Spiral Bit-string Representation of Color for Image Retrieval

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Abstract: *This paper describes a color-based image retrieval technique that uses a new representation for the color content of an image. The new representation, called Spiral Bit-string Representation, is an extension of the traditional bitmap signature representation, where the image description is performed in a spiral manner, starting from the centre of the image and moving clockwise towards the border. The major advantages of this representation are its simplicity, its suitability for retrieval of rotated and scaled images as well as for sub-image querying***.**

Keywords: *Color image retrieval, bit-string representation, rotation-invariant, scale-invariant.*

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1. Introduction

During the last decade, a new image retrieval approach, called Content-Based Image Retrieval (CBIR), emerged. In this approach, the content of an image is described using low-level features such as color, texture, and shape. Despite their advantages over the traditional text-base image retrieval systems, CBIR systems face a major problem commonly referred to as the semantic gap, whereby the description of the images using the low-level features is unable to capture the semantic intended by the user in his/her queries. Therefore, CBIR systems produce a large amount of false positives in the retrieval process. A significant improvement is obtained by integrating the spatial distribution of the visual features since it captures better the contents of the images and reduces the number of false positives.

This research work investigates efficient ways to represent and use spatial distribution of color contents in an image retrieval system. Our study of the recent research works published in the literature showed a strong need for rotation-invariant representations. We have also noticed the lack of approaches allowing image retrieval based on sub-image similarity.

2. Related Works

This section presents a review of the major color-based approaches that integrate spatial distribution information. We refer to these approaches as spatial-color-based image retrieval approaches. Chua *et al.* [10] proposed a signature-based approach where an image is represented by its major dominant colors. The dominant colors consist of the colors that have highest frequencies in the global color histogram of the image. In order to represent the spatial distribution of the colors, the image is partitioned into *m x n* cells of equal size, where each cell is assigned an index *k* in the range [1, 2, …, *n x m*]. A bit-string is assigned to each dominant color to describe its spatial distribution. A bit *k* is set to 1 if the cell number *k* contains significant number of pixels of that color. The image representation consists of the set of all the bit-strings (also called bit signatures). This method has interesting advantages when compared to traditional histogram based representations, but it is not invariant to rotation or scaling.

Jo and Um [9] produced a better result than Chua, et al's approach by proposing a signature-based method that uses two basic representations: the Dominant Color Composition (DCC) representation that describes the dominant colors found in the image, and the Dominant Color Distribution (DCD) signature that describes the spatial distribution of the dominant colors. The DCD signature consists of two bit-strings called DCD_h and DCD_v signatures. These bit-strings record the dominant colors that are found in the horizontal and vertical axis of the image. This approach can be used for the retrieval of rotated images but like Chua *et al.*'s approach, it is not suitable for retrieving scaled images.

Chitkara *et al.* [11] proposed a compact representation of the colors found in the image that takes into account both dominant and less dominant colors. The percentages of each color in the image is calculated and stored in bins that accommodate varying percentage compositions. The representation is called Variable Bin Allocation (VBA). The spatial distribution of the color information is captured by the *n x n* cells that constitute the image partition. Each cell of the image is described by a bit-string, representing its compact signature. The similarity between two images is calculated as the cumulative similarities of their respective cells. This approach is also not invariant to rotations and scaling.

Cinque *et al*. [6] approach partitions the image into *n x m* regions and represents it using a 2D coordinate system. The spatial distribution of each color is represented by the mean and the standard deviation of the pixels having that color. This approach is suitable mainly for continuous and homogeneous regions and it is not invariant to rotation and scaling.

Mohan *et al*. [8] developed a cluster-based approach for color image retrieval. The dominant colors (called color clusters) are first extracted and their spatial distribution is then described by performing a connected component labeling. Each connected component is called spatial cluster. The Euclidean distance is used for both clustering and similarity measurement process. This approach is also not invariant to rotation and scaling.

Abdesselam and Wang [1] proposed a cluster-based approach that produces better result than Mohan *et al.* approach [8]. A predefined HSV color set is constructed instead of the RGB color set. Each pixel of the image is assigned to one color among the n predefined color clusters using clustering process. The image is partitioned into *m x m* sub areas to get the spatial distribution of the color. For each sub-area, dominant cluster is then obtained to form the so called Color Cluster Distribution (CCD) image that captures the spatial distribution of the colors. The image similarity is defined by the cumulative distance between all corresponding sub-regions in each orientation. This approach is also capable of retrieving rotated images (main rotations only such as 90^o, 180^o, *etc*.) but cannot retrieve scaled images.

To summarize, different spatial-color-based image retrieval approaches have been studied, most of these approaches did not address properly the problem of retrieving rotated and scaled images neither they did address the problem of sub-image retrieval. The following section describes our approach and describes how it can be used for retrieval of rotated and scaled images as well as for sub-image retrieval.

3. Spiral Bit-string Representation of Color

3.1. Building a CCM Image

In order to extract the spiral representation of the color content, the image undergoes a labeling process that assigns every pixel in the image the closest color from a predefined color table. The output of this preprocessing is called Color Cluster Mapping image (CCM image).

3.2. Sub Area Labeling

The CCM image is then equally divided into *m x m* sub-areas and a Single Color Mapping (SCM) image is derived for each predefined color. It is an *(m x m)* binary image in which a bit is set to 1 if the corresponding sub-area contains enough pixels (more than a predefined threshold) of that predefined color. The output of this process consists of *n* Single Color Mapping (SCM) images, where n is the number of predefined colors**.**

3.3. Spiral Bit-String

The SCM images undergo the Spiral Feature Extraction process in which a bit-string signature is calculated for each SCM image (or color). The content of the corresponding Single Color Mapping image is read in a spiral manner, frame by frame, starting from the inner frame until all bits are read. Within each frame, bits are read in a clockwise manner, starting from its upper left corner. Obtained bit-string is called the Spiral Bit-string Representation of the particular Single Color Mapping image.

It is easy to show that for an SCM image of size 2^n x 2^n, there are 2^{n-1} frames and that frame k contains 8k–4 bits. The feature representation of each single color is defined as follows:

$Fc_i = \{Fr_0, Fr_1, Fr_2 \ldots\ldots Fr_n \mid n = \text{number of frames}\}$

$Fr_j = \{b^j_0, b^j_1, b^j_2 \ldots b^j_i \mid i = \textit{number of bits in the frame } Fr_j\}$

Figure 1 shows an 8x8 SCM image and its 4 frames.

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

Frame 1(inner): 0100
Frame 2: 101000100010
Frame 3: 10101001001001010000
Frame 4: 0010000000111000000011000110

Figure 1. Single Color Mapping Image of size 8x8.

4. Spiral Representation and Image Rotation

Most of existing CBIR systems are not suitable for retrieval of rotated images such as the one shown in Figure 2.

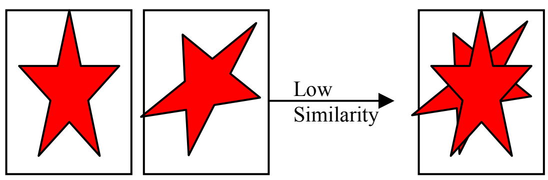


Figure 2. Example of images that produce low similarity measure in most existing CBIR systems.

In our approach, the bit-string of a rotated image is derived from the original bit-string by just right shifting the different frames. The number of bits to be shifted depends on the rotation angle and the frame position.

It can be easily shown that shifting by 1 bit frame *k* has an effect of rotating that frame by an angle of □/(2k–1) degrees which means that we need to shift frame k by (2k-1)/90 bits to get 1 degree rotation. Therefore, rotating an image by □ degrees will have an effect of shifting frame *k* by *Ceil((2k-1)*□/90), Ceil(x)* function calculates the ceiling of the real value *x*. For efficiency reasons, we use a lookup table that indicates the relationship between the number of bits to be shifted, the frame number and the rotation angle. Table 1 shows an example of lookup table for an 8x8 SCM image (4 frames). We can read from the table that to obtain a 90-degree rotation on an 8x8 SCM image, we need to shift: Frame1 (inner) by 1 bit, Frame2 by 3 bits Frame 3 by 5 bits, and Frame 4 by 7 bits.

Table 1. Lookup table for an 8x8 SCM.

	Frame number (k)			
Rotation	**1**	**2**	**3**	**4**
30	0	1	2	2
60	1	2	3	5
90	1	3	5	7
120	1	4	7	9
150	2	5	8	12
180	2	6	10	14
210	2	7	12	16
240	3	8	13	19
270	3	9	15	21
300	3	10	17	23
330	4	11	18	26

Figure 3 shows an SCM image and corresponding spiral bit-string resulting from a 90-degree rotation of the image.

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

Original SCM Image
Frame 1(inner). 0100
Frame 2. 101000100010
Frame 3. 10101001001001010000
Frame 4. 0010000000111000000011000110

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

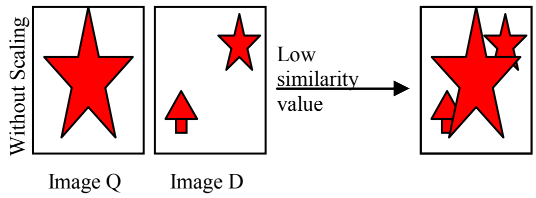
Rotated Image
Frame 1(inner). 0010
Frame 2. 010101000100
Frame 3. 10000101010010010010
Frame 4. 1000110001000000011100000001

Figure 3. Deriving rotated spatial feature from the original SCM.

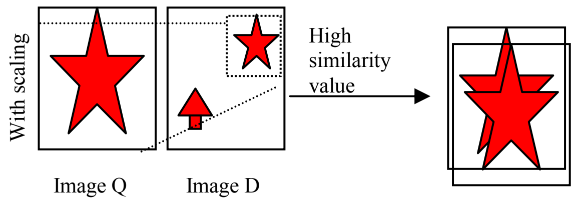
The rotation resolution (i.e. the number of rotations that can be considered) depends on the resolution of the SCM images (i.e. the size of the SCM images) which is the result of image partitioning process. The highest rotation resolution we can obtain for an 2^n x 2^n SCM image is $90/(2^n$-1). In the example shown in Figure 3, n=8 and the highest resolution is therefore 13 degrees.

5. Spiral Representation and Image Scaling

Most of the existing CBIR systems estimate similarity between whole images. They do not take into account cases where the query image is a sub-image of a database image. As shows in Figure 4.



(a) Whole image similarity measurement between these two images will be very low.



(b) Similarity measurement between image Q and one of the partial images of D will produce a higher score.

Figure 4. Example of sub-image retrieval.

In order to handle this kind of queries, database images are described at different levels of resolutions (different partitioning) 2^n x 2^n, 2^{n+1} x 2^{n+1}, 2^{n+2} x 2^{n+2}, *etc*. A query SCM image of size 2^n x 2^n will be compared with 2^n x 2^n partial SCM database images extracted from larger SCM images of sizes 2^{n+1} x 2^{n+1}, 2^{n+2} x 2^{n+2}, *etc*. This allows retrieval of similar images of different scales (1/4x, 1/16x, *etc*.). There are (*p-n+1*) x (*p-n+1*) sub-images of size *n x n* to compare with in an image of size *p x p* (p>=n).

In our experimentation, query SCM images are of size 8x8 and the database SCM images are of three levels of resolution 8x8, 16x16 and 32x32. This allows retrieval of sub-images scaled at 1x, 1/4x and 1/16x. Figure 5 shows a query image, and one of its 8x8 SCM images.

We assign to each image in the database, spiral bit-strings at three levels of scaling: the spiral representation F^1 of its 8x8 SCM image, the spiral representations $F^{1\backslash 4}_1$, $F^{1/4}_2$, … $F^{1/4}_p$ of p 8x8 sub-SCM images extracted from its 16x16 SCM image, and the spiral representations $F^{1\backslash 16}_1$, $F^{1/16}_2$, … $F^{1/16}_q$ of q 8x8 sub-SCM images extracted from its 32x32 SCM image.

As mentioned earlier, in an *(p x p)* image, we may extract (n-p+1) x (n-p+1) *n x n* sub-image, which means will have 9x9 (=81) and 25x25 (=625) 8x8 sub-images in a 16x16- and 32x32- image respectively. For efficiency purposes, we use 5x5(=25) sub-images for 1/4 scaling (we select 1 for every 2 in each direction) and 7x7 (=49) sub-images for 1/16 scaling (we select 1 for every 4 in each direction). This means that every image in the database will be assigned 75 spiral bit-strings per predefined color. Figure 6 shows a sample of 8x8 SCM images extracted from 16x16 SCM image shown in Figure 5.

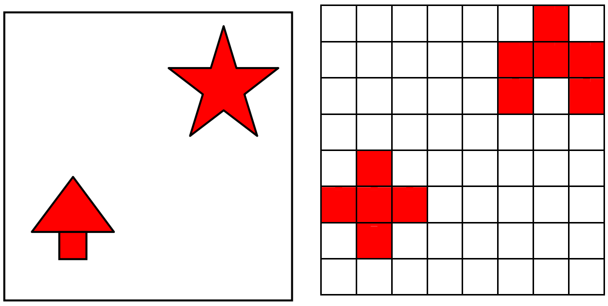


Figure 5. Sample image with red arrow and star and its red color 8x8 SCM image.

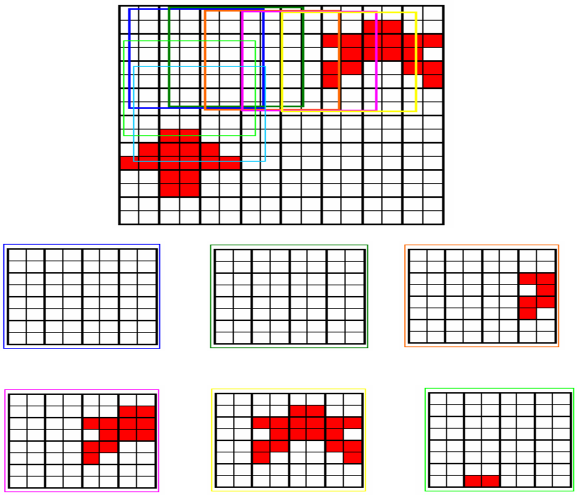


Figure 6. A sample of six 8x8 sub-images extracted from a 16x16 image.

6. Our Image Retrieval System

The diagram shown in Figure 7 describes the major modules of the spiral bit-string -based image retrieval system.

6.1. Similarity Measurement

There are two types of similarity measurements: the whole image similarity and the partial image similarity. The whole image similarity involves estimation of the degree of similarity between a query image and a database at various rotations. More explicitly, the spiral bit-string representation of a query image is compared with the spiral bit-string representation of a database image and with its shifted versions that represent various rotations of the database image.

The partial image similarity involves estimation of the degree of similarity of a query image with various sub-images extracted from the database image under consideration. For each sub-image, a set of predefined rotations is considered. More explicitly, the spiral representation of the query image is compared with the spiral representation of every sub-image extracted from the database image and with its shifted versions representing predefined rotations.

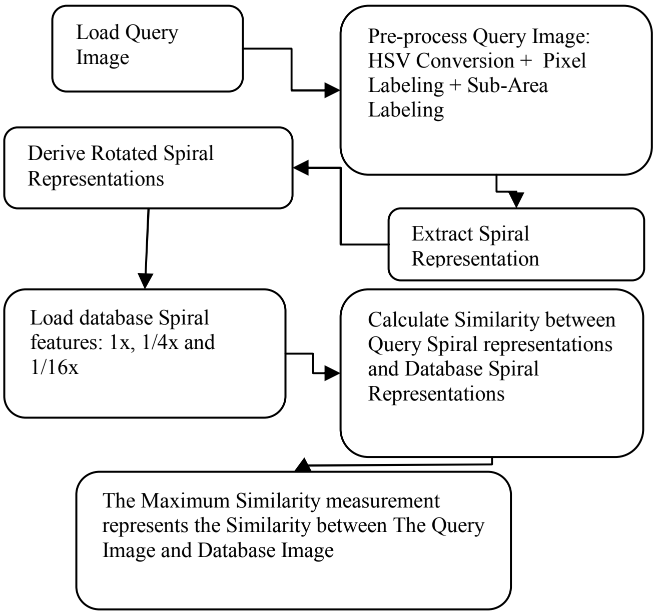


Figure 7. Major modules of the proposed image retrieval system.

6.2. Similarity Measurement Function

The similarity between a query image Q and a database image D at scale s and rotation α, for color C, $S^{s,\alpha}_c$ (Q, D) is defined by equation 1:

$$S^{s,\alpha}_{c}(Q, D)=\sum_{i=1}^{i=M}\left[\frac{Count(Sp_{Q_0^1}^{C,i}\ \overline{XOR}\ Sp_{D_\alpha^s}^{C,i})}{Count(Sp_{Q_0^1}^{C,i})}\right] \quad (1)$$

where $Sp_{Q_0^1}^{C,i}$ denotes the spiral representation of the frame i of the original query image Q for the color C, $Sp_{D_0^s}^{C,i}$ denotes the spiral representation of the frame i of the rotated database image D by angle □, for the color C, $\overline{XOR}$ denotes the bit-wise negation of the logical exclusive OR operation, Count (Sp) represents the number of 1's in the binary string Sp, and M denotes the number of frames in an image. The similarity between a query image Q and a database image D rotated by angle α, is therefore defined as the weighted average of the similarities of all colors as shown in equation 2:

$$S^{s,\alpha}(Q,D)=\sum_{c=1}^{NC} w_c S_c^{s,\alpha}(Q, D) \quad (2)$$

where NC denotes the total number of predefined colors, and w_c denotes the weight assigned to color c. In order to take into account all the predefined rotations and scales the final similarity function is defined as the maximum similarity between the image Q and all rotated versions of image D and all rotated sub-images extracted from image D at different scales. This can be defined as shown in equation 3.

$$S(Q, D)= max \{ S^{s,a}(Q,D) \} \quad (3)$$

where s is all predefined scales and a= all predefined rotations.

The image similarity ranges from 0 to 1. The value 1 indicates a perfect match of the two images.

7. Experimental Results

We designed an experimentation that tests different aspects of the prototype

7.1. Accuracy of the Similarity Function

We conducted a series of experiments to check the accuracy of the proposed similarity function. The matching function produced very good results when comparing images that represent the same scene but with different rotations or scaling. An overall accuracy of 93% was obtained, Figure 8 shows two samples of the retrieval results obtained by our system.

7.2. Accuracy of the Whole System

Nine experiments were carried out to test the accuracy and efficiency of the prototype. Each experiment involves 100 images carefully selected to address all the situations mentioned previously, i.e. retrieval of rotated, scaled images as well as retrieval of sub-images (see Table 2.).The experiments starts with the selection of a set of query images and the identification of similar images in the database (15 were identified for each query image). This phase is undertaken by a human operator. In order to obtain a quantitative estimation of the accuracy of the prototype, we used the classical retrieval accuracy function R (also known as recall-precision measure), defined by equation 4 [1, 5] .

$$R=\begin{cases} \frac{n}{N}, if\ N \le T; \\ \frac{n}{T}, otherwise \end{cases} \quad (4)$$

where n is the number of relevant images retrieved by the system, N is the total number of relevant images in the database, and T is the number of images displayed by the system. Two short-list sizes are used: T=10 and T=15.

The results of these experiments are summarized in Table 3. As shown in the table, our prototype has an average retrieval accuracy of 93%.

Table 2. Characteristics of the nine experiments.

Characteristics/ Experiments	Rotated images	Scaled images	Partial images
A	√		√
B	√	√	√
C	√	√	√
D	√	√	√
E	√		
F	√		
G	√	√	√
H	√		
I	√		√

Table 3. Retrieval efficiency obtained for each experiments when T=10 and T=15, respectively.

Experiment	T = 10	T = 15
A	10/10 = **1.00**	12/15 =**0.80**
B	10/10 = **1.00**	15/15 =**1.00**
C	10/10 = **1.00**	14/15 = **0.93**
D	10/10 = **1.00**	14/15 = **1.00**
E	10/10 = **1.00**	15/15 =**1.00**
F	10/10 = **1.00**	15/15 =**1.00**
G	10/10 = **1.00**	13/15 = **0.87**
H	10/10 = **1.00**	15/15 = **1.00**
I	10/10 = **1.00**	12/15=**0.80**
Average	**1.00**	**0.93**

7.3. Retrieval Efficiency of the Whole System

The prototype was written in Microsoft Visual Basic 6.0 and implemented on a 1.0 GHz Pentium-based PC with 256 MB memory. We used Microsoft Access to build the image database system. Obviously, two parameters affect directly the retrieval time: the image size and the number of color clusters. The results we obtained on the nine series of images were recorded in Table 4 and Table 5.

Table 4. Influence of the image size on the retrieval time.

Image Size	Time per Image (seconds)			
	Whole-Image Matching		Partial-Image Matching	
	Basic	Rotation	¼x scaling	1/16 x Scaling
32x32	<1	<1	6	9
64x64	1	1	7	10
128x128	3	3	8	12

Table 5. Influence of the number of color clusters on the retrieval time.

Number of Color Clusters	Time per Image (seconds)			
	Whole-Image Matching		Partial-Image Matching	
	Basic	Rotation	¼x Scaling	1/16 x Scaling
8	3	3	8	12
10	4	4	9	14
12	5	5	12	23
16	5	5	14	26

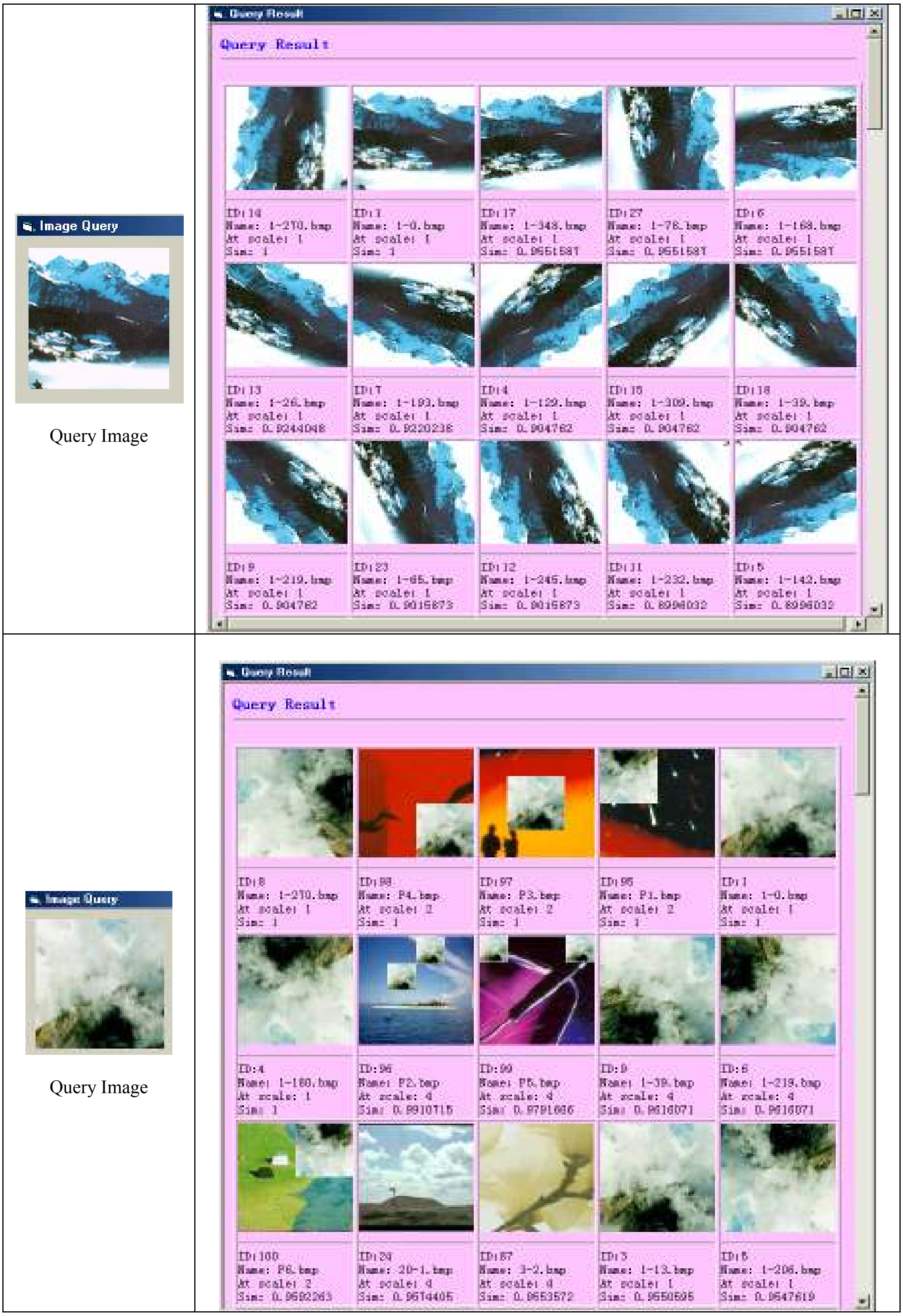


Figure 8. Samples of retrieval results obtained by our system

These tables show clearly that the incorporation of rotation detection to the prototype did not increase significantly the retrieval time. The tables also show that detection of scaled images is sensibly more expensive especially when it is applied to detect sub-images. The ½x scaling matching takes in average 28% more time than the whole-image matching and ¼x scaling matching, takes in average about 17% more time than ½x scaling matching.

8. Conclusions

In this paper, we have presented a new representation: Spiral Bit-string Representation of Color (SBRC). SBRC allows capturing the color information of an image as well as its spatial distribution. We used this representation to build an approach that has the ability to retrieve rotated images as well as scaled images. We have also used successfully this approach for sub-image retrieval. The results we obtained allow us to claim that our approach brings enhancements to the existing color based retrieval techniques.

Our experimentation showed that the use of SBRC in retrieving rotated images is efficient and can be easily incorporated in real-life CBIR systems but the algorithms used in sub-image retrieval need to be optimized before they can be used in real-life CBIR system.

References

[1] Abdesselam A. and Wang Y., "Color-Clustering for Image Retrieval," *in Proceedings of International Conference on Pattern Recognition and Computer Vision*, 2000.

[2] Modhaddam B., Biermann H., and Margaritis D., "Image Retrieval with Local and Spatial Querie," *in Proceedings of Mitsubishi Electric Research Laboratory*, pp. 542-545, New York University, 2000.

[3] Ooi B., Tan K., Chua T., and Hsu W., "Fast Image Retrieval Using Color-Spatial Information," *Technical Report, Department of Information Systems and Computer Science, National University of Singapore*, 1998.

[4] Yee C., Tan K., Chua T., and Ooi B., "An Empirical Study of Color-Spatial Retrieval Techniques for Large Image Database," *in Proceedings of the IEEE International Conference on Multimedia Computing and Systems*, pp. 218-221, 1998.

[5] Mehtre B., Kankanhalli M., Narasimhalu A., and Man G., "Colour Matching for Image Retrieval," *Pattern Recognition Letters*, vol. 16, no. 3, pp. 325-331, 1995.

[6] Cinque L., Levialdi S., Olsen K., and Pellicano A., "Color-Based Image Retrieval Using Spatial Chromatic Histogram," *in Proceedings of IEEE International Conference on Multimedia Computing and Systems*, pp. 969-973, 1999.

[7] Manmatha R. and Ravela S., "Retrieving Image by Appearance," *University of Massachussets*, Amherst, pp. 608-613, 1998.

[8] Kankanhalli M., Mehtre B., and Huang H., "Color and Spatial Feature for Content Based Image Retrieval," *Institute of System Science*, National University of Singapore, vol. 20, no. 1, pp. 109-118, 1999.

[9] Seongtaek J. and Kyhyun U., "A Signature Representation and Indexing Scheme of Color-Spatial Information for Similar Image Retrieval," *in Proceedings of IEEE International Conference on Multimedia Computing and Systems*, pp. 290-294, 2000.

[10] Chua T., Tan K., and Ooi B., "Fast Signatured Color-Sptial Image Retrieval," *in Proceedings of IEEE*, pp. 362-369, 1997.

[11] Chitkara V., Mario A., and Cur M., "Content-Based Image Retrieval Using Binary Signatures," *Technical Report TR00-18,* Department of Computer Science, university of Alberta, Canada, 2001.

[12] Chitkara V., "Color-Based Image Retrieval Using Compact Binary Signature," *Technical Report TR01-08*, Department of Computer Science, University of Alberta, Canada, 2001.

[13] Chung W. and Abdesselam A., "Spatial Distribution of Color Clusters for Image Retrieval," *in Proceedings of IEEE*, pp. 290-294, 2000.

[14] Abdesselam A. and Wang Y., "Using Color for Image Retrieval," *Colloquium on Research Contribution Under National Technology Action Plan*, 1998.

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