A New Color Descriptor for Content-Based Image Retrieval: Application to COIL-100

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ABSTRACT: *In this study, a new technique for image retrieval based on color feature is presented. This new algorithm is based on two defined equations, the standard deviation and the mean of the image. The performance of the proposed approach is tested on a large image collection of the COIL-100 database. Experimental results show that the proposed approach can achieve significant precision (up to 95% better) and, at the same time, the system is fast.*

Subject Categories and Descriptors
I.4.8 Scene Analysis; [Color]: **H.3.3 [Information Search and Retrieval] ; H.3.1 [Content Analysis and Indexing]**

General Terms: Image Retrieval, Color Indexes

Keywords: Image retrieval, COIL database, Query Image, Color features, Indexing.

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1. Introduction

Recently, the development of image archives has grown rapidly due to the advancement and popularization of internet technologies and data storage devices. Content-Based Image Retrieval (CBIR) was an active research domain for decades. In addition, image retrieval has an important role, because this sort of system can help efficiently users to find specific images in a database. One of the fundamental problems for image retrieval is how to represent the image. In general, to represent an image, the image features (texture, color, shape) are extracted from it and stored within an descriptor.

When handling an image database, the image characteristics are extracted and stored in another database for future uses. Given a query image, the system extracts the visual content (in the form of a feature vector), and checks similarity between the query image and the images stored in the database. If the distance between feature vectors of the query image and images in the database is small enough, according to a threshold, the corresponding image in the database is considered as a match for the query. The search is usually based on similarity rather than on correctness, and the retrieved results are then ranked accordingly to a similarity index.

We outline the main application domains of content-based image retrieval such as biometrics fingerprint or eye color recognition, handwriting recognition, pattern recognition, and medical imaging.

The CBIR system diagram is shown in (Fig. 1).

The remainder of this paper is organized as follows. We first present overview of related work in section 2. The proposed method is described in section 3. The similarity measure is discussed in section 4. Section 5 deals with the result and evaluation. We provide the conclusions and future works in section 6.

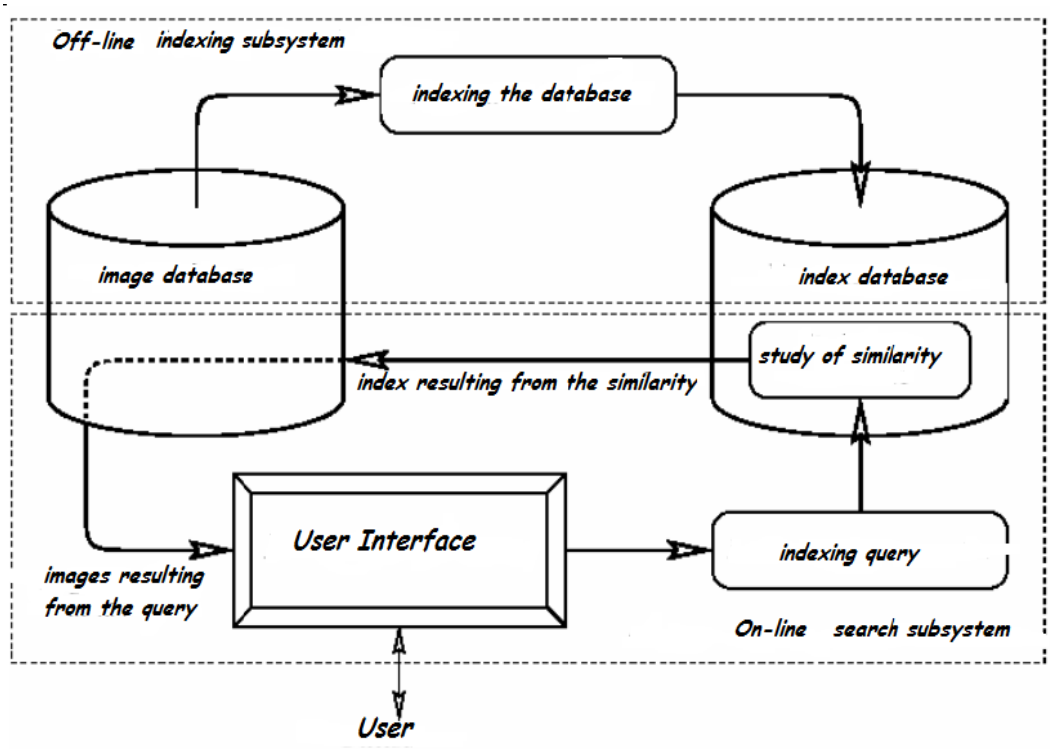

Figure 1. Block diagram of CBIR system

2. Related Works

Recently, there are many CBIR approaches e.g., [1,2,3,4,5,6,7,8,9,10,11]. In this section, we will briefly outline some of the already developed methods as described in the literature.

Alaoui et al. [12], introduced the local histograms to describe the spatial information of colors, even though, a single local histogram is not enough for efficient and robust image retrieval system. He proposed the use of color local histograms on multi-resolution. The multi-resolution color local histograms give much better retrieval efficiency. The multi-resolution images are generated using the median filter.

The technique presented in Kundua et al. [13], introduces a new CBIR scheme that abstracts each image in the database in terms of statistical features computed using the Multi-scale Geometric Analysis (MGA) of Non-subsampled Contourlet Transform (NSCT).

The method proposed by Talib et al. [14], uses a semantic feature extracted from dominant colors (DC). This technique helps reduce the effect of image background on the image matching decision where an object's colors receive much more focus. In addition, a modification to DC-based similarity measure is also proposed.

The technique given by Ren et al. [15], proposes to use a local mode histogram as the texture feature to match images and applying the residual coefficients to filter non-confident modes. The geometrical correspondence between two images is also considered.

In Fazal et al. [16], the quantized histogram statistical texture features are extracted from the DCT (Discrete Cosine Transformation) blocks of the image using the significant energy of the DC and the first three AC coefficients of the blocks.

ElAlami [17] proposed a model composed of four major phases, namely: features extraction, dimensionality reduction, artificial neural network classifier and matching strategy. As for the feature extraction phase, it extracts a color and texture features, respectively, called color co-occurrence matrix (CCM) and the difference between pixels of scan pattern (DBPSP). However, integrating multiple features can overcome the problems of single feature, but the system works slowly, mainly because of the high dimensionality of the feature space. Therefore, the dimensionality reduction technique selects the effective features that jointly have the largest dependency on the target class and minimal redundancy among themselves. These features reduce the calculation work and the computation time in the retrieval process. The artificial neural network (ANN) serves as a classifier so that the selected features of query image are the input and its output is one of the multi classes that have the largest similarity to the query image. In addition, the matching strategy depends on the idea of the minimum area between two vectors to compute the similarity value between a query image and the images in the determined class.

The color information of the image is also used in Elasnaoui et al. [18]. The proposed approach is based on the intersection of 2-D histograms in HSV space. The used histogram is based not only on the intensity of pixels but also on a 3x3 window. This approach overcomes the

drawback of the classical histogram which ignores the spatial distribution of pixels in the image.

To escape the effects of the discretisation of the color space, which is intrinsic to the use of histograms [18], another approach has been successfully used by Elasnaoui et al. [19]. This approach combines 2-D histogram and statistical moments in the HSV color space. The method was applied to different real images to demonstrate the performance of the algorithm of color image retrieval. The results obtained were compared to other methods and show that that the new method is more efficient than other methods.

Image indexing has grown in recent years and rapidly became color-oriented, since most of the images are colors.

The method proposed in this paper is based on color feature and provides an effective solution to the problems identified in existing studies.

3. Proposed Algorithm

We use RGB color space where R refers to the Red, G to the Green and B to the Blue (Figure 2).

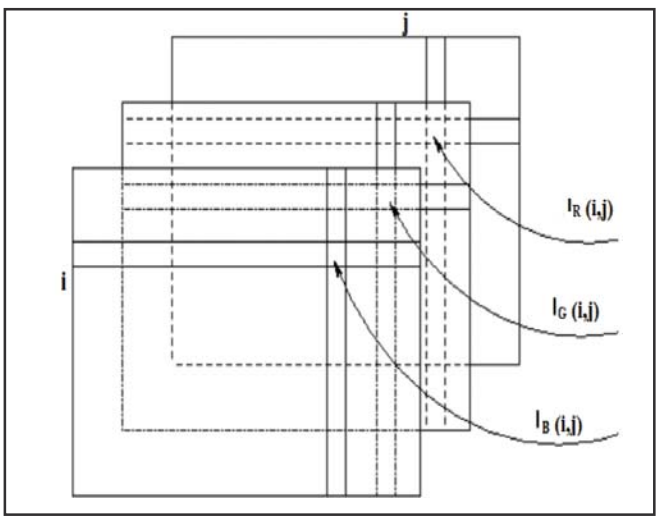

Figure 2. Color image in RGB space

Let M and σ be the mean and the standard deviation of an image I, for each I of $H*W$ pixels in a database and for each components (R, G and B) of I, the mean and the standard deviationare defined as follow:

$$M = \frac{1}{H*W}\sum_{i=1}^{H}\sum_{j=1}^{W} I(i,j) \qquad (1)$$

$$\sigma = \sqrt{\frac{1}{H*W}\sum_{i=1}^{H}\sum_{j=1}^{W}\left(I(i,j)-M\right)^2} \qquad (2)$$

After calculating the mean and standard deviation, we define two equations Gx and Gy according respectively to i and j axis of the image I.

$$Gx \leftarrow \frac{\sum_{i=1}^{H}\sum_{j=1}^{W} I(i,j)*i}{H*W} \qquad (3)$$

$$Gy \leftarrow \frac{\sum_{i=1}^{H}\sum_{j=1}^{W} I(i,j)*j}{H*W} \qquad (4)$$

3.1 Algorithm

Based on the equations described above, we will develop this algorithm.

1: D: database; V: Descriptor
2: **for** j in D **do**
3: $I \leftarrow$ Read image (j)
4: $[H,W] \leftarrow size(I)$
5: $m \leftarrow H*W$
6: **for** all Components I_l of the image I ; $l \leftarrow I(R,G,B)$ **do**
7: $M_l \leftarrow \frac{1}{m}\sum_{k=1}^{m} I_{lk}$
8: $\sigma_l \leftarrow \sqrt{\frac{1}{m}\sum_{k=1}^{m}\left(I_{lk}-M_l\right)^2}$
9: $Gx_l \leftarrow \frac{\sum_{a=1}^{H}\sum_{b=1}^{W} I_l(a,b)*a}{m}$
10: $Gy_l \leftarrow \frac{\sum_{a=1}^{H}\sum_{b=1}^{W} I_l(a,b)*b}{m}$
11: $\lambda_l \leftarrow I_l(Gx_l, Gy_l)$
12 $V_j \leftarrow (M_l, \sigma_l, G_l)$
13: **endFor**
14: **Return V_i**
15: **endFor**

The algorithm consists to calculate the mean and the standard deviation for each component, it also calculates the sum of the values of the three components $l = R, G,$ or B of I image along the i axis, then the resulting sum is divided by m ($m = H*W$) and thus we find the Gx value. For Gy, we follow the same calculation along the j axis.

Then we take for calculating λ where $\lambda = I(Gx, Gy)$:

$\lambda_R = I_R(G_{xR}, G_{yR})$, $\lambda_G = I_G(G_{xG}, G_{yG})$, $\lambda_B = I_B(G_{xB}, G_{yB})$.

Thereby, for each component ($l = R, G,$ or B) of the I image, there will be one triplet of values: 3 values for the mean, 3 for the standard deviation and 3 for the λ.

Finally, the final descriptor V is given by combination of 9 values:

$$V = \{M_R, M_G, M_B, \sigma_R, \sigma_G, \sigma_B, \lambda_R, \lambda_G, \lambda_B\}$$

Where: M, σ and λ are respectively the mean value, the standard deviation value and I (Gx, Gy) value for each component in RGB color space.

4. Similarity Measure

In order to quantify the similarity degree, we suggest the following calculation method:

Let V_Q and V_I be the descriptors -created from our new algorithm- of query image and image I in a database respectively. We associate to V_Q and V_I the following values:

$$V_Q = \{M_{R_Q}, M_{G_Q}, M_{B_Q}, \sigma_{R_Q}, \sigma_{G_Q}, \sigma_{B_Q}, \lambda_{R_Q}, \lambda_{G_Q}, \lambda_{BQ}\}$$
$$V_I = \{M_{R_I}, M_{G_I}, M_{B_I}, \sigma_{R_I}, \sigma_{G_I}, \sigma_{B_I}, \lambda_{R_I}, \lambda_{G_I}, \lambda_{B_I}\}$$

After calculating the descriptor V_Q of query image, we will compare it with the V_I of database images, which already are processed and stored in descriptors database. Having had the final imagedescriptor, the distance between two images is the distance between two descriptors. This distance can be calculated by the following formula [20]:

$$D(Q,I) = \frac{\sum_{i=1}^{9} |V_Q - V_I|}{\sum_{i=1}^{9} V_Q} \qquad (5)$$

Where Q is the query image, I an image in database, V_Q descriptor of Q, V_I descriptor of I and $D(Q, I)$ the distance between the images Q and I.

5. Experiments and Discussion

5.1 Applied Database

We use in our work Columbia Object Image Library (COIL-100) database which is well known for object recognition. The Columbia Object Image Library (COIL-100) is the dataset used for the experimental purpose. COIL-100 contains 7200 color images of 100 objects, which corresponds to 72 different orientations of each object (Fig 3).

Figure 3. The COIL-100 database contains images of 100 objects

5.2 Performed Tests

To evaluate the retrieval effectiveness, we used the precision and recall as statistical comparison parameters for the proposed CBIR method. The definitions of these two measures are given by following equations.

$$\text{Precision}(\%) = \frac{R_A}{A} * 100 \qquad (6)$$

Where R_A is the relevant retrieved images and A is the total retrieved images.

$$\text{Recall}(\%) = \frac{R_A}{B} * 100 \qquad (7)$$

Where R_A is the relevant retrieved images and B is the total number of relevant images in the database.

For example, a CBIR method for a query image retrieves totally 14 images with 8 relevant images out of totally 72 relevant images in database. Then the precision is 8/14 = 57% and recall is 8/72 = 11, 11%.

5.3 Image Retrieval

To check the retrieval performance and robustness of the proposed method, 24 experiments are conducted on COIL-100 database. On the basis on the distance (equation (5)), each image below the threshold **0.08** will be taken into consideration. We display the best 14 similar images found to prove the performances of our proposed algorithm. The results are presented separately (Fig 4, 5 and 6).

We recall that the same tests were performed using HSV, HSL space, etc, with following distance measures: Euclidean, Manhattan, Chebyshev and Minkowski with $p = 3$ and we find that the choice that achieves the best results is to use RGB space with Swain distance (equation 5). Other comparisons using COIL-100 are presented in the table (Table II).

5.4 Implementation

The implementation of the proposed CBIR technique is done in MATLAB 2009a using computer with Processor: Intel(R) Core (TM) 2 CPU T5200 @ 1.60 GHz, 1.60 GHz, 2Go RAM running on a Microsoft Windows 7 Professional (32-bit). In this section we report the query time. The results obtained are given in the table (Table III).

4. Conclusion and Future Work

We suggest in this work a novel method for color image retrieval. This approach is simple, and itcan be used to overcome limitations of existing algorithms that use the color feature. The evaluation of the proposed approach shows that the ability of the CBIR system to retrieve relevant information from all images collection is better. It is possible to achieve up to 95% of efficiency in retrieval of images. Satisfactory retrieval of expected images is provided faster due to the lower number of iterations in the searching process.

Experiment#1

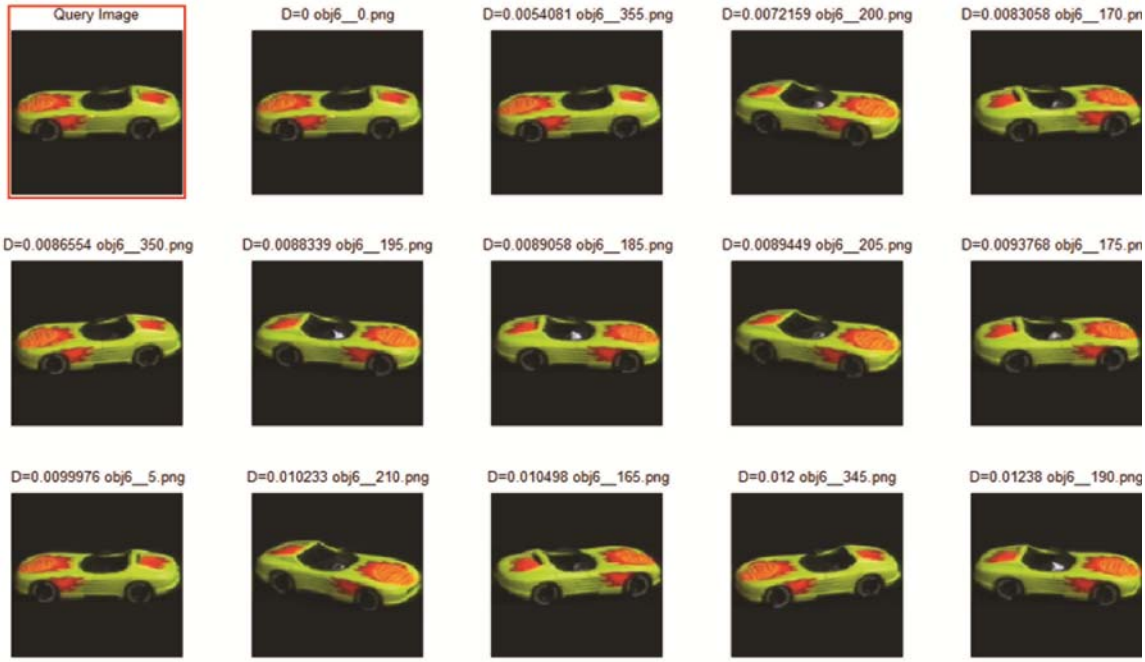

Figure 4. Retrieval results of our algorithm on obj6__0 with the query image in the top-left corner

Experiment#2

Figure 5. Retrieval results ofour algorithm on obj50__0 with the query image in the top-left corner

The results obtained indicate that the proposed approach might be considered as a solution for the development of visual information retrieval.

In future, the performance may be improved using more databases, more sophisticated feature extraction techniques and other distance metrics.

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Experiment#3

Figure 6. Retrieval results ofour algorithm on obj79__0 with the query image in the top-left corner

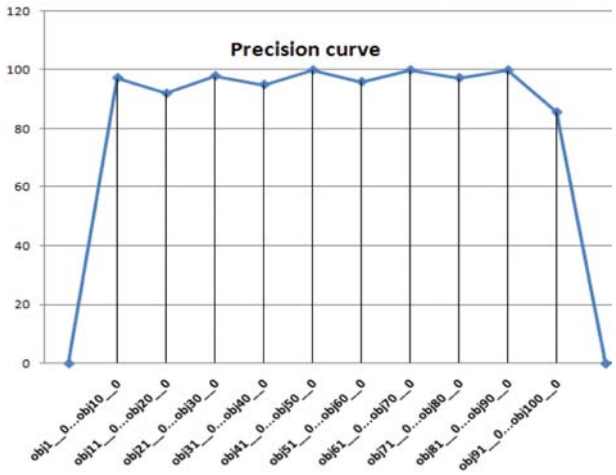

Figure 7. Precision curve of the proposed method

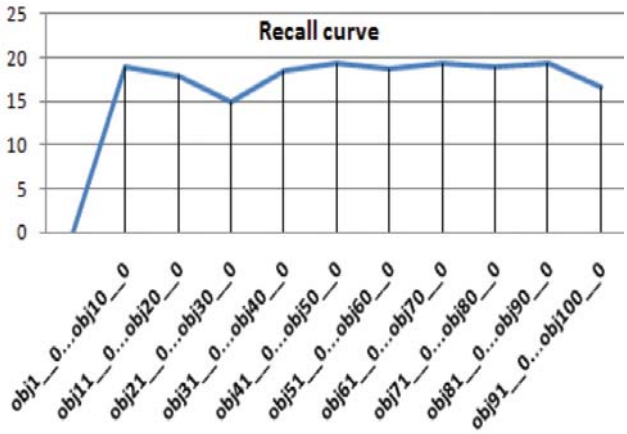

Figure 8. Recall acurve of the proposed method

Other experiments are tabulated below.

Imagea	Returned Images	Recall (%)	Precision (%)
obj1__0	14	18,05	92
obj2__0	14	19,44	100
obj3__0	14	18,05	92
obj4__0	14	19,44	100
obj5__0	14	19,44	100
obj6__0	14	19,44	100
obj17__0	14	18,05	92
obj39__0	2	2,77	100
obj43__0	14	19,44	100
obj45__0	14	19,44	100
obj46__0	14	18,05	92
obj50__0	14	19,44	100
obj58__0	14	16,66	85
obj59__0	14	19,44	100
obj63__0	11	15,27	100
obj74__0	14	18,05	92
obj79__0	14	19,44	100
obj83__0	14	19,44	100
obj84__0	14	19,44	100
obj86__0	14	19,44	100
obj92__0	14	19,44	100
obj93__0	14	9,72	50
obj95__0	14	19,44	100
obj96__0	14	18,05	92
		Average Recall (%)	**Average Precision (%)**
		17,70	**95,29**

Table 1. The Average Precision and Recall

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Method	Average Precision (%)	Average Recall (%)
Elasnaoui [18]	85	16,66
Elasnaoui [19]	92	18,05
RedNew [21]	60	16.25
IRWC [21]	92,5	31
GCBA[22]	90.92	63.14
Transform based Haar [23]	68.84	68.84
Cluster based using LBG Algorithm [23]	85.55	85.55
Proposed method	**96,11**	18,31

Table 2. Average Precision And Recall For Different Methods

Database	$SIFT_{BoW}$[24]	$IFFS_{BoW}$[24]	$IFFS_{GBR}$[24]	Proposed method
Coil - 100	28	37	1555	**3.812**

Table 3. Response time in seconds

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