Indexing and Retrieval Scheme of the Image Database Based on Color and Spatial Relations

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ABSTRACT

We propose a new approach to retrieve images from an image database. We combine both color and spatial features of a picture to index and measure the similarity of images. We propose a new automatic indexing scheme of image database according to our clustering method, which could filter the image efficiently. As a technical contribution, a Seed-Filling like algorithm that could extract the shape and spatial relationship feature of image is proposed. Also, the system is incorporated with a visual interface, which allows the user to specify objects as the spatial specification of pictures. With color identification and spatial similarity functions, the preliminary experience shows that the system is able to retrieve image information of a very high satisfaction.

1. INTRODUCTION

Most conventional image databases are text-annotated. As a result, image retrieval is based on keyword searching. Text-annotated images are simple and easy to manipulate. However, there are two major problems with this method. First, creating keywords for a large amount of image is time consuming. Moreover, the keywords are inherently subjective and not unique. With these disadvantages, automatic indexing and retrieval based on image content becomes more desirable for developing large image retrieval applications.

Color, shape, and texture are the main features for human beings as well as computers to recognize the image. Several systems have been proposed in recent years in the research community of content-based information retrieval. QBIC is the first CBIR system actually been built [1]. It allows query by color, shape, texture, example and sketch. VisualSeek allows content-based and spatial similarity evaluations [2]. For indexing the database, Swain and Ballard [3] using histogram intersection as color indexing.

In this paper, we select the HSI color space to construct the index structure. Besides, the chromatic and spatial information of the image are retained in this paper. We proposal a fast database indexing scheme according to our clustering method based on MTM (Mathematical Transform to Munsell) for filtering out the non-similar images effectively. Then, we combine the color and spatial relationship of objects to measure the similarity of images.

Many researchers propose temporal modeling of multimedia objects. The discussion in [4] identified various temporal interaction forms and discussed their temporal dependencies. The 2D Projection Interval Relations (i.e., PIR) [5] is based on both directional and topological temporal relations. Image retrieval algorithms were discussed based on PIR. The use of spatio-temporal relations serves as a reasonable semantic tool for the underlying representation of objects in many multimedia applications. In this paper, we extend temporal interval relation by means of a complete analysis for spatial computation. Therefore our image content-based information retrieval system is developed based on color and spatial relation properties.

This rest of our paper is organized as follows. In Section 2, the color clustering and indexing scheme of image database are discussed. Shape extraction method is given in Section 3. Section 4, describes the computation of spatial similarity of values corresponding to the query object sets of images. Section 5 describes the procedure of image retrieval in our system. Finally, conclusions and the discussion of our future works are given in Section 6.

2. COLOR CLUSTERING AND INDEXING SCHEME OF IMAGE DATABASE

There are common issues underlying all color-based retrieval methods: the selection of a proper color space [6,7], and the use of a proper color quantization scheme to reduce the color resolution. In our study, HSI is the chosen color space because of its better sensibility, similarity, and accuracy compared to others.

The quantization scheme and the procedure of color clustering are showed in Figure 1. Firstly, we equally quantized the RGB color space to change color levels from 256 to 16 levels in each axis. Secondly, we convert the 16-level RGB color bins to the HSI coordinates by an MTM transformer. And, we cluster the hue to 12 levels, since hue is represented as circle and primary hues are located on the equal space at 60 degrees (Red, Yellow,

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Green, Cyan, Blue and Magenta) in the HSI color space. And, since the human visual system is more sensitive to hues as compared to saturation and intensity, the H axis should be quantized finer than S axis and I axis. In experimenting, we quantized the HSI color space into 12 bins for hue, 4 bins for saturation, and 4 bins for intensity. Finally, We normalize the resolution of all images to be 400*300.

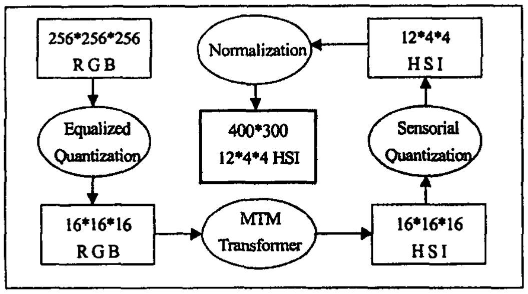


Fig.1 Procedure diagram of the color clustering and normalization

After the quantization and normalization, system will calculate the histogram and dominant colors of the image. The color histogram is an array that is computed by differentiating the colors within the images and counting the number of pixels of each color. From the color histogram, we could choose the dominant colors whose numbers of pixels exceeds the threshold.

After getting the dominant colors, we saving the image ID to each corresponding color bin. And, the logical address of length equals to 1 byte only (01000101=69) of each color bin in the database could be obtained immediately according to their hue (0100), saturation (01), and intensity (01).

3. THE EXTRACTION OF OBJECT AND SPATIAL RELATIONSHIP

In this system, We divide the image and use the Seed Filling algorithm to extract the shape feature. The procedure is described below:

Step1: Quantization and Normalization the image

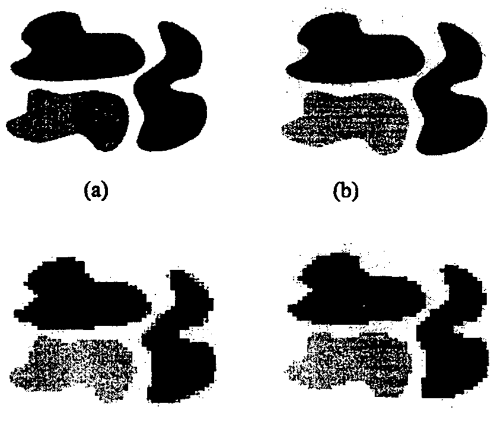
Step2: Dividing the image. We divide an image into a number of boxes on the chessboard. The size of each box is 4*4 pixels and the representative color of a box is calculated by the average color of all pixels in the HSI color space.

Step3: Filling the Seed. Starting from the upper-left corner, a box is chosen as a seed with the next box four units away both in the vertical and horizontal directions.

Step4: Extract the objects. Starting from a seed box, the program looks at the left, right, up, and down directions. And, the program tries to combine as many boxes in a region as possible, if the color similarity between the seed box and the neighbor box is within a threshold.

Step5: Refine the image. The result of front steps will contain many regions (see Figure 2c). Each region contains some boxes. We remove the scattered small regions, Because in general it is unless to retrieval the image and will decrease the performance (see Figure 2d).

Step6: Project the objects from 2-D space to two 1-D spaces and record those spatial relations of objects. Then compute the similarity on structure.



(a) (b)

(c) (d)

Fig. 2 Example of processed image (a) Original image.(b) Color clustering image. (c) Shape extraction image (d) Refined image

4. SIMILARITY FUNCTIONS OF SPATIAL RELATION

In order to recognize and identify objects, the vision system must have stored object models. In this section, we split the objects orthogonally to the coordinate axis and compute spatial relation similarity for image information retrieval. We focus on 2-D spatial relational representation to demonstrate the usefulness in the spatial domain. It is the simplest kind of spatial information of practical relevance. The 1-D spatial relation case, while different from the temporal relations, can be handled by a simple modification of temporal interval relations.

Qualitative calculus is a calculus of intervals instead of real numbers. To deal with qualitative representation, we subdivide the real number in timeline into three intervals: $[-\infty, 0]$, $[0, 0]$ and $[0, +\infty]$. We denote these three intervals by $\{<\}$, $\{=\}$ and $\{>\}$ for representing relation between two points. Qualitative variables take these values only.

Based on qualitative point relations, we use an encoding method to generalize and prove the 13 interval exclusion relations. Suppose A_s and A_e are the starting and ending points of the line segment A. And, B_s and B_e are those of B. We define a binary relation, ✧, (either <, =, or > for "*A* is before *B*", "*A* is the same as *B*", or "*A* is after *B*") of two points. The 13 *interval relations* introduced by Allen [8] make the binary relations hold in the first part of the following table:

Table 1: Starting and Ending Point Relations

As◇Bs	As◇Be	Ae◇Bs	Ae◇Be	ID	Interval Relations
<	<	<	<	1	{ < }
>	>	>	>	2	{ > }
>	<	>	<	3	{ d }
<	<	>	>	4	{ di }
<	<	>	<	5	{ o }
>	<	>	>	6	{ oi }
<	<	=	<	7	{ m }
>	=	>	>	8	{ mi }
=	<	>	<	9	{ s }
=	<	>	>	10	{ si }
>	<	>	=	11	{ f }
<	<	>	=	12	{ fi }
=	<	>	=	13	{ e }
=	=	>	>	14	{los}
<	<	=	=	15	{loe}
=	<	=	<	16	{ols}
>	=	>	=	17	{ole}
=	=	=	=	18	{oo}

The second part of the table has five special cases for *point-interval relations*. For instance, we use *A 1os B* to represent *A* is a line and *B* is a point, where *A* and *B* meets at the starting point of *A*. The situations of points of two line segments could have unto 3^4 = 81 rows in the above table. However, except for the 18 cases illustrated in Table 1, others are conflict situations (i.e., it is physically impossible for the situation to occur). For example, a relation (*As* < *Bs*, *As* < *Be*, *Ae* > *Bs*, *Ae* < *Be*) has conflict between four point relations.

Relations are similar to each other in certain degree. For example, "during" and "starts" are similar since the only difference is the starting points of the two intervals are different. However, "before" and the inverse of "meets" are not quite the same.

In Table 1, each of the 13 interval relations and 5 point-interval relations are defined by four "✧" relations. These relations can be used as a base of our evaluation criterion. Let's starts with some definitions. A *relational-distance* of two "✧" relations belong to two different temporal relations occurs if those two temporal relations hold different relations in the same column of Table 1.

Definition 4.1: A *point relation distance* (PRD) defined with respect to a point relation *r* of index *n* have *n* incompatible differences from *r*. The following table gives a definition of point relation distance:

Table 2: Point Relation Distance (PRD)

PRD	>	=	<
>	0	1	2
=	1	0	1
<	2	1	0

Definition 4.2: An extended point-interval relation distance (EPIRD) defined with respect to a point-interval or interval relation *r* of index *n* have *n* incompatible differences from *r*. Let R and R' are two interval relations or point-interval relations. The encoding point relation of R (see Table 1) is $R_{As◇Bs}$, $R_{As◇Be}$, $R_{Ae◇Bs}$, $R_{Ae◇Be}$, and the encoding point relation of R' is $R'_{As◇Bs}$, $R'_{As◇Be}$, $R'_{Ae◇Bs}$, $R'_{Ae◇Be}$. We have a *EPIRD* formula:

$$EPIRD\,(R, R') = PRD\,(R_{As◇Bs}, R'_{As◇Bs}) + PRD\,(R_{As◇Be}, R'_{As◇Be}) + PRD\,(R_{Ae◇Bs}, R'_{Ae◇Bs}) + PRD\,(R_{Ae◇Be}, R'_{Ae◇Be})$$

We derived the EPIRD Table from *EPRD* formula:

Table 3: The Extented Point-Interval Relation Distance

EPIRD	<	>	D	di	o	oi	m	mi	s	si	f	fi	e	los	loe	ols	ole	oo
<	0	8	4	4	2	6	1	7	3	5	5	3	4	6	2	2	6	4
>	8	0	4	4	6	2	7	1	5	3	3	5	4	2	6	6	2	4
D	4	4	0	4	2	2	3	3	1	3	1	3	2	4	4	2	2	4
Di	4	4	4	0	2	2	3	3	3	1	3	1	2	2	2	4	4	4
O	2	6	2	2	0	4	1	5	1	3	3	1	2	4	2	2	4	4
Oi	6	2	2	2	4	0	5	1	3	1	1	3	2	2	4	4	2	4
M	1	7	3	3	1	5	0	6	2	4	4	2	3	5	1	1	5	3
Mi	7	1	3	3	5	1	6	0	4	2	2	4	3	1	5	5	1	3
S	3	5	1	3	1	3	2	4	0	2	2	2	1	3	3	1	3	3
Si	5	3	3	1	3	1	4	2	2	0	2	2	1	1	3	3	3	3
F	5	3	1	3	3	1	4	2	2	2	0	2	1	3	3	3	1	3
Fi	3	5	3	1	1	3	2	4	2	2	2	0	1	3	1	3	3	3
E	4	4	2	2	2	2	3	3	1	1	1	1	0	2	2	2	2	2
Los	6	2	4	2	4	2	5	1	3	1	3	3	2	0	4	4	2	2
Loe	2	6	4	2	2	4	1	5	3	3	3	1	2	4	0	2	4	2
Ols	2	6	2	4	2	4	1	5	1	3	3	3	2	4	2	0	4	2
Ole	6	2	2	4	4	2	5	1	3	3	1	3	2	2	4	4	0	2
Oo	4	4	4	4	4	4	3	3	3	3	3	3	2	2	2	2	2	0

Since there are four ✧ relations used in each temporal relation, the index of a IRD is from 1 to 8. Note that, the lower the index, the closer the relation to the relations in its IRD.

Also, let $EPIRD18(r_i, r_j)$ be a EPIRD index function takes as input two relations, $r_i, r_j \in 18REL$, and returns a similarity index from 0 to 8. We have:

$$distance = EPIRD18(r_1, r_2)$$

Assume that A_s, A_e, B_s, and B_e are the starting and ending points of the two line segments on a plan, we want to define a *length ratio function*, $LR(r_{ix})$ and $LR(r_{iy})$:

$$LR(r_{ix}) = (A_{e.x} - A_{s.x}) / (max(A_{e.x}, B_{e.x}) - min(A_{s.x}, B_{s.x}))$$

$$LR(r_{iy}) = (A_{e.y} - A_{s.y}) / (max(A_{e.y}, B_{e.y}) - min(A_{s.y}, B_{s.y}))$$

where $A_{s.x}$ and $A_{s.y}$ are the X and the Y coordinates of the starting point of project line segment A.

Let function $sim(r_i, r_j)$ be a similarity function, which takes as input two relations, r_i, and r_j, and returns a similarity:

$$r_i = r_j \Rightarrow sim(r_i, r_j) = (LR(r_{ix}) + LR(r_{iy})) - (LR(r_{jx}) + LR(r_{jy})) \lor$$

$$r_i \neq r_j \Rightarrow sim(r_i, r_j) = EPIRD18(r_i, r_j) * (LR(r_{ix}) + LR(r_{iy})) - (LR(r_{jx}) + LR(r_{jy}))$$

The similarity function, $sim(r_i, r_j)$, estimates the similarity between two project line segments on a plan based on distance similarity index and the length ratio function.

5. PROCEDURE OF IMAGES RETRIEVAL

There are two main steps of similarity measure in our system: the briefly measure according to the clustering color index (Step 4) that could filter the images effectively and the detail measure according to the color and spatial relations (Step 5) that compare the similarity of images particularly. We use a simple example to describe the procedure of the similarity measure below:

Step1: Quantization and Normalization the image

Step2: Calculating the histogram and dominant colors

Step3: Load the image ID arrays of its dominant colors from the database: If the dominant colors of an image are 69 (01000101), 70 (01000110), 71 (01000111), 184 (10111000), 186(10111010). And the image ID arrays of those color bins are 1,2,3; 1,2,8; 2,7,9; 2,3,7,9 and 1,2,9.

Step4: Conjunction and ranking the image ID arrays according to the number of appearance. Because image ID 2 appear 5 times, image ID 1 and 9 appear 3 times, image ID 3 and 7 appear twice and image ID 8 appear only once, the result of conjunction and ranking those arrays are: 2,1,9,3,7,8. After this step, We could filter out the images effectively (ex: 4,5,6,10...).

Step5: Detail comparison the spatial relations and color histograms of the images produced in step4 and display the final result. Consider an attributed relation $A \subseteq C \times R$ over color attribute space C and spatial relation space R. Assume that if $(c_1,\ldots,c_n) \in C$ and $(r_1,\ldots,r_m) \in R$, then the attributed function is given by

$$Att(Q, P) = norm\_sim((c_1,\ldots,c_n), (r_1,\ldots,r_m))$$

Where norm_sim returns the Euclidean distance between two vector. Each attribute is assigned a weight, this weight is adjusted after training and learning.

6. CONCLUSIONS

In this paper, a new approach to retrieval images from the color image database based on color, shape and spatial relationship is proposed. We not only proposed a color clustering method and designed the image database hierarchy that could improve the efficiency of image retrieval according to the chromatology, but also proposed a revised Seed Filling algorithm to extract the spatial information of the image. And we combine the spatial relationships of objects to retrieval the image. After training for adjusting attribute weight, the system is able to retrieve information from image database with high satisfactorily. The system is implemented on Windows 98. We tested 3000 pictures. The performance and accuracy are reasonable as expected.

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