Multilayered and Multi-query Approach on Image Features for CBIR

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Abstract—Digital images are the dominant multimedia type influencing human beings and internet. Image retrieval is the vital need on internet community due to the search activities applied on image databases. This circumstances turns the young research people to move towards the Content based image retrieval (CBIR) to design a software approach to solve the image retrieval issue. This paper is forwarded along with a new CBIR system with the proposed software mechanism incorporated with statistical features derived from multiple color spaces and multi-query concept. The proposed CBIR method is entitled as "Multilayered and Multi-query approach on image features for CBIR" (CBIR_MLMQ). This CBIR is keyed up by using the derived statistical features namely Mean, Standard deviation, Skewness and Entropy observed from color spaces like RGB, HSV, YCbCr and NTSC to make foundation for better image retrieval. Also, this CBIR technique empowered by a texture measurement, gray level co-occurrence matrix (GLCM) computation for each RGB channel of an image. These remarkable features are fed into Euclidean based image retrieved which is described as layer-1 and the outcome of layer-1 image retrieval is further cultured in the layer-2 with the aid of four retrieved images as multiple queries which are the original query image and the three images that are selected with minimum distance from the output of Layer-1. The proposed CBIR_MLMQ is well united with major image types with significant hikes in precision and recall analytical measures**.**

Keywords **—**Content Based Image Retrieval, GLCM, RGB, HSV. YCbCr and NTSC**.**

I. INTRODUCTION

The emergence of smart phones, digital cameras, medical imaging devices and fast internet connections, the amount of images in every image databases are tremendously high. So the image processing applications are facing the problem retrieval inaccuracy while trying to retrieve images from large image databases. Image retrieval (IR) is a research issue since 1970's as the research community is expecting efficient IR. Content based image retrieval is one type of image retrieval method. In CBIR, image retrieval is based on visual contents like color, texture, shape and other information that are incurred from images. So CBIR retrieve images similar to the query image from the database by matching the visual contents of the query image and he database image.

Color feature is widely used in CBIR as it is easy to extract and is invariant to translations. Texture gives the information about the spatial arrangement of patterns. Shape refers the shape of the particular regions that is being sought out.

M. Heikkila et al., [1] published a novel method for interest region description. They adopted the idea that the appearance of an interest region can be well characterized by the distribution of its local features. The most well-known descriptor built on this idea is the SIFT descriptor that uses gradient as the local feature. Thus far, existing texture features are not widely utilized in the context of region description. This research introduce a new texture feature called center-symmetric local binary pattern (CS-LBP) that is a modified version of the well-known local binary pattern (LBP) feature. CS-LBP, the local feature in the SIFT algorithm is used to combine the strengths of the SIFT and LBP. The resulting descriptor is called the CS-LBP descriptor. In the matching and object category classification experiments, this descriptor performs favorably compared to the SIFT. Furthermore, the CS-LBP descriptor was computationally simpler than the SIF

T.Z. Guo, L. Zhang and D. Zhang [2] suggested rotation invariant texture classification using LBP variance (LBPV) with global matching. Local or global rotation invariant feature extraction has been widely used in texture classification. Local invariant features, e.g. local binary pattern (LBP), have the drawback of losing global spatial information, while global features preserve little local texture information. To overcome from that, T.Z. Guo *et al.* introduce an alternative hybrid scheme, globally rotation invariant matching with locally variant LBP texture features. Using LBP distribution, the principal orientations of the texture image is estimated and then used to align LBP histograms. The aligned histograms are then in turn used to measure the dissimilarity between images. A texture descriptor, LBP variance (LBPV), is introduced to characterize the local contrast information into the one- dimensional LBP histogram. LBPV does not need any quantization and it is totally training-free. To further speed up the proposed matching scheme, a method to reduce feature dimensions using distance measurement has been adopted. The experimental results on representative databases show that the proposed LBPV operator and global matching scheme can achieve significant improvement, sometimes more than 10% in terms of classification accuracy, over traditional locally rotation invariant LBP method.

S. Liao, M.W.K. Law and A.C.S. Chung [3] proposed a novel approach to extract image features for texture classification. The proposed features are robust to image rotation, less sensitive to histogram equalization and noise. It comprises of two sets of features: dominant local binary patterns (DLBP) in a texture image and the supplementary features extracted by using the circularly symmetric Gabor filter responses. The dominant local binary pattern method makes use of the most frequently occurred patterns to capture descriptive textural information, while the Gabor-based features aim at supplying additional global textural information to the DLBP features. Through experiments, the proposed approach has been intensively evaluated by applying a large number of classification tests to histogram-equalized, randomly rotated and noise corrupted images in Outex, Brodatz, Meastex, and CUReT texture image databases. This method has also been compared with six published texture features in the experiments. It was experimentally demonstrated that the proposed method achieves the highest classification accuracy in various texture databases and image conditions.

A new logical compact LBP co-occurrence matrix for texture analysis [4] is demonstrated by the author B.Sujatha. This method first evaluates the micro textured features using textons. Then logical compact LBP with logical OR operation is evaluated on textons to make the texture feature invariant in terms of change illuminations and image rotation. Finally gray level co-occurrence matrix is calculated. This paper suggests that success rate can be improved much by combining statistical and structural approaches. Ronald Kwitt *et al.* [5] propose that joint statistical modeling of DWT/DCT coefficients coupled with Bayesian framework improves the retrieval performance.

Wei Bian and Dacheng Tao [6] have used color, texture and shape features for image retrieval. Under the color space domain, 128-D color coherence vectors in Lab color space and a 9-D color moment feature in Lab color space are considered. Under texture domain, pyramidal wavelet transforms for Y component is computed in the YCrCb color space. For shape feature, edge directional histogram is computed from Y component in the YCrCb color space. Texton co-occurrence matrix [7] is proposed by the author Guang-Hai Liu *et al.* The statistical information of texton is calculated for quantized image and is used as image feature.Raquel E *et al.* [8] propose an arrangement of low level descriptors into hierarchy. In this work, only two descriptors namely Color Layout Descriptor (CLD) and Edge Histogram Descriptor (EHD) are arranged into the hierarchical structure. The CLD is calculated by using Discrete Cosine Transform (DCT) in YCbCr color space and the EHD is calculated by dividing the image into 4 x 4 blocks.

Abrishami Moghddam *et al.* [9] propose an algorithm that computes the wavelet coefficient of an image using a Gabor wavelet. Finally images are retrieved by using wave correlogram. But, in this method different coefficient for each wavelet-resolution-level is not applied to increase the retrieval accuracy. A novel fusion approach is presented by Xiaojun Qi and YutaoHan [10], in which an image is first segmented into regions using color clustering. Then two set of features including color and texture properties are derived. The region based image-level-similarity is then measured by applying the fuzzy matching scheme to the fuzzified region based on color and texture features. The major limitation of this method is that the retrieval performance depends on segmentation quality.

This research article proposed a new multilayered CBIR system which works on statistical features derived from multiple color spaces and multiple-query. The "proposed CBIR named "Multilayered and Multi-query approach on image features for CBIR (CBIR_MLMQ)" is powered by the use of statistical features namely Mean, Standard deviation, Shewness and Entropy are determined from four color spaces namely RGB, HSV, YCbCr and NTSC to make better image retrieval. The feature set computation and the Euclidean based image retrieval forms layer-1 and the outcome of layer-1 is further trained in the layer-2 with the use of the four retrieved images (these four images act as multiple queries). Among the four images used in Layer-2, one is the original query image and the other three images are the images that are selected with minimum distance from the outcome of layer-1.

The remainder of this paper is constructed as follows: Section II proposes a methodology of constructing an efficient image feature sets. The performance of proposed methodology is experimentally analyzed and compared with other methodologies in Section III. Finally, Section IV precisely presents the conclusion of this paper with future expansion.

II. PROPOSED METHODOLOGY

The section has two division namely layer-1 and layer-2. Among them, statistical feature set computation and Euclidean computation form layer-1. The three images which are selected from the Layer-1 and also the original query image, altogether four images are fed as the queries for layer-2.

A. Layer-1

1) Statistical Feature computation

Statistical features can be written as the features that are obtained using mathematical functions applied on region or whole images. In this paper, 4 statistical features like mean, standard deviation, entropy and skewness over RGB, HSV, YCbCr and NTSC color space is proposed.

RGB is the widely used color space in image processing applications. In this RGB color space, 256 different colors are represented by 3 bytes (24 bits) in each pixel. Among these 3 bytes of data, first 8 bits represent the amount of red; middle 8 bits represent the amount of green and the last 8 bits represent blue. The important color attributes, Mean (μ_t), Standard Deviation ($\boldsymbol{\sigma}_t$), Entropy (h_t) and Skewness (s_t) for a RGB color component of an image can be computed using the equations from Equ.1 to Equ.4.

$$\mu_t = \frac{1}{N}\sum_{i=1}^{N} P^t{}_i \tag{1}$$

$$\boldsymbol{\sigma}_t = [\frac{1}{N-1}\sum_{i=1}^{N}(P^t{}_i - \mu_t)^2]^{1/2} \tag{2}$$

$$h_t = -\sum_{i=0}^{N}(P^t{}_i * \log(P^t{}_i))) \tag{3}$$

$$s_t = \frac{\frac{1}{N}\sum_{i=1}^{N}(P^t{}_i - \mu_t)^2}{\sigma_t} \tag{4}$$

where $t \in \{R,G,B\}$. Here $P^t{}_i$ indicates the i^{th} pixel of t^{th} color component on RGB color space of an image, N is the total number of pixels in the image and μ_t, $\boldsymbol{\sigma}_t$, h_t and s_t represent the mean, standard deviation, entropy and shewness of t color component in RGB color space of an image.

In RGB color space, 4 statistical features are extracted from three color channels. So, totally 12 statistical functions are calculated. The combined statistical feature set F_{RGB} for RGB color space is represented using Equ.5.

$$F_{RGB} = \{\mu_t, \boldsymbol{\sigma}_t, h_t, s_t\} \tag{5}$$

Similarly, for HSV, YCbCr and NTSC color spaces also 12 statistical functions for each color channel is calculated. So totally 48 feature set values are obtained for each color space.

One of the statistical methods of examining texture is the *Gray-Level Co-occurrence Matrix (GLCM)*. The GLCM examine the texture of an image by computing how often pair of neighboring pixels with specific values ccurs in an image. The GLCM can be computed for each RGB component using Equ.6.

$$M_{p,q}^t = \sum_{p=0}^{IH-1}\sum_{q=0}^{IW-1}\begin{cases} 1, if\ P_{p,q}^t = i\ AND\ P_{p+dx,q+dy}^t = j \\ 0, if\ P_{p,q}^t \neq i\ OR\ P_{p+dx,q+dy}^t \neq j \end{cases} \tag{6}$$

Here, $P_{p,q}^t$ is the pixel value at (p, q) for t^{th} color component on RGB color space of an image. $P_{p+dx,q+dy}^t$ is the neighboring pixel at the distance dx. Usually, the distance dx between center and neighboring samples is one, but greater distances can also be taken for the calculation. IH denotes the height of the image. IW denotes the weight of the image.

The database images are undergone the entropy feature extraction based on Equ.7.

$$F_{ENT}^t = -\sum_{i=0}^{IH-1}\sum_{j=0}^{IW-1} M_{p,q}^t \times \log(M_{p,q}^t) \tag{7}$$

. The statistical feature set for the proposed system can be written using Equ.8.

$$SF_{STAT} = \{\{F_{RGB}\}, \{F_{HSV}\}\{F_{YCbCr}\}, \{F_{NTSC}\}\{F_{ENT}^R\}\{F_{ENT}^G\}\{F_{ENT}^B\}\} \tag{8}$$

where

F_{RGB} - 12 statistical features for RGB color space
F_{HSV} - 12 statistical features for HSV color space
F_{YCbCr}-12 statistical features for YCbCr color space
F_{NTSC} - 12 statistical features for NTSCcolor space

2) Image Retrieval using single query

This research uses 48 statistical features collected from 4 color spaces. The query image is given as input and the extracted statistical feature set is written as SF_{QUERY} in Equ.9.

$$SF_{QUERY} = \{SF_{STAT}^{u\in[0,51]}\} \tag{9}$$

The statistical feature set is extracted from each database images and it can be represented as in Equ.10.

$$SF_{DB}^i = \{SF_{STAT}^{u\in[0,51]}\} \tag{10}$$

$$i \in [0, n-1]$$

where

SF_{DB}^i - Statistical feature set for i^{th} database image
n - Total number of images in the database

Euclidean distance [23],[24] is the disparity measurement method which is calculated between the query and every database images. Disparity(query,DB) is defined as

$$\text{Disparity(query,DB)} = \sqrt{\sum(SF_{QUERY} - SF_{DB}^{i\in[0,n-1]})^2} \tag{11}$$

The image which gives minimum disparity is the most similar image and come first in the rank and the others are ranked next. The three images are picked starting from lowest disparity and sent to layer-2 for further refinement.

B. Layer-2

This layer consists of two sections namely multiple query action and image retrieval using multiple queries. This layer process the images selected in level-1 by the aid of multiple queries, and then ten relevant images are generated.

1) Multiple Query action

The prime process in level 2 is that the multiple query based image retrieval. The selected three images at the end of level 1 and also original query image are fed into layer-2 as query images. Thus, in the layer 2, 4 query images namely Q1, Q2, Q3, and Q4 are incorporated for image retrieval.

2) Image Retrieval using multiple queries

Now, the image retrieval process continues for the entire database with the support for 4 query images. The Euclidean distance is calculated between the four query and every database images. The Disparity(query,DB) is defined in Equ.12.

$$\text{Disparity(query,DB)} = \sqrt{\sum(FS_{Q1} - FS_{DB}^{i\in[0,n-1]})^2} + \sqrt{\sum(FS_{Q2} - FS_{DB}^{i\in[0,n-1]})^2} + \sqrt{\sum(FS_{Q3} - FS_{DB}^{i\in[0,n-1]})^2} + \sqrt{\sum(FS_{Q4} - FS_{DB}^{i\in[0,n-1]})^2} \quad (12)$$

where

FS_{DB}^{i} - Statistical feature set for i^{th} database image
n - Total number of images in the database

III. EXPERIMENT RESULTS AND ANALYSIS

This paper proposes a multilayered image retrieval system using ART2. This paper is executed in Matlab 10.0 and the analysis of the proposed method is calculated using the following existing algorithms.

- Improving image retrieval effectiveness via multiple queries (ERMQ) [22].
- Microscopic Image Retrieval System for Multi-Image Queries (IRMQ) [20].
- Pareto-depth for multiple-query image retrieval (PDMQ) [19].

This analysis uses two databases for testing purpose. The first database is the standard database DB_COREL [25] and the other one is the user created database named as DB_VEG database. The first database contains Corel type of 1000 images. Thus DB_COREL database is a collection of 10 categories of images, and each category posses 100 images. The second database is a collection of 14 categories of vegetable images, and each category contains 15 images. Thus, DE_VEG database posses 210 vegetable images. The Fig.1 shows the test images of DB_COREL and DB_VEG. The Fig.2 and Fig.3 expose the results of CBIR_MLMQ for the query image of DB_COREL and the Fig.4 and Fig.5 expose the results of CBIR_MLMQ for the query image of DB_VEG.

In this work, effectiveness of the proposed system's for the databases DB_COREL and DB_VEG is analyzed by calculating precision rate and recall. Precision [23] is the ratio of relevant images to the retrieved images. The best method produces higher precision value. In this work, first 10 retrieved images are used to calculate the precision rate based on Equ.13.

$$\text{Precision} = \frac{number\ of\ images\ retrieved\ related\ to\ query\ image}{total\ number\ of\ images\ retrieved} \quad (13)$$

Table I reports the precision rate for five sample query images from five categories namely dinosaur_1, mountain_3, rose_5, building_7 and bus_9 of DB_COREL database. Table I shows the performance comparison of proposed method over the existing ERMQ, IRMQ and PDMQ methods. This table shows that, a dinosaur_1 image gives 100% result because they show soft background.

Similarly, Table II shows the precision rate for five sample query images from five categories namely banana_2, potato_4, carrot_6, tomato_8 and beans_10 of for DB_VEG database. Table 2 depicts that the proposed CBIR_MLMQ gives better precision rate of 0.9 for banana_2 and beans_10 because both category images have clear dark colors.

Recall [23] is the ratio of the related images retrieved and total relevant images in the whole database. The best method produces higher recall value. In this work, the recall rate is estimated by using the first 10 retrieved images based on Equ.14.

$$\text{Recall} = \frac{number\ of\ images\ retrieved\ related\ to\ query\ image}{number\ of\ related\ images\ in\ the\ whole\ database} \quad (14)$$

Table III and Table IV display the recall rate for DE_COREL and DB_VEG database. Here, also dinosaur_1 query image produces higher recall rate of 0.01. But building_7 and rose_5 images produce low recall rate of 0.07 as the reason of complex and overlapped textures of the images. The Table IV shows that the categories banana_2 and beans_10 gives higher recall rate of 0.60 but potato generates 0.047 recall rate. The potato images generate low recall rates because the potato images are not visually clear and the textures are not defined specifically. The time cost analysis is reported in Table V for DB_COREL database and Table VI for DB_VEG database. They report that the performance of the proposed method is better than the other. The experiment is executed and the average values for precision, recall and run time are calculated and are reported in Fig.6, Fig.7 and Fig.8. The average precision verses recall analysis is shown in Fig.9. The proposed method's plotting curve over the curve of PDMQ proves the excellent performance of CBIR_MLMQ due to the high precision and recall values.

TABLE I. PRECISION ANALYSIS FOR DB_COREL DATABASE

Image	**Precision**			
	ERMQ	***IRMQ***	***PDMQ***	***Proposed***
dinosaur_1	0.7	0.8	0.8	**1**
mountain_3	0.7	0.7	0.8	**0.8**
rose_5	0.4	0.4	0.5	**0.7**
building_7	0.5	0.6	0.6	**0.7**
bus_9	0.5	0.5	0.7	**0.9**

TABLE II. PRECISION ANALYSIS FOR DB_VEG DATABASE

Image	Precision			
	ERMQ	*IRMQ*	*PDMQ*	*Proposed*
banana_2	0.7	0.8	0.8	**0.9**
potato_4	0.4	0.6	0.6	**0.7**
carrot_6	0.5	0.5	0.6	**0.8**
tomato_8	0.5	0.6	0.7	**0.8**
beans_10	0.6	0.6	0.7	**0.9**

TABLE III. RECALL ANALYSIS FOR DB_COREL DATABASE

Image	Recall			
	ERM Q	**IRMQ**	**PDMQ**	**Proposed**
dinosaur_1	0.07	0.08	0.08	0.10
mountain_3	0.07	0.07	0.08	0.08
rose_5	0.04	0.04	0.05	0.07
building_7	0.05	0.06	0.06	0.07
bus_9	0.05	0.05	0.07	0.09

TABLE IV. RECALL ANALYSIS FOR DB_VEG DATABASE

Image	Recall			
	ERMQ	*IRMQ*	*PDMQ*	*Proposed*
banana_2	0.47	0.53	0.53	0.60
potato_4	0.27	0.40	0.40	0.47
carrot_6	0.33	0.33	0.40	0.53
tomato_8	0.33	0.40	0.47	0.53
beans_10	0.40	0.40	0.47	0.60

TABLE V. TIME COST ANALYSIS FOR DB_COREL DATABASE

Image	Time taken(in seconds)			
	ERMQ	*IRMQ*	*PDMQ*	*Proposed*
dinosaur_1	9.01	8.82	9.12	**7.16**
mountain_3	8.85	8.75	8.96	**6.96**
rose_5	8.90	8.92	8.88	**6.90**
building_7	8.95	8.78	9.08	**7.12**
bus_9	8.92	8.72	9.04	**7.03**

TABLE VI. TIME COST ANALYSIS FOR DB_VEG DATABASE

Image	Time taken(in seconds)			
	ERMQ	*IRMQ*	*PDMQ*	*Proposed*
banana_2	8.81	8.57	8.91	**6.91**
potato_4	8.68	8.50	8.78	**6.71**
carrot_6	8.67	8.72	8.63	**6.65**
tomato_8	8.70	8.55	8.83	**6.90**
beans_10	8.70	8.55	8.87	**6.87**

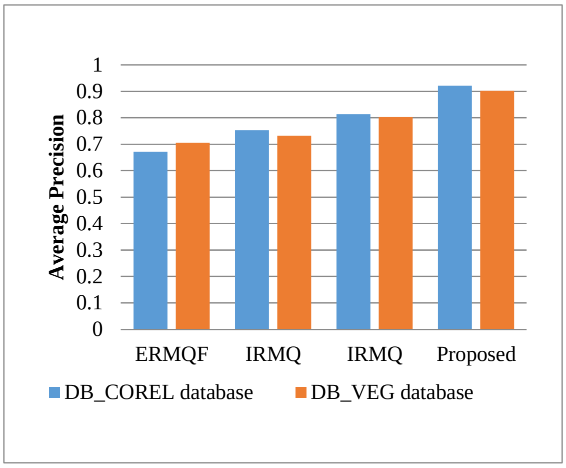

Fig.6. Average Precision analysis

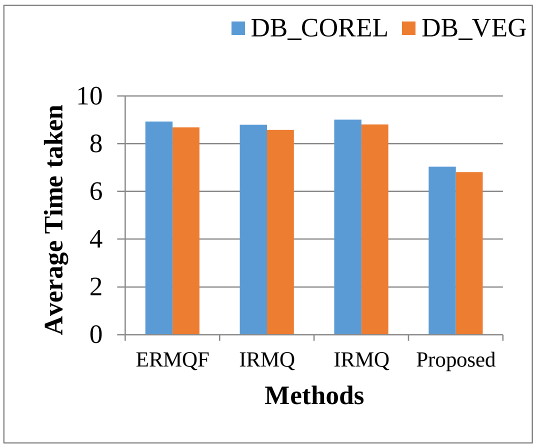

Fig.7. Average Recall analysis

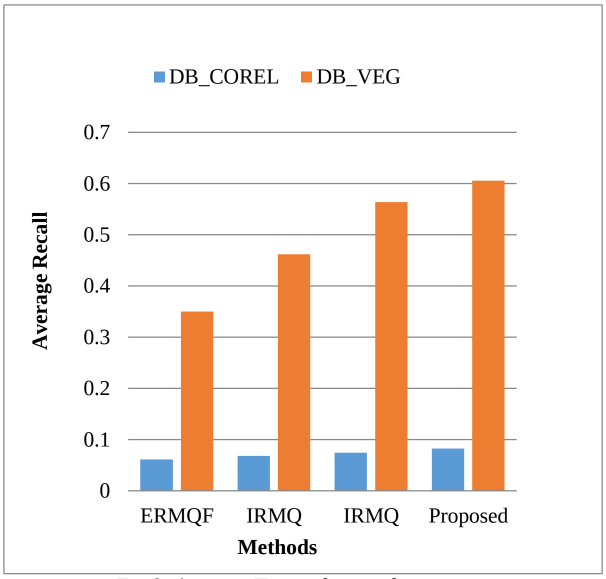

Fig.8. Average Time taken analysis

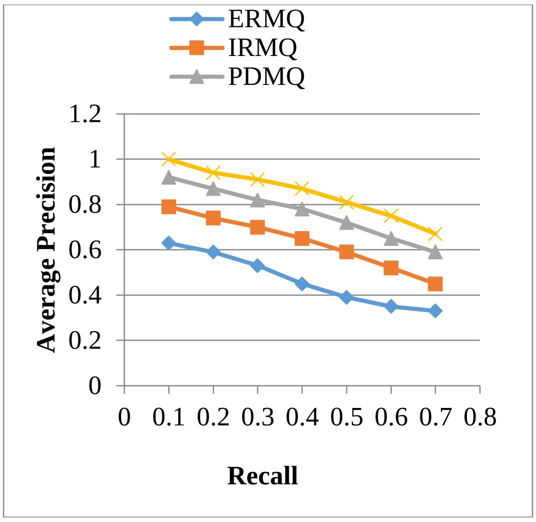

Fig. 9. Average Precision versus Recall graph

IV. CONCLUSION

This paper is the combination of multiple statistical features extracted from multiple color spaces. Herein four color spaces are concentrated to yield the feature sets. The Euclidean distance concept is linked in multilayer refinery system to obtain high quality image retrieval. The proposed CBIR_MLMQ method is highlighted than the three existing CBIR system in case of precision and recall measurements. The average accuracy of the proposed method is also higher than the earlier versions because of the benefits from the multilayer system. The average recall and average precision analysis of proposed method shines with better flame due to the multilayer approach. The overall observations decide the truth that the proposed method is the better method than the existing versions.

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