluated on the two standard Corel-1K [39] and GHIM-10K [40] image databases which are freely available on the Internet. The Corel database consists of 1000 images with different structures and contents. It is divided into 10 categories where each category contains 100 similar kinds of images with size 256×384 or 384×256 in JPEG format. The semantic names of images of each category are people, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, mountains and foods. The query image is chosen from one of the 10 category for retrieving the relevant images on the basis of the similarity measurement. The second database GHIM-10K consists of 10000 images with diverse contents and different structures. All the images of this database are collected by using web and cameras. It is divided into 20 categories, where each category contains 500 similar kinds of images of size 400×300 or 300×400 in JPEG format. The semantic names of images of each category are insects, beaches, flowers, horses, sunsets, ships, flies, cars, chickens, bikes etc. Most of these category images have high resolutions. The sample images of Corel-1K and GHIM-10K image databases are shown in Fig. 7 and Fig. 8 respectively. The accuracy of most commonly used CBIR

Figure 7. Sample images of Corel-1K database

system can be measured by two standard performance evaluation metrics [41]. These metrics are used for measuring the average recognition rate of the relevant and irrelevant retrieved images from the image database and works as a function of top retrieved images. These two metrics are Precision and Recall; Precision is the ratio of the total relevant images retrieved from the database to the total retrieved images from the database; Recall is the ratio of the total relevant images retrieved from the database to the total relevant images (category wise) available in the database. The above two metrics are not sufficient to provide overall effectiveness of the any CBIR scheme. Hence, combined metric is defined which computes the overall accuracy of the image retrieval system. This metric is known

Figure 8. Sample images of GHIM-10K database

as F-score or F-measure. The F-score is the weighted harmonic mean of the precision and recall. Let X is the total relevant images retrieved from the database; Y is the total non-relevant images retrieved from the database and Z is the remaining relevant images available in database. Then, Precision (P), Recall(R) and F-score (F) are defined as

$$P = \frac{X}{X+Y} \tag{17}$$

$$R = \frac{X}{X+Z} \tag{18}$$

$$F = \frac{2 \times P \times R}{P+R} \tag{19}$$

The proposed CBIR scheme is divided into two phases: feature extraction and novel similarity measurement. For the feature extraction, the RGB color image is decomposed into its three color components i.e. red, green and blue components and each color component is analysed by multi-resolution

Table 1. Precision, recall and F-score for top 20 retrieved images from Corel-1K database using different thresholds

Threshold	**Metrics**	**Category**										**Average**
(α)		People	Beaches	Buildings	Buses	Dinosaurs	Elephants	Flowers	Horses	Mountains	Foods	**Metrics**
0.10	Precision	60.00	60.00	50.00	70.00	100.00	80.00	90.00	80.00	75.00	45.00	**71.00**
	Recall	12.00	12.00	10.00	14.00	20.00	16.00	18.00	16.00	15.00	9.00	**14.20**
	F-score	20.00	20.00	16.67	23.33	33.33	26.67	30.00	26.67	25.00	15.00	**23.67**
0.20	Precision	70.00	70.00	50.00	80.00	100.00	85.00	100.00	85.00	75.00	50.00	**76.50**
	Recall	14.00	14.00	10.00	16.00	20.00	17.00	20.00	17.00	15.00	10.00	**15.30**
	F-score	23.33	23.33	16.67	26.67	33.33	28.33	33.33	28.33	25.00	16.67	**25.50**
0.30	Precision	80.00	75.00	60.00	80.00	100.00	85.00	95.00	90.00	85.00	45.00	**79.50**
	Recall	16.00	15.00	12.00	16.00	20.00	17.00	19.00	18.00	17.00	9.00	**15.90**
	F-score	26.67	25.00	20.00	26.67	33.33	28.33	31.67	30.00	28.33	15.00	**26.50**
0.40	Precision	80.00	75.00	45.00	85.00	100.00	70.00	100.00	95.00	85.00	55.00	**79.00**
	Recall	16.00	15.00	9.00	17.00	20.00	14.00	20.00	19.00	17.00	11.00	**15.80**
	F-score	26.67	25.00	15.00	28.33	33.33	23.33	33.33	31.67	28.33	18.33	**26.33**
0.50	Precision	60.00	70.00	50.00	50.00	100.00	75.00	100.00	95.00	80.00	50.00	**73.00**
	Recall	12.00	14.00	10.00	10.00	20.00	15.00	20.00	19.00	16.00	10.00	**14.60**
	F-score	20.00	23.33	16.67	16.67	33.33	25.00	33.33	31.67	26.67	16.67	**24.33**
0.60	Precision	50.00	65.00	50.00	60.00	100.00	70.00	95.00	95.00	75.00	45.00	**70.50**
	Recall	10.00	13.00	10.00	12.00	20.00	14.00	19.00	19.00	15.00	9.00	**14.10**
	F-score	16.67	21.67	16.67	20.00	33.33	23.33	31.67	31.67	25.00	15.00	**23.50**

technique. The 2-D discrete cosine transformation(DCT) is applied on each multi-resolution image plane and typically selected AC coefficients p_l are 128, 64, and 32 at level l where $l = 1,2,3$ respectively. The selected AC coefficients are distributed into four uniform groups. Each group contains 32, 16 and 8 AC coefficients at level 1, 2 and 3 respectively. The feature vector consists of DC coefficients and computed statistical values of the AC coefficients of each color component at different scales. Therefore the dimension of feature vector is 189. The other distances which we have discussed in Section 1 and 2 are computational high. Hence in this paper the novel similarity measure has been proposed which reduces the computational cost and storage space. Here, the dimension of feature vector is 189 which mean that the proposed distance contains 189 binary values. If proposed distance contains 189 number of ones (i.e.1's), the two images are identical otherwise they are similar or dissimilar. The proposed distances are sorted into descending order and retrieved top 20 images those having maximum number of ones. In the presented work, the achieved accuracy in terms of precision, recall and F-score are acceptable in most of the cases. We retrieved top 20 images from the database using novel distance measure based on predefined thresholds. Table 1 shows the retrieval results in terms of precision, recall and F-score for top 20 retrieved images with different threshold values ($\alpha = 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90$) where we observed that $\alpha = 0.30$ gives the best results than other values of α. For $\alpha = 0.30$, the average precision, average recall and average F-score are 79.50%, 15.90% and 26.50% respectively. We also found in Table 1 that the dinosaur images provide 100.00% precision for different threshold values because these images do not have much structural features while the building and food images provide worst results since these images have much structure contents. The overall performance of the proposed CBIR scheme in term of three metrics i.e. precision, recall and F-score is reasonably acceptable. We have also compared the proposed scheme with some existing state-of-the-art CBIR schemes and observed that the presented scheme contributes the better results in terms of precision, recall and F-score. The existing state-of-the-art CBIR schemes have been developed by ElAlami [42], Poursistani et al. [43], Irtaza et al. [44], Walia et al. [45], Shrivastava et al. [13] and Pandey et al.[46]. The literature review of their schemes are explained as: ElAlami [42] suggested CBIR scheme based on genetic algorithm where the genetic algorithm was used for optimizing 3-D color histogram and Gabor texture features to make things easier in the image retrieval process. Finally, feature selection was done on the basis of the two functions called the preliminary and the deep reduction for extraction of the most relevant features from the original feature set. The weighted similarity distance is used for the color and the texture features of the images for measuring the distance between the query image and database images. In this scheme, buses, dinosaurs and horses has got good precision 87.60%, 98.70% and 83.40% respectively, while the mountains and beaches got the acceptable results in terms of precision, recall and F-score. Poursistani et al. [43] represented image features as a histogram of DCT coefficients where, they have selected significant coefficients using vector quantization technique and k-means clustering algorithm. This method applied block level DCT on YCbCr color space for extracting color and texture features. In their scheme, dinosaurs have got 100% precision while beaches got worst precision i.e. 44.40%. Irtaza et al. [44] proposed CBIR scheme based on the neural network where they have extracted efficient texture features using the concept of in-depth texture analysis. For feature extraction and image representation, scheme has adopted the wavelet packets and eigen values of Gabor filters. This method got best precision, recall and F-score on flower images i.e. 94.00%, 18.80% and 31.33% respectively. Walia et al. [45] presented effective image retrieval scheme based on three primitive features i.e. color, texture and shape where color and texture features are computed by using modified CDH features while the global or local shape features have been derived by using Angular Radical Transformation(ART). This method has gained best precision i.e. 100% for dinosaurs, flowers, and horse respectively while worst precision i.e. 38.00% for food images. But overall it produces the acceptable results in most of the category images. Shrivastava et al. [13] presented hierarchical CBIR scheme based on three stages. At first stage, they have retrieved a fixed number of images based on the color features of the non-uniform quantized HSV color histogram of the images and store the retrieved image into new database which will be used for further retrieving. The texture feature based on the Gabor filter is used for retrieving images from new database and discard non-relevant images to the some extent. At last stage, the shape feature based on the Fourier transform are used for final retrieval of images. Their scheme provides 76.90% average precision. Pandey et al.[46] proposed image retrieval system for semantically categorized hierarchical image databases based on the clustering techniques. They utilized three visual features i.e. color texture and shape and retrieved large number of images from the database. Further the retrieved images are clustered to make different trees which contain similar image features and finally visual signatures of cluster at each node of the tree are indexed using three trees where each tree is represented by color, texture and shape features individually. Their scheme has 100% precision for dinosaur images while beaches, buildings and mountains have lowest precisions i.e. 63.00%, 62.00% and 56.00% respectively. The comparative results in terms of average precision, recall and F-score with some other existing state-of-the-art CBIR schemes are shown in Tables 2, 3 and 4 respectively. The experiments have been also performed for the Euclidean distance where results will increase but computational time will also increases since the euclidean distance is performed by the square root of the sum of the squared absolute differences of the components of the vectors of the two images. It is defined as

$$\Delta D = \sqrt{\sum_{i=1}^{n} (|FV_Q(i) - FV_t(i)|)^2}$$

Table 2. Comparison of proposed CBIR scheme with existing state-of-the-art CBIR scheme in terms of average precision

SI No.	Category	**Elalami (2011)**	**Poursistani et al. (2013)**	**Irtaza et al. (2014)**	**Walia et al. (2014)**	**Shrivastava et al.(2015)**	**Pandey et al.(2016)**	**Proposed Scheme**
1	Africans	70.30	70.20	65.00	51.00	74.80	75.00	80.00
2	Beaches	56.10	44.40	60.00	90.00	58.20	63.00	75.00
3	Building	57.10	70.80	62.00	58.00	62.10	62.00	60.00
4	Buses	87.60	76.30	85.00	78.00	80.20	89.00	80.00
5	Dinosaurs	98.70	100.00	93.00	100.00	100.00	100.00	100.00
6	Elephants	67.50	63.80	65.00	84.00	75.10	85.00	85.00
7	Flowers	91.40	92.40	94.00	100.00	92.30	89.00	95.00
8	Horses	83.40	94.70	77.00	100.00	89.60	90.00	90.00
9	Mountains	53.60	56.20	73.00	84.00	56.10	56.00	85.00
10	Foods	74.10	74.50	81.00	38.00	80.30	72.00	45.00
Average Precision		**73.90**	**74.30**	**75.50**	**78.30**	**76.90**	**78.00**	**79.50**

where $i = 1, 2, ..., n$ and n is dimension of the feature vector. but in this paper, new distance is obtained by just counting the number of ones from a binary feature vector which is discussed in the novel similarity measure section 4.2. The precision, recall and F-score for proposed distance and Euclidean distance is shown in Table 5, where in some categories the precision have been increased while for some other categories it have been decreased. For example, elephants and mountains have 70.00% and 75.00% precisions using Euclidean distance while the proposed novel distance/measure provides 85.00% and 85.00% precisions respectively. The precision, recall and F-score for large scale image database GHIM-10K have been also computed. Table 6 shows the experimental results for top 20 retrieved images for Euclidean and proposed novel distance/measure where the satisfactory results have been achieved for most of category images. The sunset and bikes images got the best precisions i.e. 100.00% while both building and beaches images have got the worst precisions i.e. 65.00% for Euclidean distance. For the proposed novel similarity measure, Fireworks, bikes,sunsets images have received the 100.00% precisions while the Chicken and horses images have gain the worst results (55.00% and 50.00% precisions) since it contains more structural contents and mixed up with other category images but the proposed CBIR scheme for both Euclidean distance and novel similarity measure produces is acceptable result. For Euclidean distance, the proposed scheme has the average precision, average recall and average F-score are 82.50%, 3.30% and 6.35% precisions respectively while the proposed similarity distance produces 76.25%, 3.05% and 5.87% precisions, recall and f-score respectively for GHIM-10K database. In both the cases, the results are satisfactory according to previous works done in some existing state-of-the-art CBIR. The average feature extraction time, searching time, average three metrices i.e precision, recall and F-score are shown in Table 7 where we have seen that the feature extraction and searching time is low as compared to the euclidean distance. For Corel-1K database, dinosaurs and flowers provide best precisions i.e. 100.00% using Euclidean distance while the novel similarity measure gives the 100.00% and 95.00% precisions for dinosaur and

Table 3. Comparison of proposed CBIR scheme with existing state-of-the-art CBIR scheme in terms of average recall

SI No.	Category	Elalami (2011)	Poursistani et al. (2013)	Irtaza et al. (2014)	Walia et al.(2014)	Shrivastava et al.(2015)	Pandey et al. (2016)	Proposed Scheme
1	Africans	15.30	14.04	13.00	10.20	15.00	15.00	16.00
2	Beaches	19.80	8.88	12.00	18.00	12.00	13.00	15.00
3	Building	18.20	14.16	12.40	11.60	12.00	12.00	12.00
4	Buses	11.60	15.26	17.00	15.60	16.00	18.00	16.00
5	Dinosaurs	9.80	20.00	18.60	20.00	20.00	20.00	20.00
6	Elephants	15.60	12.76	13.00	16.80	15.00	17.00	17.00
7	Flowers	11.80	18.48	18.80	20.00	19.00	18.00	19.00
8	Horses	13.90	18.94	15.40	20.00	18.00	18.00	18.00
9	Mountains	22.80	11.24	14.60	16.80	11.00	11.00	17.00
10	Foods	13.80	14.90	16.20	7.60	16.00	14.00	9.00
Average Recall		**15.20**	**14.86**	**15.10**	**15.66**	**15.40**	**15.60**	**15.90**

flower images respectively. The worst results for Euclidean distance has been produced for elephant and mountain images i.e. 70.00% and 75.00% precisions respectively while the novel similarity measure has 45.00% and 60.00% precisions for food and building images. The top 20 retrieved images for four categories of Corel-1K database is shown in Fig. 9 for best (i.e dinosaurs and flowers in subfigure 9(a) and 9(b) and worst (i.e foods and buildings shown in 9(c) and 9(d)) cases using novel similarity measure where D represent the distance/similarity or counting variable. Similarly for four categories of GHIM-10K database, the best results has been obtained for sunsets and bikes i.e. 100.00% precision while the worst results for building and beaches images have got i.e. 65.00% precisions using Euclidean distance. For novel similarity measure, fireworks, bikes and sunsets images have the best precisions i.e. 100.00% while the worst results for chickens and horses are 55.00% and 50.00% precisions. The four category images of GHIM-10K including two best(shown in subfigures 9(e) and 9(f)) and two worst(shown in subfigures 9(g) and 9(h)) retrieved images are depicted in Fig.9.

Table 4. Comparison of proposed CBIR scheme with existing state-of-the-art CBIR schemes in terms of average F-score

SI No.	Category	Elalami (2011)	Poursistani et al (2013)	Irtaza et al. (2014)	Walia et al. (2014)	Shrivastava et al.(2015)	Pandey et al. (2016)	Proposed Scheme
1	Africans	25.13	23.40	21.67	17.00	24.94	25.00	26.67
2	Beaches	29.27	14.80	20.00	30.00	19.89	21.55	25.00
3	Building	27.60	23.6	20.67	19.33	20.11	20.11	20.00
4	Buses	20.49	25.43	28.33	26.00	26.67	29.94	26.67
5	Dinosaurs	17.83	33.33	31.00	33.33	33.33	33.33	33.33
6	Elephants	25.34	21.27	21.67	28.00	25.00	28.33	28.33
7	Flowers	20.90	30.80	31.33	33.33	31.50	29.94	31.67
8	Horses	23.83	31.57	25.67	33.33	29.94	30.00	30.00
9	Mountains	31.99	18.73	24.33	28.00	18.39	18.39	28.33
10	Foods	23.27	24.83	27.00	12.67	26.67	23.44	15.00
Average F-score		**25.13**	**23.40**	**21.67**	**17.00**	**25.64**	**26.00**	**26.50**

Table 5. Precision, recall and F-score for top 20 retrieved images from Corel-1K database using Euclidean and novel similarity distances

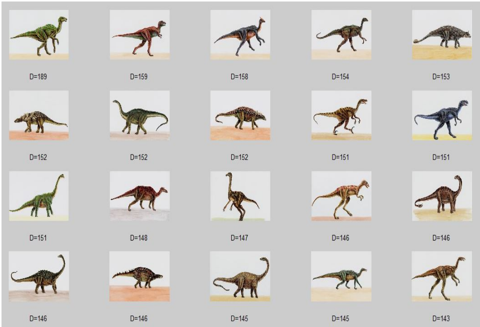
SI No.	Category	Euclidean distance			Proposed distance		
		Precision	Recall	F-score	Precision	Recall	F-score
1	People	85.00	17.00	28.33	80.00	16.00	26.67
2	Beaches	90.00	18.00	30.00	75.00	15.00	25.00
3	Buildings	80.00	16.00	26.66	60.00	12.00	20.00
4	Buses	85.00	17.00	28.33	80.00	16.00	26.67
5	Dinosaurs	100.00	20.00	33.33	100.00	20.00	33.33
6	Elephants	70.00	14.00	23.33	85.00	17.00	28.33
7	Flowers	100.00	20.00	33.33	95.00	19.00	31.67
8	Horses	100.00	20.00	33.33	90.00	18.00	30.00
9	Mountains	75.00	15.00	25.00	85.00	17.00	28.33
10	Foods	90.00	18.00	30.00	45.00	9.00	15.00

Table 6. Precision, recall and F-score for top 20 retrieved images from GHIM-10K image database using Euclidean and novel similarity measures

SI No.	Category	Euclidean distance			Proposed distance		
		Precision	Recall	F-score	Precision	Recall	F-score
1	Fireworks	95.00	3.80	7.31	100.00	4.00	7.69
2	Buildings	65.00	2.60	5.00	70.00	2.80	5.39
3	Walls	75.00	3.00	5.77	70.00	2.80	5.39
4	Cars	95.00	3.80	7.31	75.00	3.00	5.77
5	Flies	75.00	3.00	5.77	70.00	2.80	5.39
6	Mountains	75.00	3.00	5.77	70.00	2.80	5.39
7	Flowers	85.00	3.40	6.54	90.00	3.60	6.92
8	Trees	70.00	2.80	5.39	75.00	3.00	5.77
9	Grounds	95.00	3.80	7.31	95.00	3.80	7.31
10	Beaches	65.00	2.60	5.00	55.00	2.20	4.23
11	Airoplanes	85.00	3.40	6.54	90.00	3.60	6.92
12	Butterflies	70.00	2.80	5.39	75.00	3.00	5.77
13	Forts	85.00	3.40	6.54	60.00	2.40	4.62
14	Sunsets	100.00	4.00	7.69	100.00	4.00	7.69
15	Bikes	100.00	4.00	7.69	100.00	4.00	7.69
16	Boats	80.00	3.20	6.15	85.00	3.40	6.54
17	Ships	90.00	3.60	6.92	75.00	3.00	5.77
18	Chicken	85.00	3.40	6.53	55.00	2.20	4.23
19	Insects	90.00	3.60	6.92	65.00	2.60	5.00
20	Horses	70.00	2.80	5.39	50.00	2.00	3.85

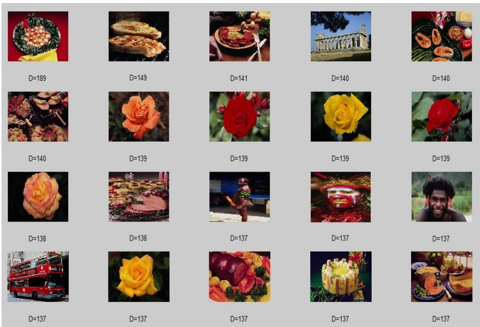
Table 7. Average feature extraction and searching time(in seconds), average Precision, recall and F-score for top 20 retrieved images for two database using Euclidean and novel similarity measures

Databases	Distances	Feature Extraction Time	Searching Time	Average		
				Precision	Recall	F-score
Corel-1K	Proposed distance	0.0182	0.1502	79.50	15.90	26.50
	Euclidean distance	-	0.275	87.50	17.50	29.16
GHIM-10K	Proposed distance	0.0244	2.132	76.25	3.05	5.87
	Euclidean distance	-	2.5125	82.50	3.30	6.35

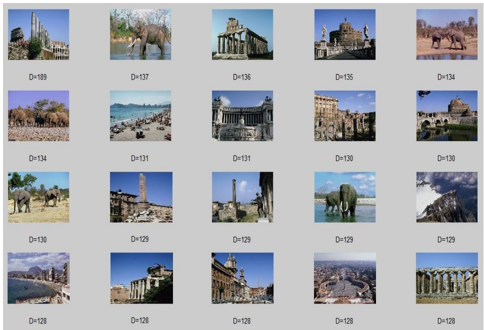


(a) Dinosaurs

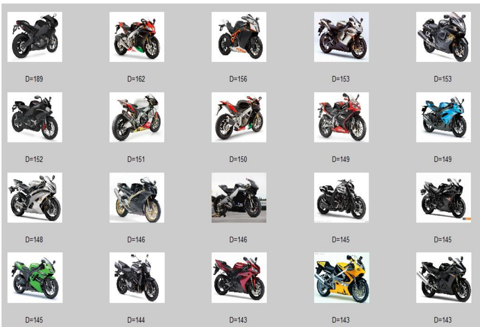
(b) Flowers



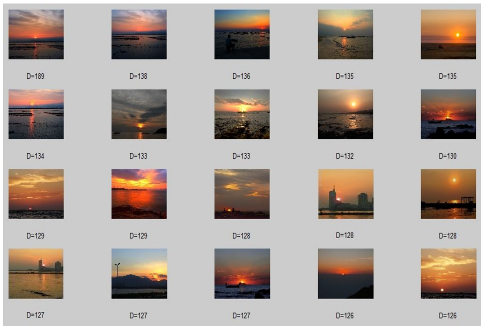
(c) Foods



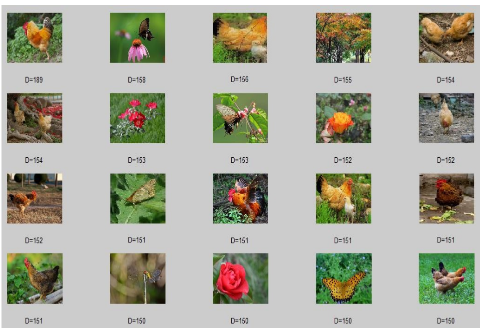
(d) Buildings



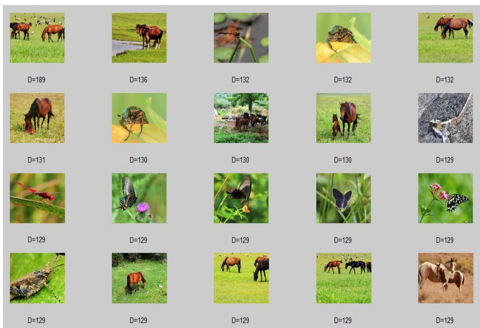
(e) Bikes



(f) Sunsets



(g) Forts



(h) Chickens

Figure 9. The simulation results for Corel-1K and GHIM-10K databases from sub figures (a)-(d) and sub figures (e)-(h) where queries are the top left corner images

6. Conclusions

In this paper, authors have proposed a novel CBIR scheme where initially color image is analyzed by multi-resolution technique at different resolutions and each decomposed image is transformed by the DCT for extracting the significant image features. The feature vector is computed by combining DC and calculated statistical values of significant AC coefficients of multi-resolution image planes. Afterwards,the novel similarity measure is proposed for retrieval purpose where it shows the speedy retrieval system with less computational cost. The effectiveness of the proposed CBIR scheme are analyzed with euclidean and novel similarity measure and satisfactory results are achieved in both the cases but novel similarity measure consume less searching and feature extraction time. Also the computational overhead of the proposed CBIR scheme is reduced because DCT has been applied to the entire color plane instead of applying in block level on images. The experimental results have been validated on two standard and large image databases where we found the satisfactory results. The proposed scheme also outperforms over some other existing state-of-the-art CBIR schemes.

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