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Content-based image retrieval using combined features of color descriptors, GLCM-SFTA, and Hu's moments

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ABSTRACT

Due to the information technology which is rapidly developing, digital content is becoming increasingly difficult to handle. This include images that are kept on digital cameras, CCTV and medical scanners. Areas such as medical and forensic science are using these databases to do critical tasks which include diagnosing of diseases or identification of criminal suspects. However, to manage and search the similar images from these databases is not an easy task. Content Based Image Retrieval (CBIR) is one of the techniques used to manage and search similar images from a database. The performance of CBIR depends on the low level (Color, Texture and Shape) features. In this paper, a new feature vector to represent the image in terms of low level features and to improve the performance of CBIR is proposed. The proposed CBIR system was developed based on the combined features of Color, Texture and Shape features. Color features are extracted by using Color moments, HSV Color Autocorrelogram Feature (CAF) and Color Layout Descriptor (CLD). Texture features are extracted by Gray Level Co-Occurrence Matrix (GLCM) and Segmentation based Fractal Texture Analysis (SFTA). Shape features are extracted by Hu Moments. The combined features which are made up of 165 Color Descriptor features, 109 GLCM-SFTA texture features and 8 shape Hu's moment values are extracted to both query and database images. The extracted feature vector of the query image is compared with extracted feature vectors of the database images to obtain the similar images.

***Keywords**: CBIR; Color Autocorrelogram Feature; Color moments; GLCM; SFTA; CLD; Hu moments; HSV; Content Based Image Retrieval; Fractal Texture Features; Color Descriptors; Shape Features.*

1. INTRODUCTION

In this era of information technology, handling digital content is an issue that is important to address. Mobile devices such as the smart phones are used by almost everyone and images are created every second to fulfill personal and social needs. Not only that, the digital cameras, CCTVs and medical images also contributed to the growing size of digital content. Images are handled on a daily basis and it has become very difficult to search these images from their contents even by using keyword based image retrieval approach. To replace the keyword based image retrieval, Content Based Image Retrieval (CBIR) was introduced. CBIR searched similar images by using image contents. The image contents are represented through their low level features such as color, texture and shape features. Shape features are mostly used for searching an image from shape databases while color and texture are the most frequently used image features.

Selection of the image features is a basic issue in designing a good CBIR system, because the selected image features should effectively represent the image contents. Color features can be extracted through Color moments, Color Histogram, Color Correlogram and Color Layout Descriptors (CLD) from MPEG-7 descriptors. The texture features are extracted through Gray Level Co-occurrence Matrix (GLCM), Segmentation-based Fractal Texture Analysis (SFTA), Gabor wavelet features, wavelets feature, Harlick features and many more. Finally, Shape is one of the most important features in Content Based Image Retrieval (CBIR). Many shape representations and retrieval methods exists such as Fourier Descriptors, Edge Histogram Descriptors (EHD), Local Binary Patter (LBP), Hu moments and so on. The combination of color, texture and shape features can be more useful as they capture the different aspects of the images. In this paper, we have proposed a new image signature by combining different color descriptors, texture and shape features. For extracting color features combination of Color moments, Color Autocorrelogram Feature (CAF) in HSV color space and Color Layout Descriptors (CLD) from MPEG-7 descriptors are selected and modified. While Gray Level Co-occurrence Matrix (GLCM) and Segmentation-based Fractal Texture Analysis (SFTA) are adopted for texture features and Hu's moments for shape features extraction. Experimental result shows that the proposed new signature with dimensions 282 has achieved high accuracyrate as compared to many existing low level feature set.

The rest of the paper is organized as follows: Section II discusses about the related work, section III describe the proposed methodology, section IV describes the features extraction, section V combines the features extracted, section VI performs the comparison of query and database image using similarity metrics and section VII is reserved for experimental setup and results. Whereas performance evaluation is available in section VIII. Finally, the paper is concluded in section IX with references in section X.

2. RELATED WORKS

Image retrieval in CBIR is based on extracting visual feature such as color, texture and shape [1]. Different CBIR systems have adopted different techniques. Few of the techniques have used global color and texture features [2,3,4] whereas few others have used local color and texture features.

Color is invariant to complexity and very much sensitive to humans than the grayscale images [5]. There are various techniques available to extract the color from images. Color coherence vector, color histogram, color correlogram are the main techniques which are used to extract the color feature. Basically color histogram finds the color distribution in image. When two different images have the same histogram then histogram techniques get fail [5]. Color Moment extracts these color distributions efficiently. So color moment is better than histogram because it also finds the spatial information of pixels [6]. Color distribution in an image is characterized by color moment so we have to find out the three order color moment- first order (mean), second order (standard deviation), third order (skewness).

Further techniques which is used in extracting the color feature are color coherence vector and color correlogram. Anucha Tungkasthan et al.,[7] presented a quick and robust color indexing techniques, particularly Color Autocorrelogram Feature (CAF) supported a color correlogram (CC), for extracting and indexing low-level features of images. This system reduces the machine time of color correlogram technique from O (m2d) to O (md). Also, It has been reported that the HSV color space gives the best color histogram feature, among the different color spaces [8]-[12]. In general, Color Autocorrelogram Feature-based retrievals in HSV color space showed better performance than in RGB color space. In a viewpoint of computation time and retrieval effectiveness, using HSV color space is faster than using RGB color space [13]. Therefore, in this work we use HSV Color Autocorrelogram model features for efficient image retrieval to improve the text based image retrieval problems.

The CLD is designed to capture the spatial distribution of color in an image or an arbitrary-shaped region [14]. The spatial distribution of color constitutes an effective descriptor for sketch based image retrieval, content filtering using image indexing, and visualization. The CLD is a compact descriptor that uses representative colors on a grid followed by a DCT and encoding of the resulting coefficients [14]. The color space adopted for CLD is YCrCb [14].

Texture is the most important native property of all surfaces which describes the visual pattern that can do discrimination of image content. Deepak, Tharani et.al have proposed local texture features from image using GLCMby partitioning the image into sub-blocks [15]. In order to accurately capture the textural characteristics of an image, texture analysis algorithms use filter banks or co-occurrence gray level matrices (GLCMs) have to consider multiple orientations and scales. The computational cost overhead for applying this method may be heavy.

It is also reported in [16] that SFTA works much faster in terms of feature extraction time, when compared to Gabor and Haralick methods. The main objective of the SFTA is to extract texture feature in an image which results in the formation of a feature vector. Haussdorf fractal dimension method is used in SFTA. To find optimal threshold Otsu algorithm is used. It is suggested in [17] that fractal dimension can be efficiently computed in linear time by the box counting algorithm. For real world images it is suggested in [18], that the Otsu‟s method provides a better selection of thresholds. In [19], it is reported that Otsu‟s method the image is assumed to be composed of only two regions: object and background, and the best threshold is the one that maximize the between-classes variance of the two regions. The Otsu‟s method is also extendable to multilevel thresholding.

Finally, Shape is one of the most important features in Content Based Image Retrieval (CBIR). Many shape representations and retrieval methods exist. In [20] Neelima.N and Sreenivasa Reddy.E have developed Fuzzy C-means clustering for image segmentation and LBP and Hu moments as features. Feature vectors used in this research work are based on the eight invariants moments of second and third order, according to Hu (1962) and Flusser [21] and T. Suk. [22].

Therefore, in this work we use Color moments, HSV Color Autocorrelogram Feature (CAF) and Color Layout Descriptor (CLD) as combined MPEG-7 Color Descriptors, GLCM-SFTA as texture features and Hu's moment as shape features to improve the image retrieval performance with good accuracy compared to other existing features.

3. METHODOLOGY

Effective image processing techniques are required to extract visual features such as color, texture and shape from an image in CBIR system. This system accepts the input query image from the user. A retrieval model CBIR performs the image retrieval by comparing the similarities between the input query image and database stored images using these extracted color, texture and shape features. Then the outcome of this system is to find out relevant image from image database to query image given by the end user.

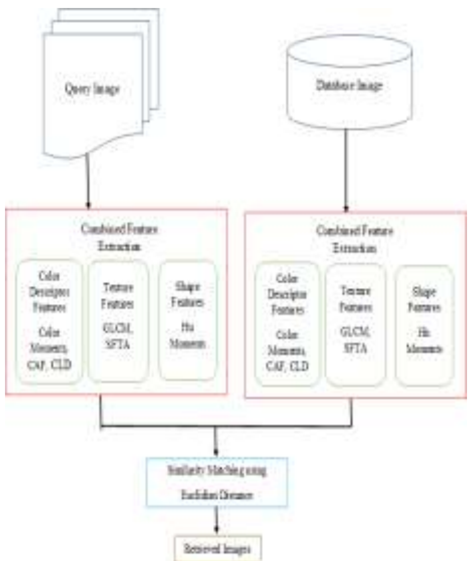

Figure 1: Block diagram for Content Based Image Retrieval

Figure 1 describes the basic functionality of content based image retrieval. Color, texture and shape features are extracted to both query image and database images. Then compare the similarity between the feature vectors of query and database image using

Euclidean distance. Precision and recall operation is carried out for analysis the performance of the system.

4. FEATURE EXTRACTION

The feature has been defined as a method of one or more measurements, each of which identifies some quantifiable properties of an object, and is calculated such that it quantifies some significant characteristics of the object. Feature extraction is a special form of dimensionality reduction. In this work, an extraction of features consists of color, texture and shape digital information. Color, texture and shape features are extracted by the combination of color moments, hsv color autocorrelogram feature (CAF), color layout descriptor (CLD), GLCM, SFTA and Hu's moments respectively.

4.1 Color Moments

Color feature is one of the most important things to access the image. The color of an image is represented from the famous color spaces like RGB, XYZ, YIQ, L*a*b, U*V*W, YUV and HSV. Several methods have been proposed in the literature for retrieving images based on the color, but most of them are varied based on similar basic idea. We extracted the color moments (statistical properties) for every image and added them as a part of feature vector in the database in addition to other color descriptors which shows the proportion of pixels of each color within the image. The Color Autocorrelogram Feature (CAF) in HSV color space and color layout descriptor (CLD) for each image is then stored in the database.

Color moment is based on numerical methods and it can describe the distribution of color by calculating the moment. Since the color distribution information mainly concentrated on the lower order moments, so first moment (mean), second moment (variance) and third moment (skewness) are commonly used methods to represent the color distribution of image.

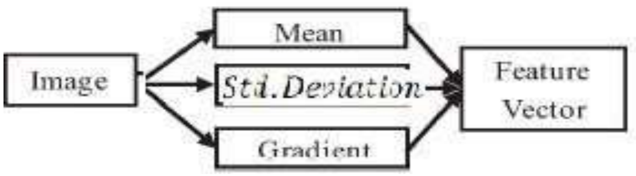

Figure 2: Color Moment Feature Extraction

The mathematical formula is as follow:

$$\text{Mean: } \mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij}$$

$$\text{Variance: } \sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^2\right)^{\frac{1}{2}}$$

$$\text{Skewness: } S_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^3\right)^{\frac{1}{3}}$$

Mean: It provides average Color value in the image.
Standard deviation: The standard deviation is the square root of the variance of the distribution.
Skewness: It gives measure of the degree of asymmetry in the distribution.

Where,
N is the number of pixels in the image, f_{ij} is the value of the i^{th} color component of pixel j.

Three moments and three color components makes 9 values that are used to represent the color content of each image. In our proposed research, all first 3 moments are considered, hence 9 valued feature vector represents the color contents.

4.2 Color Autocorrelogram Feature (CAF)

The color autocorrelogram characterizes the pixel color distribution as well as spatial correlation between color pair. It describes the probability of a pixel with the specific color and another pixel with the same color under predetermined distance. The CAF grabs the spatial correlation between identical color over two adjacent pixels.

For each image, we map the original image into the HSV color space. A color quantization is done using 36 non-uniform colors. Such like 9 levels for H channel, 2 levels for S channel and 2 levels for V channel. Then, the image is indexed and the autocorrelogram is calculated and stored in a feature vector data base and same process is Applied for query image. It can be formulated as:

Let I be the original RGB image of size m × n. The color information of an image I are quantized into m colors. The quantized color can have denoted as c1…. cm. For every pixel p (x, y) in an image I, d € [n] represents the distance between the p1(x1, y1) pixel and p2(x2, y2) pixel in an image. The distance can be fixed in computation. Then the computation for the correlogram of an image I is defined for i, j € [m] and k € [d] as

$$\gamma^{(k)}_{ci,cj}(I) = \underset{p_1\in I_{ci},\, p_2\in I}{pr}\left[p_2 \in I_{cj} \mid [p_1 - p_2] = k\right].$$

Where, $\gamma^{(k)}_{ci,cj}(I)$ results in the probability that a pixel away from the given pixel of color c_j at a distance k. Then the auto correlogram possess the spatial relationship between colors in an image I is defined as

$$\alpha^{(k)}_{c}(I) = \gamma^{(k)}_{c,c}(I)$$

Computing Color Correlogram Features is computationally expensive; the information in color correlogram requires □*(m^2d)*, whereas the information in the color autocorrelogram insist □ *(md)* space. Thus the given HSV image is transformed into an indexed image for the calculation of color autocorrelogram. An indexed image composed of two contents namely, color map matrix and data matrix of integers. The length of the color map matrix defines the number of colors.

4.3 Color Layout Descriptor (CLD)

The CLD is a very compact and resolution- invariant representation of color for high-speed image retrieval and it has been designed to efficiently represent the spatial distribution of colors. This descriptor is obtained by applying the DCT transformation on a 2-D array of local representative colors in Y or Cb or Cr color space. The extraction of the descriptor consists of four stages such as Image partitioning, Representative color selection, DCT transformation and zigzag scanning of DCT coefficients.

Following are the steps to extract the color information from the image and graphically represented in Figure 3.

1. Divide the image into 8x8 blocks
2. Single representative color is selected from each block
3. The selection results in a tiny image icon of size 8x8
4. The color space is converted from RGB to YCbCr
5. The luminance (Y), blue and red chrominance (Cb and Cr) are transformed by 8x8 DCT

6. A zigzag scanning is performed on these three sets of DCT coefficients
7. As a result, we obtain three matrixes for each block of Y, Cb and Cr color space
8. A few low frequency coefficients are selected from each block of Y (6 co-efficients), Cb (3 co-efficients) and Cr (3 co-efficients) color space to get the final feature Vector for an image

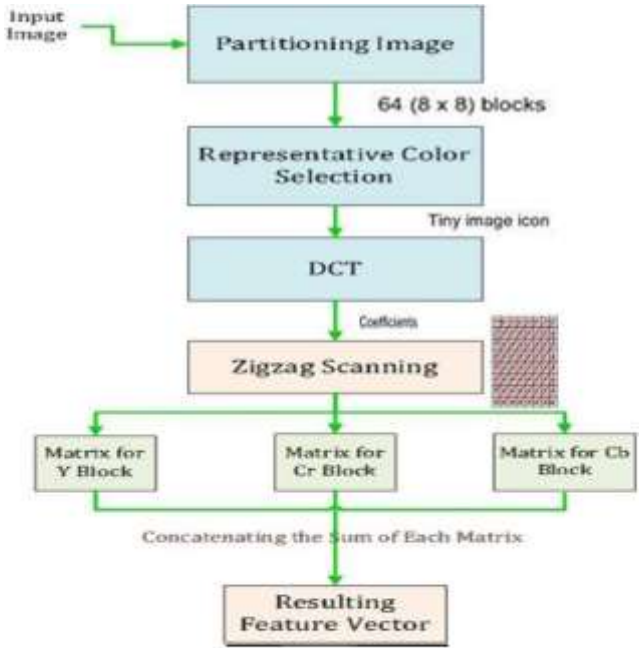

Figure 3: Flow Chart of CLD

4.4 Gray Level Co-Occurrence Matrix (GLCM)

Texture is another important feature that can help to segment images into regions of interest and to characterize those regions. Texture gives us information about the spatial arrangement of the colors or the intensities in an image. Texture analysis tries to derive a general, efficient and compact quantitative description of textures (rough, smooth, silky, or bumpy) so that various mathematical operations can be used to alter, compare and transform textures. Four major application domains related to texture analysis are texture classification, texture segmentation, shape from texture, and texture synthesis. In this sense, the roughness or bumpiness refers to variations in the intensity values, or gray levels. Texture analysis has been used in a variety of applications, including remote sensing, automated inspection, and medical image processing. Texture analysis can be crucial when objects in an image are more characterized by their texture than by intensity, and traditional thresholding techniques cannot be used effectively.

Computation of GLCM

The Gray Level Co-occurrence Matrix (GLCM) defined by Haralick can reveal certain characteristics about the spatial distribution of the gray levels in the image. It denotes how often a pixel with intensity value i occurs in a specific spatial relationship to a pixel with the value j. In GLCM, each element p(i,j) is simply the sum of the number of times that the pixel with value i occurred in a specific spatial relationship to a pixel with the value j. Four GLCM texture features commonly used which are Energy, Contrast, Correlation and Homogeneity.

$$p(i,j|d,\theta) = \frac{p(i,j|d,\theta)}{\sum_i \sum_j p(i,j|d,\theta)} \qquad (1)$$

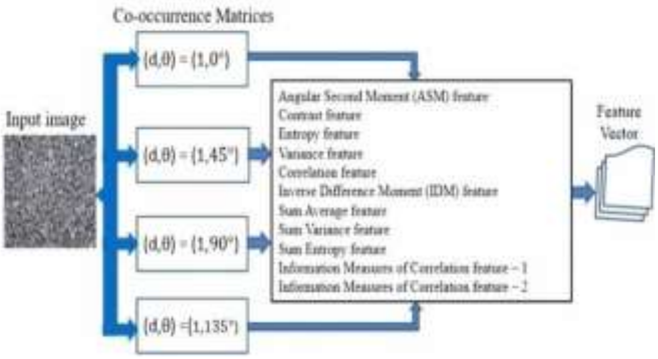

Figure 4: Features on Co-occurrence Matrix

Energy is a texture measure of gray-scale image represents homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

$$\text{Energy } E = \sum_i \sum_j p(i,j)^2 \qquad (2)$$

Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadowdepth.

$$\text{Contrast } I = \sum \sum p(i,j)(i-j)^2 \qquad (3)$$

Correlation measures image texture randomness. When the space co-occurrence matrix for all values is equal, it achieved the minimum value; on the other hand, if the value of the co-occurrence matrix is uneven, its value is greater.

$$U = \frac{\sum_i \sum_j ijp(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

Homogeneity also called as Inverse Difference Moment measures image homogeneity as it assumes larger values for smaller gray tone difference in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are same. Homogeneity decreases if contrast increases while energy is kept constant.

$$\text{Homogeneity(hom)} = \sum_i \sum_j \frac{1}{1+(i-j)^2} p_{ij}$$

The Gray Level Co-occurrence Matrix computation is explained with example.

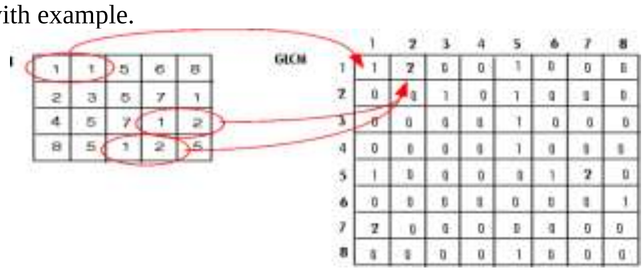

Figure 5: Gray Level Co-occurrence Matrix

4.5 Segmentation-based Fractal Texture Analysis (SFTA)

Extraction of texture feature is the time consuming process. Implementation of SFTA algorithm solves this time consuming problems shown in figure 7.

An enhanced input RGB image is converted into Grayscale Image I. SFTA texture method applied multilevel Otsu thresholding on Grayscale image I for decomposing the segmented image in several parts. This is achieved by selecting pairs of thresholds (lower threshold tl and upper threshold tu) using Two Threshold Binary Decomposition (TTBD). SFTA feature vector correlate with the number of binary images acquired in TTBD phase. If the standard total number of extracted threshold is 8, we acquire 16 different binary images shown in figure 8. Each binary image has three feature vectors that depict the boundaries fractal dimension. The purpose of fractal measurement is used to narrate the boundaries complexity and segmented image structures. An extracted vector features are fractal dimension, mean gray level, and size of area image. SFTA algorithm has been explained given below in figure 6.

Require: Grayscale image I and number of threshold n_t.
Ensure: Feature vector ***VSFTA.***

1: T□ MultiLevelOtsu (I, n_t)
2: T_A□{{t_i, t_i+1}: t_i, t_i+1∈ T, *i*∈ [1..|T|-1]}
3: T_B□ {{t_i, *nl*}: t_i∈ T, *i*∈ [1... ||]}
4: *i*□0
5: for {{t_l, t_u}: {t_l, t_u}∈ T_A ∪ T_B} do
6: Ib□**TwoThresholdSegmentation** (*I,tl,tu*) 7: ∆(x, y)□**FindBorders** (I_b)
8: $V_{SFTA}[i]$□**BoxCounting** (∆)
9: $V_{SFTA}[i+1]$□**MeanGrayLevel**(*I*, I_b)
10: $V_{SFTA}[i+2]$□**PixelCount**(I_b)
11: *i*□*i*+3
12: **end for**
13: **return** *VSFTA*

Figure 6: SFTA Algorithm

The symbol *I*, I_b, ∆, *T*, n_t, t_l, t_u and *VSFTA* denotes input Grayscale image, binary image, border image, set of threshold values, and total number of thresholds, lower threshold, upper threshold and extracted SFTA feature vectors respectively.

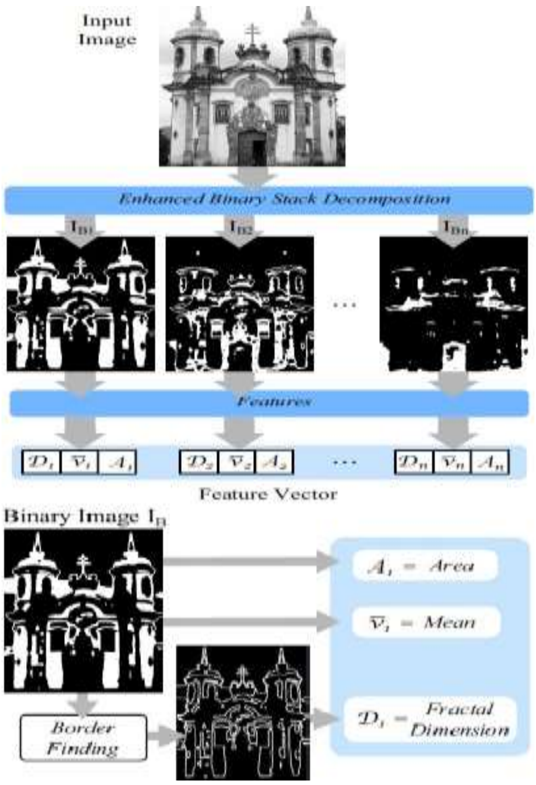

Figure 7: SFTA Extraction Process Overview

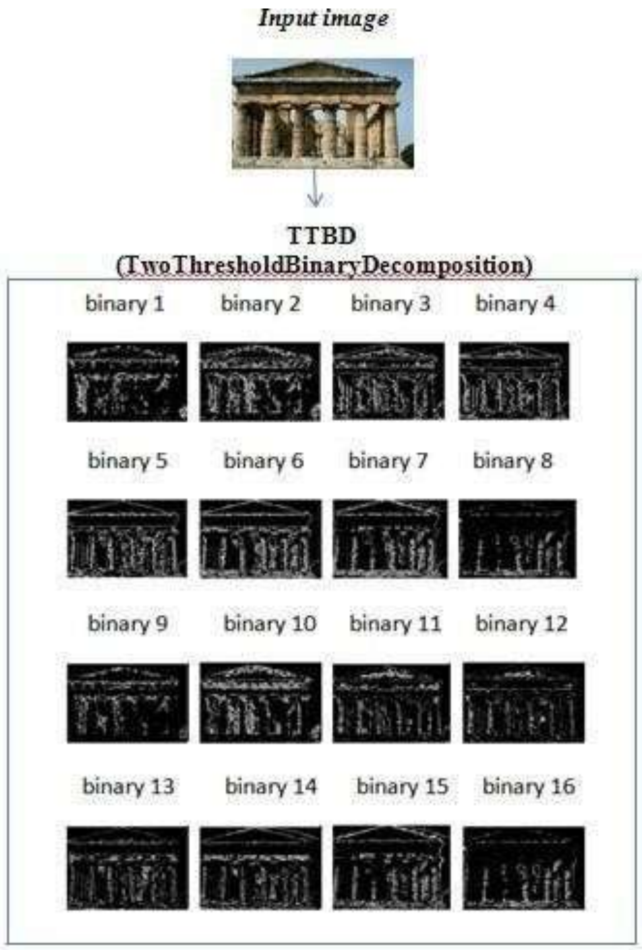

Figure 8: The results of binary images generated from Two Thresholding Binary Image. There are 16 images output of a single input RGB image

4.6 Hu's Moments

Shape plays an important role in describing image contents and for CBIR purpose, a shape representation should be robust, invariant, easy to derive and match. Two dimensional Shapes can be described by two different ways such as external representation and internal representation. Boundary based representation is called the External representation which is classified into two categories, spatial and transform. Gabor filter and Gaussian Derivatives comes under this category. Region based representation is also called as Internal representation. Hu moment invariant comes under this category.

In the proposed system, a common method in describing a meaningful shape representation is to use Hu moment Invariant descriptor. Hu derived expressions from algebraic invariants applied to the moment generating function under a rotation transformation. Moment functions capture global features and thus are suitable for shape recognition. Some moment functions exhibit natural invariance properties including invariance to translation, rotation or scaling. They consist of groups of nonlinear centralized moment expressions.

Assume the image function as f (x, y) and the standard two-dimension moment as

$$m(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)x^u y^v dxdy$$

Where *u*, *v* are positive integers denoting the order of the moment.

$$cm(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)(x-\bar{x})^u (y-\bar{y})^v dxdy$$

$$\text{where } \bar{x} = \frac{m(1,0)}{m(0,0)}, \bar{y} = \frac{m(0,1)}{m(0,0)}$$

$$I_1 = \eta_{20} + \eta_{02}$$

$$I_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$I_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$I_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$I_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$I_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$I_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2].$$

$$I_8 = \eta_{11}[(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2] - (\eta_{20} - \eta_{02})(\eta_{30} + \eta_{12})(\eta_{03} + \eta_{21})$$

5. SIMILARITY MEASUREMENT

Examining large databases of images is a challenging task especially for retrieval by content. The similarity is measured between the query image feature vector and database image feature vector are compared using distance metric. The images are ranked based on the distance value. Different similarity metrics are existing such as Euclidean, Manhattan, Mahalanobis etc.,

Algorithm

The central moment is defined as:
This description possesses the ability of data retention and shift invariance. Based on these moments, Hu moment invariants have the properties of shifting, scaling and rotating invariant, which derives from the normalized second and third order of central moments:

6. COMBINING FEATURE

The retrieval result using only single feature may be inefficient. It may either retrieve images not similar to query image or may fail to retrieve images similar to query image. Hence, to produce efficient results, we use combination of color, shape and texture features. The similarity between query and target image is measured from three types of characteristic features which includes color, shape and texture features. So, during similarity measure, appropriate weights are considered to combine the features. The distance between the query image and the image in the database is calculated as follows:
If I is the database image and I' is the query image, then the similarity measure is computed as follows:

1. Calculate combined Color Descriptors (Color moments, CAF, CLD) vector C = [C1, C2, …. Cn], Combined GLCM-SFTA Texture Vector T = [T1, T2, …. Tn] and Hu's Moments Shape Vector S= [S1, S2, …. Sn] of the database images.
2. Calculate the vectors C', T' and S' for the query image also.
3. The Euclidean distance between two feature vectors can then be used as the similarity measurement.
4. From all the matching images we display top 20 images as a result.

7. EXPERIMENTAL SETUP AND RESULTS

The discussed image retrieval methods are implemented using MATLAB R2015A. The Corel image dataset comprising of 1000 images grouped into 10 categories, within each category, it contains 100 images. The images in Corel image database having the size of 384 x 256 in which the images are categorized as African people, Beach, Buildings, Buses, Dinosaurs, Elephants, Flowers, Horses, Mountains and Food. The images with other size are resized to 384 x 256. The feature set comprises color, shape and texture descriptors computed for each pixel of an image. The experiments are performed for the retrieval of top 15 or 20 images, where top 20 means user is interested to show the 20 most similar images.

Figure.9. Retrieved results for different Query image categories

Figure.10. CBIR output using combination of color descriptors, shape and texture.

8. PERFORMANCE EVALUATION

In this work, performance is evaluated to measure the efficiency of the proposed method in comparison with the existing method. The proposed method returns the desired set of similar images from database based on the score computed by the Euclidean distance metric. The performance of this system measures by recall and precision.

$$Precision = \frac{Number\ of\ relevant\ images\ retrieved}{Number\ of\ images\ retrieved}$$

$$Recall = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ relevant\ images\ in\ the\ Database}$$

A. Comparison Based on Precision with Previous Methods

To validate the proposed approach, Figure 11 shows the comparison of proposed Image retrieval technique based on Precision with previous CBIR techniques. As the coral database has 10 classes, therefore, precision achieved of each class is selected to compare the performance of proposed Image retrieval approach with previews approaches. The performance of proposed approach is better for all most all 10 classes. However, overall performance of proposed Image Retrieval approach using combined color descriptors, Texture and Shape features is better than other 4 methods.

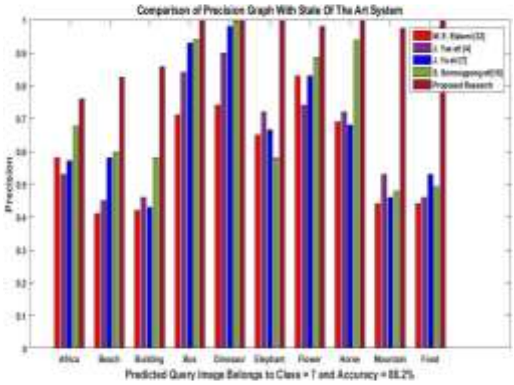

Figure.11. Class wise Precision performance comparisons with previous methods

B. Comparison Based on Recall with Previous Methods

To further validate the performance of proposed Image retrieval technique, Recall is calculated and compared with the previous approaches. The overall performance of proposed Image Retrieval approach using combined color descriptors, Texture and Shape features is better than other 4 methods.

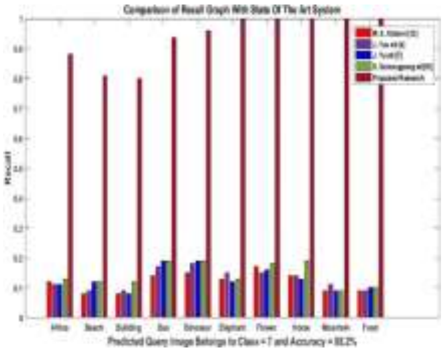

Figure.12. Class wise Recall performance comparisons with previous methods

6. CONCLUSION

This paper proposed a new signature to represent the image in terms of feature vector which improved the performance of CBIR. The proposed Image retrieval approach retrieves similar images from a database of digital images using visual contents such as Color, Texture and Shape. These features are extracted using the combination of Color descriptors such as Color Moments, Color Autocorrelogram Feature (CAF), Color Layout Descriptor (CLD), GLCM-SFTA Texture and Shape Hu's Moments techniques respectively and the Corel DB is used for the creation of dataset with 10 categories of images. This algorithm has better performance against others in retrieving all 10 categories of images in the Corel database having 1000 images. Future work of the study are Grey Level Co- occurrence matrices with different angle with different distances and different features and HSV color space different levels of H, S, V with different quantization levels to generate autocorrelogram vector.

7. REFERENCES

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