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A Survey Over Preprocessing and Similarity Matching of Trademark Images Based on Color

Numa Bajaj**, *Jagbir Singh Gill
Department of Computer Science, CGC College of Engineering, Landran, Mohali, Punjab, India

Abstract
Relevant retrieval from a large high dimension data set is quite cumbersome but a significant task to survive in this world of images. A company's trademark plays an important in expansion of its business. In this paper techniques have been discussed to retrieve the trademark images on the basis of its color feature. Color is a very important part of any image. It provides strong descriptor and also helps them to distinguish between two images. Therefore, many techniques have been explained thoroughly in this paper to describe the color features and their advantages and disadvantages. Special emphasis has been laid on how similarity matching is performed in each of the techniques, which include color histogram, color correlogram, color moments and various color descriptors.

Keywords: *Color histogram, Color correlogram, Color moments, Color descriptor*

****Author for Correspondence*** E-mail: numabajaj@gmail.com

INTRODUCTION

Automatic image retrieval based on some similarity either by color or shape or both on trademark images has gained a significant recognition in the world wide business development and research area because they are exclusively prepared signs or marks to recognize a particular product or brand and define not only the attractive features of products but also the position and status of companies. Trademark for any organization plays a significant and vital role in current market of developing world.

A company's trademarks are the essential elements of its industrial property, similar trademark images arise doubtful cases in identification. The logos images are remarkable things in world's largest business and trade applications. Trademark can be a design of a small image, simple graphics, unique texture and combination of text and figures.

In this present age, virtually all fields of people's life architecture, academics, hospitals, crime prevention, surveillance, journalism, fashion and graphic design, engineering including commerce, and historical research use different images for reliable and efficient services. A collection of number of images is referred to as image database. Registration of trademark images and its evaluation for particularity is thus becoming a herculean task for registration offices.

The number of registered trademark images is growing rapidly. Several trademarks for several brands and companies have been already designed and registered in trademark registration office. So protecting a newly introduced trademark for any new or existing organization without inadvertent infringement of the copyright is really very fractious task.

The image retrieval techniques characterize images databases based on some property such as; color, shape, texture and object. The most important hurdle in image retrieval is in what way to determine strong features in order to gain more efficient and robust retrieval results.

Figure 1 shows block diagram for trademark retrieval system. A very basic idea of the retrieval of the similar images is feature extraction. A feature is a characteristic that can capture a certain visual property of the image. System differs from classical information retrieval in that the databases are essentially irregular, digital images contain pixel intensities.

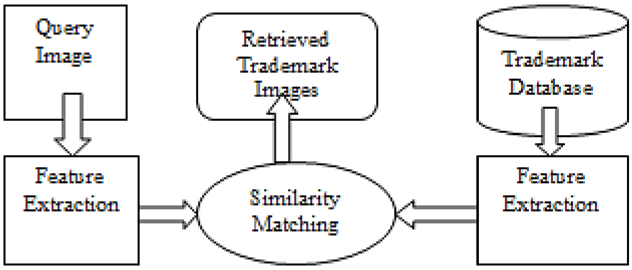

Fig. 1: *Basic Diagram for Trademark Retrieval System.*

In this paper, work has been done on color. Color is the basic characteristics of the images through which we can identify an image. In image processing colors are used because they provide strong descriptors that can be used to determine and extract objects from a scene. The eyes are sensitive to colors, and color features enable human to discriminate between objects in the images or different images from dataset.

Color features provide influential information of images, and they are very effective for image retrieval. Many techniques can be used to describe color feature. There are color histogram, color moments, color correlation, and scalable color descriptor (SCD), color structure descriptor (CSD) [1]. For defining the color features from an image, we have to choose a proper color space and use its properties in the retrieval [2]. But in this paper only color feature extraction techniques are discussed.

VARIOUS TECHNIQUES FOR DESCRIBING COLOR FEATURE

Color Histogram

This is one of the simple and widely used techniques for describing color feature. With the help of color histogram retrieval and indexing is far more efficient and effective than any other technique [3]. First of all histogram intersection technique was used. But this technique extracts only the color frequency which may lead to quantization error and in erratic retrievals as well.

After this a new method was proposed to recover the disadvantages of method discussed above in which both color frequency as well as color value is extracted [2]. In this method first of all an image is divided into various parts according to pixels present. Then for each part of the image color value and color frequency is extracted separately. The mean value of R, G, B in each part defines the color value of that part of image.

Color feature of an image is given by:
Color feature = $[r_i, g_i, b_i, p_i]$ (i=1, 2, 3, .M) [2]
where, M means the total number of colors; p_i means the ratio value of relevant colors with r, g, and b value; they all satisfy $\sum p_i$=1.

Now, suppose there are two images, i.e., the query image and the target image. To find similarity between both the images their corresponding color features are extracted. Then similarity can be measured on the basis of two functions:

i) Membership Function.
ii) Distance Function [2].

In color histogram, images can be indexed on the basis of two features, i.e., Global features and Local features [4]. Global feature focuses on the whole image to perform task while local feature focuses only on the part of image or it can be said that local feature selects a representative color for every part of the image. For, similarity matching of the queried image and the image in database Euclidean distance is used. The image with highest similarity in the database will be retrieved at first place [3]. Also formula used for histogram similarity matching is [5];

$$S^{hist}(Q,I) = \sum_{i=1}^{m} min\{h_{c_i}(Q), h_{c_i}(I)\} \Big/ \sum_{i=1}^{m} h_{c_i}(Q)$$

where, Q be the query image and I be the image from the database. Despite several advantages, color histogram has some disadvantages as well. In color histogram calculating large number of bins is not feasible as it will increase the computational cost and increasing number of bins can't result in

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efficient indexing of images in the large databases. At the same moment, color histogram doesn't consider spatial information of any image, which is quite an important factor for retrieval of image in large databases [5].

Color Moments

In this era of images and graphics in every field, retrieval of correct images according to the need of user is quite an important task. But there is a semantic gap between the user and machine. User wants to retrieve something and write it down but machine takes it in some other manner and this result in wrong retrievals. In this case, color moment feature can help in filling the gap.

These color moments can be used to calculate the similarity between query image and the images present in database. Basically color moment is calculated for images those have some probability distribution. Means colors are distributed over the image in some probability function [4]. The moments are calculated independently in each of the eight maps for every color channel. Then, a 16-dimensional feature vector is obtained for each channel. By concatenating the feature vectors extracted in different color channels, the color information can be fully utilized [6].

In this representation technique, the image is segmented according to the color present in it. But image is segmented into four fixed minimum sized rectangular boxes rather than dividing it into region of arbitrary shapes [1].

The image is represented in the form of tree, where each tree can have at the most four children. The root of the tree represents the original image, while the four children represent the four subparts of the image. The nodes are ordered in the tree corresponding to the position in the subimage. Figure 2 shows the relationship between node ordering and subimage location [1].

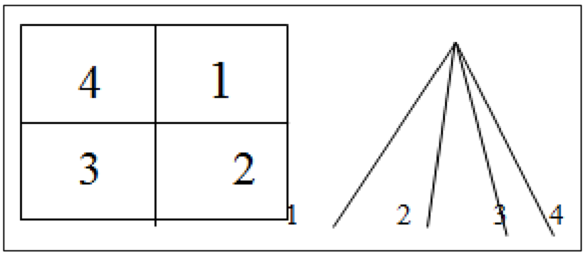

Fig. 2: *Relationship between Node Ordering and Subimage Location.*

The next step is to check, whether the image needs to be further divided or not. This can be decided by using homogeneity predicate using color on each subimage. If the image is homogeneous in terms of color, i.e., if the predicate is true, then there is no need to sub divide the image. On the other hand, if the color is nonuniform then, the image is subdivided into four equal parts.

This subdivision process can be carried out upto two levels only. Therefore, any image can be subdivided into maximum of 16 blocks. As shown in the figure below, an image is subdivided into four subimages. Where for subimage one, two and four predicate is true, which means there is no requirement of any subdivision. While the predicate for subimage three turns out to be false, therefore it is subdivided into further four subimages as shown in Figure 3 [1].

In addition to above segmentation each image is also represented into hierarchy of color moment. Each root has the color moment of the original image. While, children show the color moment of the subimages present in the image. The position of the moment in the moment tree depends on the position of the subimage in the original image. Therefore, it can be said that this representation technique not only gives the information of color distribution but also keeps the positional information as well.

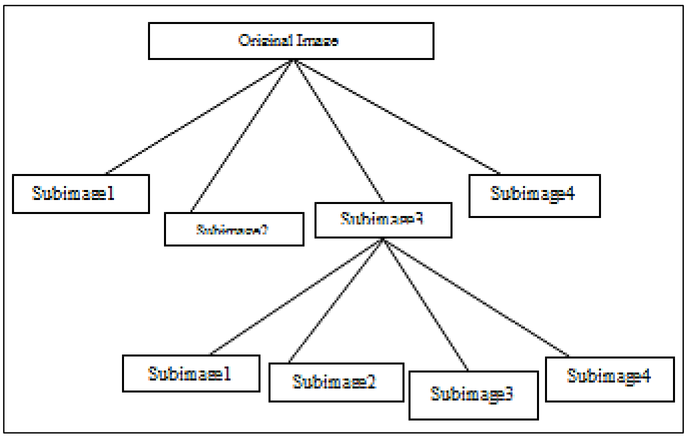

Fig. 3: *Hierarchy of Image.*

To measure the similarity basically we have three color moments. These three color moments are defined as [7]:

Moment 1-Mean:

$$E_i = \sum_{j=1}^{N} \frac{1}{N} p_{ij}$$

Mean can be understood as the average color value in the image. p_{ij} is the value of i-th channel of the j-th image.

Moment 2-Standard Deviation:

$$\sigma_i = \sqrt{\left(\frac{1}{N}\left(\sum_{j=1}^{N}\left(p_{ij} - E_i\right)\right)^2\right)}$$

The standard deviation is the square root of the variance of the distribution.

Moment 3-Skewness:

$$s_i = \sqrt[3]{\left(\frac{1}{N}\left(\sum_{j=1}^{N}\left(p_{ij} - E_i\right)\right)^2\right)}$$

Color Correlation

When an image is queried, this is not necessary that retrieved image has every pixel relevant to the query image. Therefore, the irrelevant pixels can be omitted from the query image so as to get the most relevant results. An image has to be mined so as to get to know, each and every pixel row set of the image. For this pixel sets are found which have background color and object color most frequently occurred. This is called finding co-occurrence of the pixels.

Color correlation not only work on three dimensional colors but it also work on the spatial distance [5]. Color correlation can be found using a color correlogram. Color correlogram is a table having indexed entries of the all the color pixels present in the image. Where each entry defines the probability of finding pixel at some distance k from the pixel present in the image. Therefore, the color correlogram is defined as [5]:

$$\gamma_{c_i,c_j}^{(k)} = {}_{p_1 \in I_{c_i},} Pr_{p_2 \in I}\left[p_2 \in I_{c_j} \middle| |p_1 - p_2| = k\right]$$

where, (ci,cj)€{ c1, ... cm}, kε {1, …, d} and |p1–p2| is the distance between pixels p1 and p2.

In order to find correlation of the pixels there are two concepts defined [8]:

Correlation: Suppose, there is an image which has pixel row set, where each row R has quantized color set. Suppose A is some other quantized color set. Therefore, the percentage of A in every row set R is known as correlation of quantized colors in A.

Correcolor: If a minimum correlation (min_corr) is given, the quantized color sets, whose correlation are equal or bigger than min_corr are called correcolor set.

But, this is not feasible to consider every color pair of the color correlogram. As the number of pairs are very large and considering each color pair can lead to a complexity of O($n^2 d$), where n is the number of color pairs and d is the distance between the pixels.

To resolve this problem auto correlogram is used, this auto correlogram consider only the spatial correlation only between the identical colors and thus this reduces the complexity to O(nd) [5]. Auto-correlogram is defined as:

$$\alpha_{c_i}^{(k)}(\mathrm{I}) = \gamma_{c_i,c_j}^{(k)}(\mathrm{I})$$

Further, there are two types of auto-correlation. Which are defined as [9]:
0th order R_0 (i) = $\sum_r c_i(r)$
1st order R_1(i, j,a) = $\sum_r c_i\,(r) c_j(r+a)$
2nd order R_2 (i, j, k, a,b) = $\sum_r c_i(r)\, c_j(r+a) c_k(r+b)$ [10]

where a, b is a displacement vector from the reference point
r= (*x*, *y*), c_i is the i-th element value of the D-dimensional vector
c, and i, j, k ∈ {1, ..,D}.

Here, 0th order corresponds to any normal histogram. While, 1st and 2nd order work on the local texture, also 1st order contain two types of auto-correlation, i.e., spatial auto-correlation and color index auto-correlation [9]. Therefore, so as to reduce the computational cost this technique can work best. This technique can be used where fast microprocessors are used [5]. For color correlation following formula is used for similarity matching [6].

$$S^{correl}(Q,I) = \frac{\sum_{c_i c_j \in [m], k\in[d]} min\left\{\gamma^{(k)}_{c_i,c_j}(Q), \gamma^{(k)}_{c_i,c_j}(I)\right\}}{\sum_{i=1} \gamma^{(k)}_{c_i,c_j}(Q)}$$

where, Q is the query image and I be the image the database.

Color Descripter

Color descriptors are basically originated from the histograms. Color descriptors have played a very inmost role in extracting the color features of any image, especially Mpeg images [11]. In past era, histograms were defined that were able to capture the color distribution. With these histograms there were lots of choices that user has to make such as color space, quantization in color space and quantization of histogram values. But after several experiments it was perceived that these choices should not be left to the user for better results [11]. After that histogram with descriptors came into existence. Several color descriptors are shown in Figure 4.

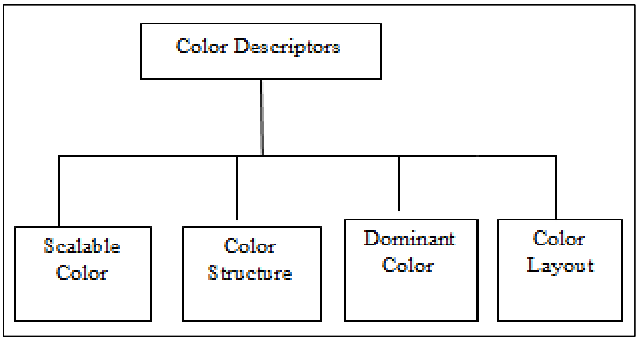

Fig. 4: *Types of Color Descriptors.*

Scalable Color Descriptor

The features of Scalable Color Descriptor (SCD) are near to the elementary color histogram approach. The slight difference is, in color histogram there is a choice of color space, color quantization etc. but in SCD color space is made fixed which is HSV (Hue, Saturation, Value) color model. This is done so as to not provide too much of complexity, as it would limit the interoperability between the descriptors [11]. The HSV color space which is used in SCD is uniformly quantized, into a total of 256 bins. This results in 16 levels in H, four levels in S, and four levels in V. After that, histogram values are truncated into representation of 11 integer bits. To achieve a more efficient encoding, the 11-bit integer values are first mapped into a nonlinear 4-bit representation of 11-bit representation. That will give higher significance to small values with higher probability. This 4-bit representation would require large number of histograms, which is a very large number [12]. Therefore, to make the application scalable the histograms are encoded using Haar transform. The Figure 5 below shows the basic unit of Haar transform, which mainly have two operations which are, sum operation and difference operation which corresponds to primitive low and high pass filters, respectively.

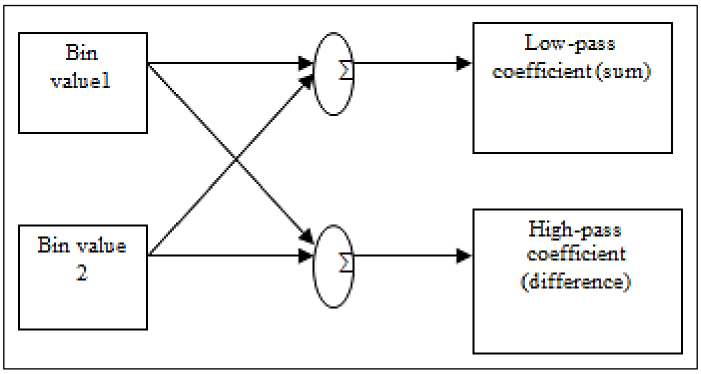

Fig. 5: *Basic Unit of Haar Transform.*

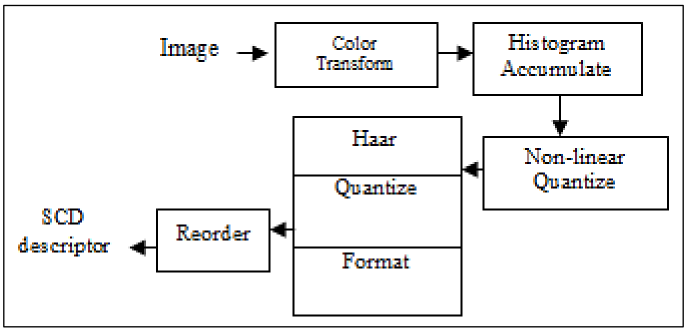

Fig. 6: *SCD Extraction Flow Chart.*

The SCD flow chart and block diagram is shown in Figure 6 below. First of all, RGB is converted to HSV color space. After that histogram is calculated for the image. The results are then transformed using Haar transform filter. Then the output of Haar transform is reordered according to the concept of energy centralization. Finally, the SCD description is transmitted from low band to high band [13].

For similarity matching of histograms, L1 norm (sum of absolute differences) is the best in retrieving accurate results. L1-norm-based matching can also be applied in Haar-transform domain, however, the results are distinguishable (except when "high-pass" coefficients have the identical signs in the two descriptions compared) as matching directly in the histogram domain. If only sign bit is used or it can be said that if all bit planes represents the absolute value discarded, then the L1 norm degenerates to a hamming distance, that reduce the complexity in the search.

Color Structure Descriptor

Color Structure Descriptor (CSD) performs the same work as performed by any ordinary color histogram. In addition, CSD not only captures the content of color, like color histogram, it also considers the structure of image. This consideration of structure makes CSD a different and efficient technique than the color histogram.

CSD not only works on color content but is also works on semantic content [12]. This additional feature makes the color structure descriptor more sensitive to certain features of image, which are not seen by color histogram.

The extraction method is performed by using an 8×8 pixel size structuring window, so as to gather information about distribution of colors. Figure 7 given below explains the flow chart of CSD extraction procedure [13].

The CSD is basically a 1D array of 8-bit quantized values. In CSD extracting operation the structuring element searches throughout the entire image for data which is needed for color histogram. The element visits each and every available position in the pixel grid and it always lies entirely within the image.

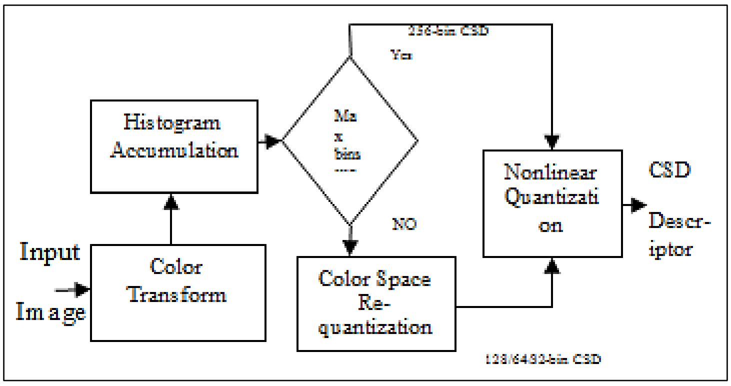

Fig. 7: *CSD Extraction Flow.*

In the figure, the upper most path shows the path of 256-bin CSD that starts with color transformation from RGB to HSV. For the next step, histogram is accumulated which is followed by a decision of number of bins needed. After a nonlinear quantization, CSD description is derived.

Further, to ensure interoperability the CSD technique is constructed in hue-min-max-difference (HMMD) color space. In which hue represents the same meaning as represented in HSV space, while min and max are maximum and minimum among the values, respectively. It was observed that HMMD color space is more favourable than the HSV color space [11]. Therefore, using HMMD color space gives efficient results in Color structure descriptor. Method to convert RGB into HMMD is shown in Figure 8 below.

Diff = Max-Min Sum = (max + min)/2 Hue as defined for the HSV

Fig. 8: *Conversion of RGB to HMMD Color Space.*

For similarity matching, it is required to calculate the distance between two images that can be done by using formula shown below [12]:

$$D(X,Y) = \sum_{i=0}^{79} \left| Local_{X[i]} - Local_{Y[i]} \right| + 5 \times \sum_{i=0}^{4} \left| Global_{X[i]} - Global_{Y[i]} \right| + \sum_{i=0}^{64} \left| Semi_{X[i]} - Semi_{Y[i]} \right|$$

Distance measurement between two global histograms is based on the sum of absolute difference also known as L1 norm.

Dominant Color

This technique is simple, compact and quite effective. In this technique, no bin quantization is done in color histograms; rather in this technique only color space quantization is performed. This descriptor defines the distribution of salient color present in the image. This technique, gives the description of all the colors in given area of interest in the image which helps in indexing. For this technique, the feature descriptor consist of the representative colors, percentage of the color in the region, spatial coherency of dominant colors and color variance for each dominant color [11]. A 3-D space is used to define all the representative colors, this usage of 3-D space helps in indexing of high dimensional image which was a limitation in color histogram. For similarity retrieval, each representative color in the query image or region is used independently to find regions containing that color.

All the query colors are matched and finally they are combined to obtain the final retrieval. This technique computes all the representative colors rather than confining only to a single color space, this property makes this descriptor compact and quite accurate than the color histogram. The descriptor is defined as [11]:

$F = \{\{c_i, p_i, v_i\}s\}$, (i = 1,2,3...N)

where, c_i denotes ith dominant color, p_i denotes its percentage value, v_i denotes its color variance.

The color variance is the optional field. The spatial coherency is a single number that represents the overall spatial homogeneity of dominant colors in the image. The number of dominant colors can differ in different image. A maximum of eight dominant colors can be used to represent the region. The percentage values are quantized to 5 bits each. The quantized color depends on the color space specifications defined for entire database, it need not to be defined for every with each and every descriptor [11].

For similarity matching distance between two descriptors can be computed as follow [11]:

$$D^2(F_1, F_2) = \sum_{i=1}^{N_1} p_{1i}^2 + \sum_{j=1}^{N_2} p_{2j}^2 - \sum_{i=1}^{N_1}\sum_{j=1}^{N_2} 2a_{1i,\,2j}p1_i p_{\,2j}$$

Where the subscripts 1 and 2 in all variables stand for descriptor F_1 and F_2, respectively, and $a_{k,l}$ is the similarity coefficient between two colors c_k and c_l

$$a_{k,l} = \begin{cases} 1 - d_{k,l}/d_{max}, & d_{k,l} \le T_d \\ 0, & d_{k,l} > T_d \end{cases}$$

where, $d_{k,l}$ is the $\|c_k\text{-}c_l\|$ Euclidean distance between c_k and c_l, T_d is the maximum distance to be consider similar, D_{max} is the αT_d.

Color Layout

The Color Layout Descriptor (CLD) is composed for estimating the spatial distribution of color in full image or in any part of an image which can be of any arbitrary shape. This descriptor is really a compact one and can be used with smaller software and hardware resources. This descriptor is used where fast image retrievals are required, as this descriptor consider images and sequences for matching. Representation of this technique is based on DCT (Discrete Cosine Transform).

In CLD YCbCr color space is used for representing the calculated DCT. Extraction of descriptor basically divided into four steps (Figure 9), which are [12]:

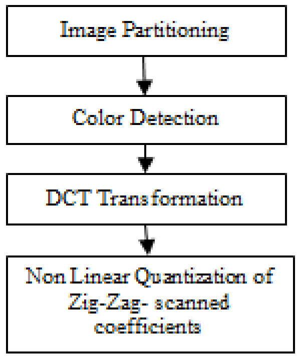

Fig. 9: *Steps to Extract Color Layout Descriptor.*

Image Partitioning: In this step, the input image is divided into 8×8 blocks. In this step resolution or scale invariance is guaranteed.

Color Detection: Once the partitioning is done, single dominant color is selected from each block. Though any method can be used for color representation but using average of pixel color gives the best result as it is a simple technique and description accuracy is enough.

DCT Transformation: In this step color components are transformed by 8×8 DCT. That gives three sets of 64 DCT-coefficients.

Zigzag Scanning: Next step is the zigzag scanning and then the first few coefficients are nonlinearly quantized (64 and 32 levels for DC and AC coefficients, respectively). By controlling the number of enclosed coefficients it is possible to scale the representation of the feature. It is recommended to use a total of 12 coefficients (6 for luminance, 3 for each chrominance) [12].

The total bit-length of 12 coefficients is 64 bits including one signalling bit, which specifies the extension of the number of coefficients. For high-quality still pictures, option to use a total 18 coefficients (6 for both luminance and chrominance) can also be considered.

For similarity matching, the following formula is used [12]:

$$D = \sqrt{\sum_i \omega_{yi}(DY_i - DY'_i)^2} + \sqrt{\sum_i \omega_{bi}(DCb_i - DCb'_i)^2} + \sqrt{\sum_i \omega_{ri}(DCr_i - DCr'_i)^2}$$

where, {DY, DCr, DCb} and {DY', DCr', DCb'} are two CLds and subscript "i" represents zigzag scanning order of respective color coefficients.

CONCLUSION

In this paper, all the techniques have been explained thoroughly. These techniques are used to extract a very important feature of image which is color. Above survey includes technique such as; color histogram, color correlogram, color moment and color descriptor such as; SCD, CSD, Dominant Color, Color Layout. In this color histogram captures the global distribution of color while if images that are prone to result in semantic gap are used than, color moment is used. On the other hand if an image is used where co-occurrence of color is on large scale then color correlogram can be used. Color descriptor is the most modern way to extract color feature. With this technique most of the retrieval process is digitized and choice left to the user is very less, which leads to improved results.

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