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AN EFFICIENT CONTENT BASED IMAGE RETRIEVAL METHOD FOR RETRIEVING IMAGES

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Abstract. *Quality, efficiency and scalability are the key issues in the design of image retrieval systems for large image databases. Although the quality of image retrieval methods still depends strongly on the application domain, color based retrieval techniques have been shown to be competitive and generally applicable. However, the retrieval algorithms based on color histograms largely ignore spatial information in the matching process. In this paper, we propose a technique to improve the retrieval process by image regions matching. We carried out an experiment on an image database containing 8000 images. The experimental results show that our proposed technique is more effective than the other retrieval techniques such as color histogram based and Color Based Clustering based techniques.*

Keywords: Content based image retrieval, Image retrieval, Color histogram

1. **Introduction.** Content-based image and video retrieval has become an important research topic in recent years. Research interest in this field has escalated because of the proliferation of video and image data in digital form. The growing popularity of the Internet, the introduction of new consumer products for digital image and video creation, and the emergence of digital standards for television broadcasting have resulted in a greater demand for efficient storage and retrieval of multimedia data. Therefore, developing an effective and efficient image retrieval method to manage the image data is necessary.

The traditional way of retrieving images is by manually annotated keywords (text-based). There are two main disadvantages. First, it is labor-intensive and therefore, time-consuming and expensive. Secondly, the rich semantics of an image is difficult to be precisely described and different people may describe the same image in different ways [1,2,5-7,36,37]. To overcome the drawbacks of the text-based approach, the content-based image retrieval (CBIR) approach that tries to retrieve images directly and automatically based on their visual contents such as color, texture and shape was proposed [1,2,24-26]. In a typical content-based image retrieval system, the query pattern is query by example, which searches the top N images similar to an example image. Before the retrieval, the visual features are extracted from all images in an image database offline. During the retrieval, the visual features of the example image are compared with those of all images in the image database and the top N images are returned as the query result [1,2,25,26].

Current content based image retrieval techniques are divided into three categories: color, texture and shape. Shape information of images is used for special image retrieval systems. Color and texture based retrieval techniques are used for universal and quite automatic systems.

Retrieval methods based on color features are a promising track [19,20] to provide for the required functionality. However, the retrieval techniques based on color histograms largely ignore spatial information in the matching process. At best, a query can be specified in terms of color percentages or the user has to outline objects as part of entering the image into the database. Then color histograms for the sub objects can be used in the retrieval process. In both cases, this leads to a high percentage of false hits. Many research results suggested that using color layout (both color feature and spatial relations) is a better solution to image retrieval. To extend the global color feature to a local one, a natural approach is to divide the whole image into blocks and extract color features from each of the blocks [27,28]. A variation of this approach is the quadtree-based color layout approach [29], where the entire image was split into a quadtree structure and each tree branch had its own histogram to describe its color content. Although conceptually simple, this regular block-based approach cannot provide accurate local color feature and is computation and storage-expensive. This shortcoming was shown by the following example [30].

The paper presents an image matching technique that is used to overcome the above shortcomings. The technique finds a best match for retrieving images using both spatial information and color feature. The input to the query engine is a representative sample of the desired answer set. The system extracts color and spatial information from this example and returns a list of matching images sorted by similarity.

The rest of the paper is organized as follows. In Section 2, some issues about content based image retrieval and related works are presented. In Section 3, we will deal with a technique for comparing images using both the spatial information color feature of images to facilitate the retrieval process. Section 4 describes the architecture of our proposed region-based image retrieval system. The experimental results are carried out on a database of 8000 images are presented in Section 5. Finally, we provide the conclusion and future work in Section 6.

2. **Related Works.** In this section, we deal with some techniques of content-based image retrieval. Kuo [33] adapted a statistical method to analyze the distribution of the pixel colors of each bin in the color histogram of an image. First, this method uses k-means algorithm [31,32] to group the pixels of all the database images into k clusters according to their similarities by colors. It employs the mean of all the pixel colors in a cluster as the center of gravity in this cluster. Here, each cluster corresponds to one bin in a color histogram.

The approach proposed by Guibas et al. [38], decomposes images using a fixed quadtree [44]. In Leung and Ng's approach [39], each image has a 4-level multi-resolution representation. At the first level, the image is represented by a single color histogram. In the second level, the image is divided into four non-overlapping blocks, each one represented by one color histogram. In the next levels, each block is successively divided into four new blocks. The idea is the same as the in quadtree-based approaches. The work of Sebe et al. [42] decomposes images into three levels. The first level is the whole image itself. The second level is a 3×3 grid and the third level is a 5×5 grid. This decomposition results in 34 regions plus the image (level 1). The regions in this approach are of different sizes (according to their level) and overlap in different levels. The approach of Malki et al. [41] is similar to the previous approach: they use a quadtree of three levels to decompose an image. The idea of hierarchical partitioning of images has also been proposed by Lin [40], where a three-dimensional hash table was used for efficient indexing of images. Color-WISE approach [43] uses a fixed image partitioning scheme which allows overlapping blocks.

Spatial grids partition the images from space into equally sized blocks, where each block corresponds to a spatial portion of the image. The QBIC system [47] decompose an image using two approaches: partition-based and region-based. The partition-based approach is similar to the method described in [48]. The images are divided into a 6×8 or a 9×12 grid of cells. The region-based approach uses an approximate segmentation of each image into a hierarchical set of colored rectangles. Sciascio et al. [49] also uses a 4×4 grid to partition the images. Androutsos et al. [45] uses color segmentation, in the HSV color-space, to extract regions of prominent color. The approach presented by Appas et al. [46] decomposes an image into five regions (the center and the four corners).

The image retrieval system [7] is based on color feature. The document [8,9] shows image retrieval method based on shapes of objects in the images. The color-pair matching technique compares positions of corresponding pixels in two images. Although, this technique concentrated on image's spatial information, it matches images with equal sizes. This technique take image's spatial information into account but it only works on images of the same size and proves better histogram method.

Owing to issues inherent that in pattern matching, matching global characterizations used to retrieve image. Beside of using a global color attributes such as unique basic of retrieval [10], techniques combining attributes were investigated. Niblack [11] implemented systems to use color features, texture, and shape of images for retrieval.

Global characteristic features based image retrieval techniques are restricted because they do not use spatial information. Wang [12] proposed a method that uses spatial features for matching images and this method is stable with the rotation and the transition of objects.

A technique of color-pair matching to model different contour of objects of an image was proposed by A. Nagasaka et al., Y. Tanaka [5] and improved by Chua et al. [6]. Fields related to model objects in images is research on image-segmented techniques.

Image segmentation used for detecting homogeneous areas of the image. The most of current techniques already to implement image segmentation technique that involve filling region according to histogram [13], clustering space [15] and splitting/merging [16].

3. **Proposed Technique.**

Color plays a very important role in image retrieval, but it is not enough to define an image. For example, we consider two images, their composition is similarity but their palettes are different. If the retrieval is based only on color, these images are different, otherwise they are similarity. Therefore, we can consider that the combining of spatial and color features are very necessary.

3.1. **Motivation.**

Human eyes are sensitive to large color patches [17,18]. Two images are similarity, if they contain similar patches with correspondence positions of two images. Therefore, two images in Figure 1 are similarity, because they contain regions with similar color positions. A color can be selected, if its frequency is excess a given tolerance.

In order to calculate color content, they use color histogram. Histogram H (Img, i) of an image can be estimated as a number of pixels with the same color i. During the constructing color histogram, histogram $\mathrm{H}_{\mathrm{Img}}$ represents color compositions of whole image. After that, color histogram is resorted by frequency of each color.

Denote $\mathrm{OH}_{\mathrm{Img}}$, T_c be a color histogram $\mathrm{H}_{\mathrm{Img}}$ that is arranged descending order of frequency of its colors and number of selected colors respectively.

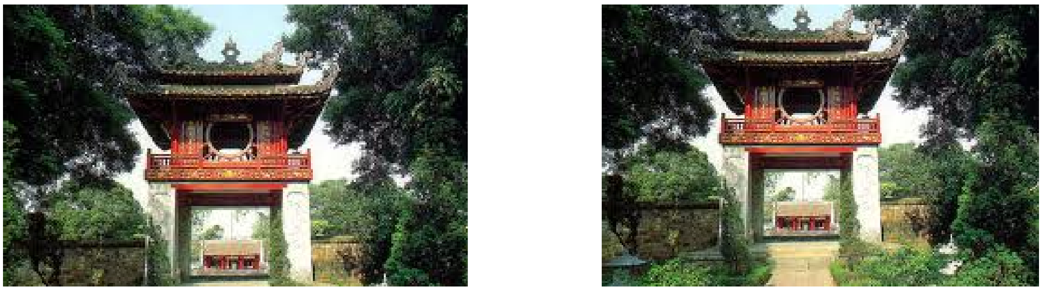

Figure 1. Similarity images

3.2. **Spatial features.** Depending on color we perform extracting spatial information features that are used for estimating a similarity of images.

3.2.1. *Color quantization.* In this section, we will deal with an algorithm extracting spatial information of any given color. This algorithm is based on histogram equalization method [14].

Let us consider a data represented by n variables $(X_1, X_2, \ldots, X_n)$. A process determining k points on each axis of an n dimension space defines separating k^n. These points partition the space into k^n cells $BR = \{BR_i | i = 1, 2, \ldots, k^n\}$, where the projection of BR_i into jth axis determine an interval $I_{i(j)}$ on X_j $(1 \leq j \leq n)$.

Given a probability distribution function P on the n-dimensional space, the process partitioning P into $P(BR_i)$, $i = 1, 2, \ldots, k^n$ and probability distribution is determined by the following formulation:

$$\tau = \begin{pmatrix} BR_i \\ P(BR_i) \end{pmatrix}, \quad i = 1, 2, \ldots, k^n$$

where P is partitioned by histogram equalization technique [14].

Denote $h(g)$, $t(g)$ be a histogram of gray g of an image and total number of pixel which gray value is not greater than g respectively.

Denote N, level be a number of equalization pixels and number of gray level needed for equalizing.

Thus, in each gray group includes N/level. Therefore, we easy define an equalization function $f(g) = \text{round}(t(g) * \text{level}/\text{N})$.

3.2.2. *Extracting spatial feature.* We apply the algorithm of histogram equalization for clustering selected colors. With each selected color, the algorithm is applied with an image space according to axis's x and y. The result of the algorithm is a set of regions with each color. It is very simple, because the region BR_i is represented by space of rectangle $(x^i_{tl}, y^i_{tl}, x^i_{br}, y^i_{br})$. This algorithm is described as follows: Firstly, whole image is considered as a region. In the first step, image can be split into two regions depending on the value of cost function $Cost(BR_i)$ and clustering color using histogram equalization technique. With each region, a split criterion is used to determine whether a region is split. If the observations fall into the significant deviation compared with the expected frequency, the region is continuously needed, with each region need to determine the value of cost function $Cost(BR_i)$ to determine region BR_i partitioning according to horizontal or vertical direction. Expect frequency is calculated by experience of pattern distribution. If observation patterns is excess the expect frequency, the partition needs to be continued and with each region need to determine the value of cost function.

The algorithm based on knowledge of distribution depends on an experience expert will can estimate expect frequency is described as below.

Deviation between an observation i and expect frequency can be estimated by the following formulation.

$$DX = \frac{obs(i) - \exp(i)}{\sqrt{\exp(i)}}.$$

If DX is excess the threshold E, the region is not stored for next partition. Otherwise, current region will be added to stack for next partition. The process of partition is repeated until the following conditions are satisfied: all of cells are homogeneous regions or number of samples in a cell is less than a given threshold.

The value $Cost(BR_i)$ is calculated as follows.

$$Cost(BR_i) = Max(DX_{selectedrow}, DX_{selectedcol}),$$

Let $DX_{selectedrow}$, $DX_{selectedcol}$ denote the expected frequency count in row *selectedrow* or column *selectedcol* respectively, where

$$DX_{selectedrow} = Max(DX_{toprow}, DX_{bottomrow}).$$

Let DX_{toprow} and $DX_{bottomrow}$ denote the expected frequency count in row *toprow* and *bottomrow* according to top-down/bottom-up directions and these values are calculated by below formula:

$$DX_{toprow} = \frac{obs_{toprow}(i) - \exp_{toprow}(i)}{\sqrt{\exp_{toprow}(i)}},$$

$$DX_{bottomrow} = \frac{obs_{bottomrow}(i) - \exp_{bottomrow}(i)}{\sqrt{\exp_{bottomrow}(i)}},$$

$$DX_{selectedcol} = Max(DX_{leftcol}, DX_{rightcol}).$$

Let $DX_{leftcol}$, $DX_{rightcol}$ denote the expected frequency count in row *leftcol/rightcol* according to left-right/right-left directions and these values are calculated by the following formula:

$$DX_{leftcol} = \frac{obs_{leftcol}(i) - \exp_{leftcol}(i)}{\sqrt{\exp_{leftcol}(i)}},$$

$$DX_{rightcol} = \frac{obs_{rightcol}(i) - \exp_{rightcol}(i)}{\sqrt{\exp_{rightcol}(i)}}$$

If $Cost(BR_i) = DX_{selectedrow}$, then BR_i is partitioned by vertical. Otherwise, if $Cost(BR_i) = DX_{selectedcol}$ is partitioned by horizontal.

Below, we present algorithm extracting color and spatial feature, called the **SCF** (Spatial-Color Feature).

In the algorithm **SCF**, there are three parameters *minarea, Cost(BR$_i$)* and E, where *minarea* is minnimun area of a region. If area of a region is less than *minarea*, the region is not used for next partition. If $Cost(BR_i) = DX_{selectedrow}$, this region is partitioned by vertical. Otherwise, if $Cost(BR_i) = DX_{selectedcol}$, the region is partitioned by horizontal. E is accepted noise threshold of each region. The result of this algorithm is set of regions of the image that is represented by a list $\langle (c_1; br_1), (c_2; br_2), \ldots, (c_n; br_n) \rangle$, where c_i is the selected color and br_i is a set of regions of color c_i. Each br_i is a list of $\langle (x^1_{tl}, y^1_{tl}, x^1_{br}, y^1_{br}); \ldots; (x^n_{tl}, y^n_{tl}, x^n_{br}, y^n_{br}) \rangle$. Let $(x^i_{tl}, y^i_{tl}, x^i_{br}, y^i_{br})$ denote a rectangle with (x^i_{tl}, y^i_{tl}) and (x^i_{br}, y^i_{br}) coordinates of top left corner and right bottom of the rectangle respectively.

Algorithm SCF

Input:
- *Img* - image ,
- *minarea* - threshold of area of an region,
- *E* - threshold of noise.

Output:
- *C* - Color information,
- *BR* - spatial information of Img.

1. Stack ← Img
2. do
   2.1 BR ← Stack
   2.2 If (area (BR) > minarea)
      2.2.1 Split BR into 2 regions $\{BR_j\}$, j=1,2 by the horizontal or vertical depending on the cost function value Cost(BR)=Max($D_{selectedrow}$, $D_{selectedcol}$).
      2.2.2 for each BR_j
         - calculate $DX = \frac{obs(j) - \exp(j)}{\sqrt{\exp(j)}}$
         - If (DX < E) Stack ← BR_j
         - else output (C_i, BR_j)
   2.3 else delete(BR)
3. while (Stack # ∅)

1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	0	0	1	1	1
1	1	1	0	0	1	1	1	1	1
1	1	1	0	0	1	0	0	1	1
1	1	1	0	0	1	0	0	1	1
1	1	1	0	0	1	0	0	1	1
1	1	1	1	0	1	1	1	1	1
1	1	1	1	0	1	1	1	1	1
1	1	1	1	0	1	1	1	1	1

Figure 2. Image I with size of 10×10 pixels

Example 3.1. *Figure 2 shows an image of* 10×10 *pixels.*

In this example, the image I in Figure 2 is split into two regions in the horizontal direction from left to right as shown in Figure 3.

The image I is split into two regions BR_1 *and* BR_2 *as shown in Figure 3 because of the value of deviation by column* $DX_{selectedcol}$ *greater than the value of deviation by row* $DX_{selectedrow}$. *In addition, the value of* $DX_{selectedcol}$ *is maximum on column 3 from left to right. Therefore, homogeneous score of the region* BR_1 *(include column 1, column 2 and column 3) is highest (see Table 1 and Table 2).*

1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1

(a) Region BR_1

1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	0	0	1	1	1
0	0	1	1	1	1	1
0	0	1	0	0	1	1
0	0	1	0	0	1	1
0	0	1	0	0	1	1
1	0	1	1	1	1	1
1	0	1	1	1	1	1
1	0	1	1	1	1	1

(b) Region BR_2

FIGURE 3. Image I after being split into two regions BR_1 and BR_2

TABLE 1. Computing the deviation $DX_{selectedrow}$ for row based partition of image I

Row	Frequency	Frequency total (row)	Frequency total from row + 1	Above block average (row)	Remain part	DX_{toprow}	$DX_{bottomrow}$	$Max(DX_{toprow}, DX_{bottomrow})$	$DX_{selectedrow}$
1	10	10	71	9	81	0.33	−1.11	0.33	0.47
2	10	20	61	18	72	0.47	−1.3	0.47	
3	8	28	53	27	63	0.19	−1.26	0.19	
4	8	36	45	36	54	0	−1.22	0	
5	6	42	39	45	45	−0.45	−0.89	−0.45	
6	6	48	33	54	36	−0.82	−0.5	−0.5	
7	6	54	27	63	27	−1.13	0	0	
8	9	63	18	72	18	−1.06	0	0	
9	9	72	9	81	9	−1	0	0	
10	9	81	0	90	0	−0.95			

TABLE 2. Computing deviation $DX_{selectedcol}$ for column based partition of image I

Column	Frequency	Frequency total (column)	Frequency total from (column + 1)	Left block average (column)	Remain part	$DX_{leftcol}$	$DX_{rightcol}$	$Max(DX_{leftcol}, DX_{rightcol})$	$DX_{selectedcol}$
1	10	10	71	9	81	0.33	−1.11	0.33	0.58
2	10	20	61	18	72	0.47	−1.3	0.47	
3	10	30	51	27	63	0.58	−1.51	0.58	
4	6	36	45	36	54	0	−1.22	0	
5	3	39	42	45	45	−0.89	−0.45	−0.45	
6	9	48	33	54	36	−0.82	−0.5	−0.5	
7	6	54	27	63	27	−1.13	0	0	
8	7	61	20	72	18	−1.3	0.47	0.47	
9	10	71	10	81	9	−1.11	0.33	0.33	
10	10	81	0	90	0	−0.95			

3.3. **Similarity measurement.** In this section, we use color feature and spatial information to calculate similarity index between two images Img_1 and Img_2. Let $C(i,k)$ denote ith cluster of kth color. Similarity measurement between two images Img_1 and Img_2 are determined as following function:

Function DRC

Input: T_c - the total number of colors of color set
R_{Img_1} - the number of regions of image Img_1
R_{Img_2} - the number of regions of image Img_2
Output : dist – distance between two images Img_1 and Img_2

1.dist←0;
2. for k←1 to T_c do
2.1 for i←1 to T_k^{g1} do
2.1.1 for j←1 to T_k^{g2} do
if $(R_{Img_1}(i,k) \cap R_{Img_2}(j,k))$ then
dist+←$| R_{Img_1}(i,k) \cap R_{Img_2}(j,k) |$
3. Return dist

where T_c is total number of colors of color set, T_k^{g1} is number of clusters of color k of the image Img_1, T_k^{g2} is number of clusters of color k of the image Img_2.

4. **Architecture of System.** Figure 4 shows architecture of our proposed image retrieval system. The system consists of two main modules: pre-processing and retrieval module. The pre-processing subsystem is responsible for extracting appropriate features from images and storing them into the image database. This process is performed offline. The retrieval module, intern, is constructed as follows: the interface allows a user to specify a query by means of a query pattern and to visualize the retrieved similar images. The retrieval module extracts a feature vector from a query pattern and applies a metric as the Euclidean distance to evaluate the similarity between the query image and the database images. Next, it ranks the database images in a decreasing order of similarity to the query image and forwards the most similar images to the interface module.

Figure 5 shows the interface of a query.

5. **Experiments.**

5.1. **Experimental environment.** The retrieval performance was evaluated using a test database of 8000 images. This image database will be used to reflect effectiveness of technique. The images with 25 colors and size of 128×85 pixels were downloaded from url: http://www-db.stanford.edu/∼wangz/image.vary.jpg.tar.

5.2. **Experimental results.** In order to verify the effectiveness of searching technique, three queries were carried out and each query is used with three methods **SCF**, **QT**, **CBC**.

Our experiment used the following parameters *minarea* and E, where $minarea = 36$ and $E = 0.39$.

The method based on probability distribution experiment was used to calculate DX.

Retrieval results were estimated by a Precision-Recall graph [21].

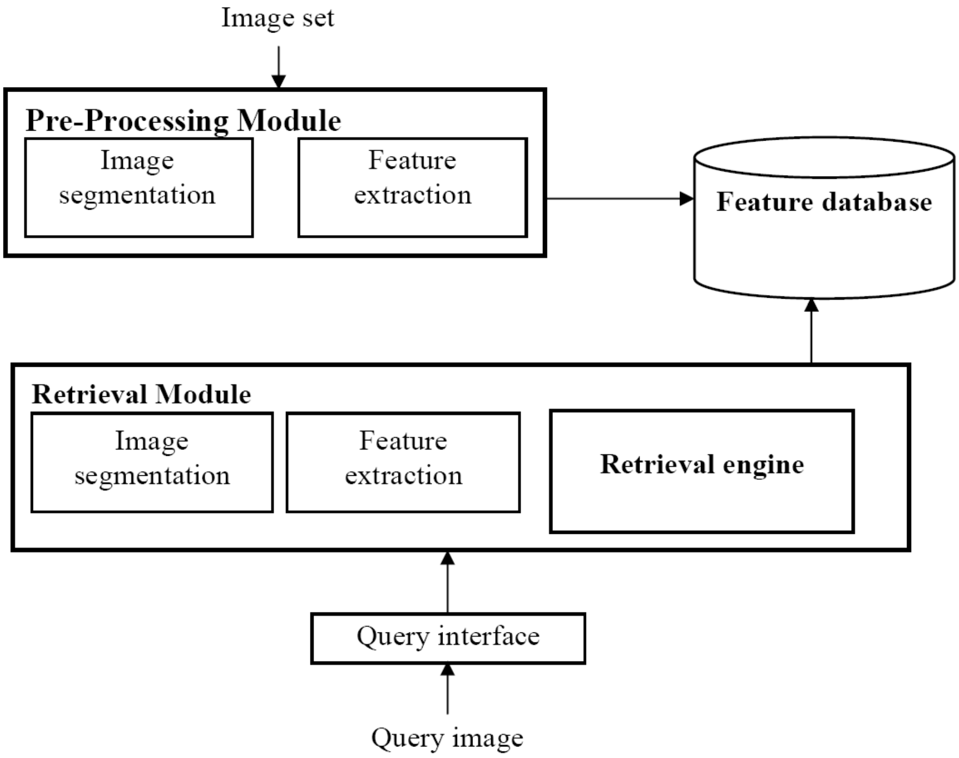

FIGURE 4. Architecture of the proposed system

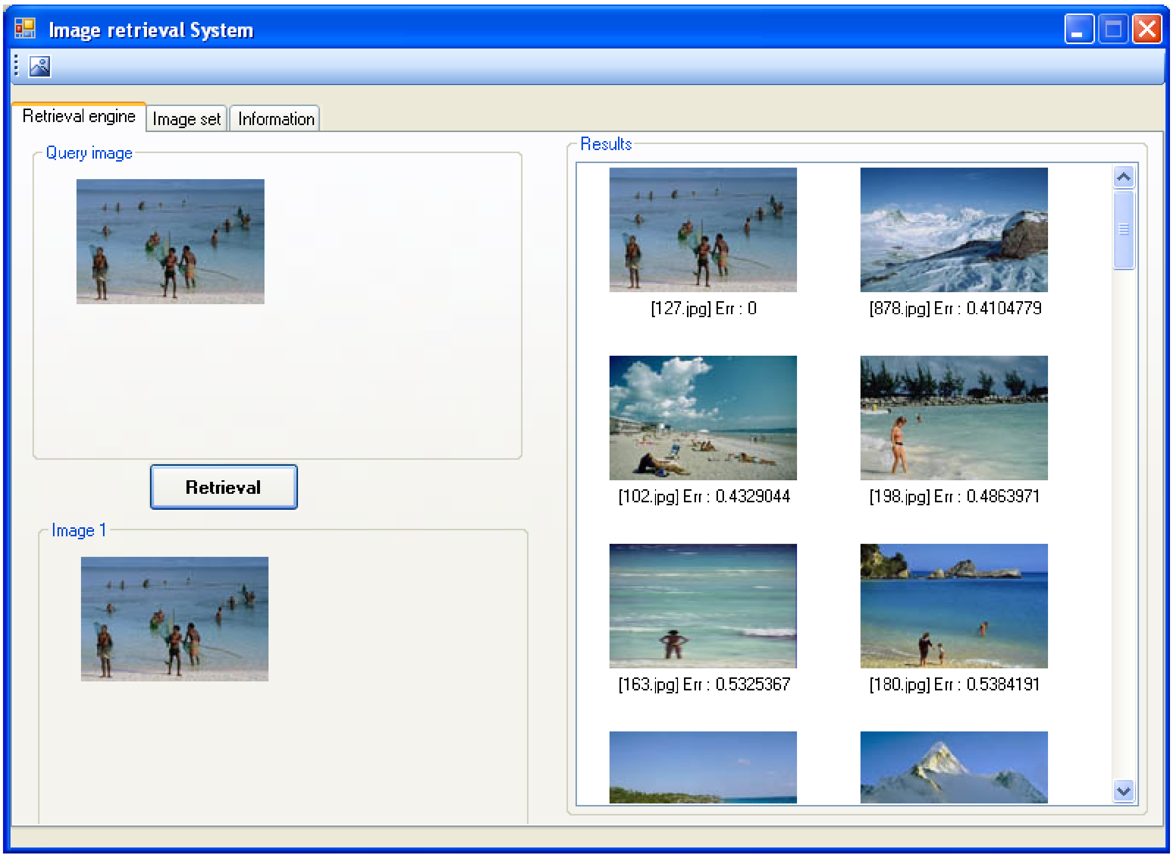

FIGURE 5. Interface of query 1

Let R denote a set of images related to image database, A denotes a set of relevance images extracted from image database, and R_A denotes a set of relevance images from A (see Figure 6).

$$recall = \frac{area(R_A)}{area(R)},$$

$$precision = \frac{area(R_A)}{area(A)}$$

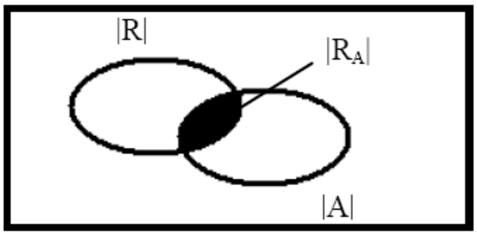

Figure 6. Precision and recall for query results

If there are many queries, we can estimate the average precision of all queries:

$$precision_{avg}(l) = \sum_{i=1}^{|Q|} \frac{precision_i(l)}{|Q|}$$

where $precision_{avg}(l)$ is the average precision with gray l, $precision_i(l)$ is the precision of query i at the level l, and $|Q|$ is a number of queries.

Tables 3-6 give the summary of the results of query 1, 2, 3, 4 respectively. The results of retrieval are summarized in terms of recall and precision. For each query, three experiments are performed. In the first experiment, the SCF technique is used for the retrieval process. The QT technique [34] is used in the second experiment and CBC [35] is used in the final experiment.

Figure 7 shows that the result of the **SCF** technique is better than the **QT**, **CBC** techniques.

Table 3. Results of query 1

Recall	***Precision***		
	SCF	***QT***	***CBC***
0.1	0.92	0.91	0.91
0.2	0.91	0.67	0.83
0.3	0.74	0.58	0.72
0.4	0.7	0.49	0.68
0.5	0.45	0.47	0.49
0.6	0.53	0.31	0.48
0.7	0.44	0.29	0.34
0.8	0.42	0.15	0.36
0.9	0.39	0.14	0.26
1	0.08	0.03	0.07

TABLE 4. Results of query 2

Recall	***Precision***		
	SCF	***QT***	***CBC***
0.1	0.87	0.83	0.86
0.2	0.84	0.67	0.71
0.3	0.69	0.57	0.52
0.4	0.65	0.54	0.5
0.5	0.42	0.52	0.42
0.6	0.48	0.36	0.34
0.7	0.39	0.35	0.29
0.8	0.37	0.25	0.27
0.9	0.34	0.24	0.21
1	0.03	0.13	0.15

TABLE 5. Results of query 3

Recall	***Precision***		
	SCF	***QT***	***CBC***
0.1	0.88	0.97	0.87
0.2	0.81	0.69	0.81
0.3	0.7	0.58	0.7
0.4	0.66	0.52	0.65
0.5	0.47	0.49	0.49
0.6	0.49	0.43	0.47
0.7	0.4	0.45	0.34
0.8	0.38	0.31	0.31
0.9	0.35	0.29	0.27
1	0.05	0.06	0.05

TABLE 6. Results of query 4

Recall	***Precision***		
	SCF	***QT***	***CBC***
0.1	0.95	0.92	0.9
0.2	0.89	0.68	0.86
0.3	0.75	0.59	0.73
0.4	0.73	0.51	0.71
0.5	0.54	0.46	0.48
0.6	0.59	0.32	0.51
0.7	0.51	0.33	0.38
0.8	0.47	0.19	0.39
0.9	0.39	0.15	0.26
1	0.08	0.05	0.08

6. **Conclusion and Future Work.** In this paper, we have proposed a technique of spatial feature and color feature based image retrieval, called the **SCF**. The technique compares images through employ both the color feature and spatial of images to facilitate the retrieval process. Our experimental results on an image database of 8000 images

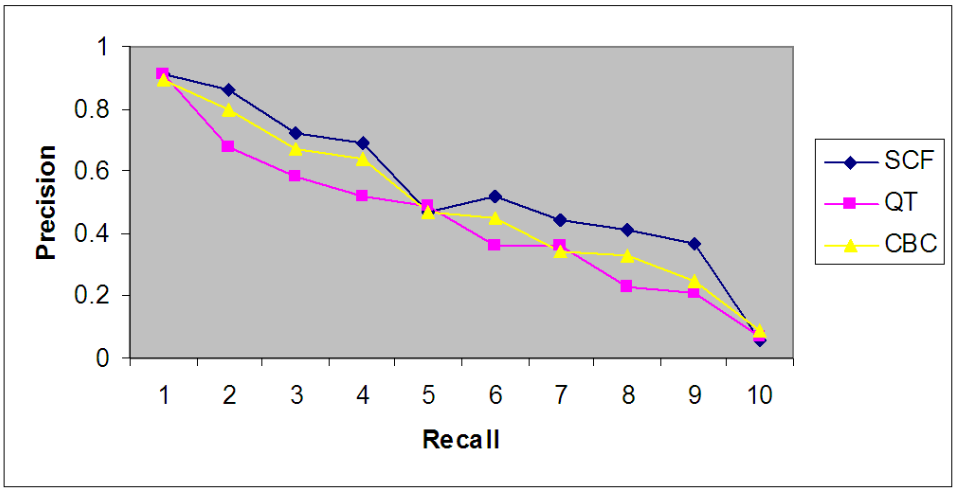

FIGURE 7. Comparing precision-recall of SCF with QT and CBC techniques

demonstrated the effectiveness of the proposed technique in terms of normalized recall and precision.

In future, we will carry out experiment on different databases of images and performance indexing sets of images with different criteria.

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