AN IMAGE RETRIEVAL METHOD BASED ON SPATIAL DISTRIBUTION OF COLOR[1]

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Abstract Color histogram is now widely used in image retrieval. Color histogram-based image retrieval methods are simple and efficient but without considering the spatial distribution information of the color. To overcome the shortcoming of conventional color histogram-based image retrieval methods, an image retrieval method based on Radon Transform (RT) is proposed. In order to reduce the computational complexity, wavelet decomposition is used to compress image data. Firstly, images are decomposed by Mallat algorithm. The low-frequency components are then projected by RT to generate the spatial color feature. Finally the moment feature matrices which are saved along with original images are obtained. Experimental results show that the RT based retrieval is more accurate and efficient than traditional color histogram-based method in case that there are obvious objects in images. Further more, RT based retrieval runs significantly faster than the traditional color histogram methods.

Key words Content-Based Image Retrieval (CBIR); Radon transform; Wavelet transform

I. Introduction

With the rapid development of internet and multimedia technology, the information distributed changes from pure text into image, video, audio and so on. Digital media including digital images with its convenient sharing and distributing properties has grown rapidly in volume and size. The large repository of digital media arise the challenge of various digital search applications in many fields. The conventional image databases are usually searched by keywords or text descriptions. However, ‘A picture is worth a thousand words’, i.e., it is impossible to predict an image in several keywords. Some features in images are extremely difficult to describe in text. Besides, description is sometimes subjective, and different people may give quite different description for the same image. In a word, previous methods did not take into account the image content. As a result, the search results may probably not meet the original expectation of users. To overcome the problems of text-based approaches, a new mechanism was proposed in recent years, i.e. Content-Based Image Retrieval (CBIR). Several practical CBIR systems such as Chabot, QBIC (Query By Image Content) have been already developed in various fields. Such systems retrieve images according to specified features in which users are interested. These features such as texture, color, shape, and locations can reflect the contents of an image. However, the features directly extracted from image data are low-level ones, which are not sufficient to describe the high-level semantics. There is a gap between the machine and human in similarity measurement for these feature vectors. As a result, it causes a serious obstacle that two different semantic objects may share the similar low-level feature, while two similar objects may stay far away in feature. So there are still many problems in CBIR.

Color is an important clue for CBIR systems and many CBIR systems have been designed with color as main feature in retrieval. Color histogram[1] is one of the most common methods used in image retrieval based on color feature. However, color histograms do not contain the spatial distribution information of the color. For example, two images, which have the same color histogram and different spatial distribution of color, may be much different in contents. Some different systems were designed to improve the performance related to spatial distribution of color, such as accumulative histogram[2] and dominant color matching[3]. Stricker, *et al*.[2] tried to build up the robustness of the color histogram through accumulation while Androustsos *et al*.[3] managed to reduce the interferential information which is less important in images. However, those methods did not solve the problem of losing spatial

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distribution information of color. So Messer, *et al*.[4] developed a new system in which images were divided into several blocks and similarity measurement was obtained based on the corresponding blocks of two images. However, this method was a little bit rigescent and coarse. Image retrieval based on color-spatial feature proposed in Ref.[5] was a novel method, where the first step was to find the main objects in the image and then obtain their color and location features. Similarity of two images was measured based on those features. However, distilling main objects of an image is not simple and this method is usually not ideal in many positions.

Enlightened by the method of 2-D image projection and reconstruction, we propose a novel and efficient scheme for spatial color feature exaction and color image retrieval. We project an image at several angles and obtain the moment feature matrix of the image, which is saved along with original images. The similarity between two images is computed according to their moment feature matrices and then realizes the retrieval. Experimental results show that the Radon Transform (RT) based method is more accurate and more efficient than color histogram-based method in case that there are obvious objects in images.

II. Radon Transform

RT[6] (as shown in Fig.1) is one of the academic bases of image projection and reconstruction[7]. Images can completely be reconstructed when RT is employed. Therefore, it is easy to consider that when we project an image from a direction, the projection chart represents the color-density of the image in that direction. So, if we project an image from several directions, the projection-chart contains the color-spatial feature information of the image.

Figs.2 (b)~(d) are the RT of the R, G and B components of the left-most image (the original image) where $\Delta\theta = 1^\circ$ and M=133 (M is the number of lines).

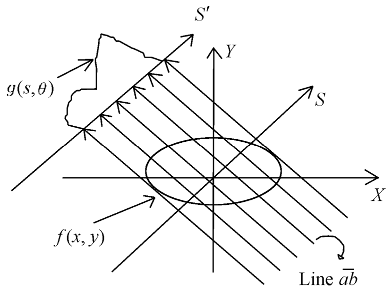


Fig.1 Radon transform

Real-time performance is a critical requirement proposed by general image retrieval systems. Unfortunately, RT is time-consuming. If users have to spend a lot of time in waiting for the retrieval results, the system is far from a perfect system even though the system is accurate. A natural way to solve this problem is to save the moment feature matrices along with images in databases. But, on the other hand, it will need much more memory storage. Therefore, we need to find ways to reduce the amount of data needed to represent the moment feature matrix. In RT, a well-proportional relation exists between the number of the radiating lines and the number of pixels in the diagonal direction of original images. To compress the original image data in advance is a practical method to realize our intention. In recent years, the wavelet transform attracts much interest of researchers in various fields. One of the classical applications of wavelet transform is image compression. So, wavelet transform may be used in our image retrieval scheme to compress image data before RT is applied. The experimental results show that the amount of data of the projection matrix obtained from the low-frequency component of wavelet coefficients is less than 1.5% of that of data obtained from the original image.

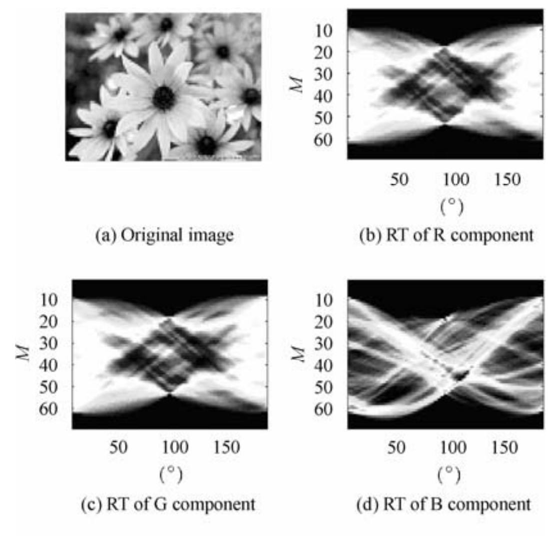
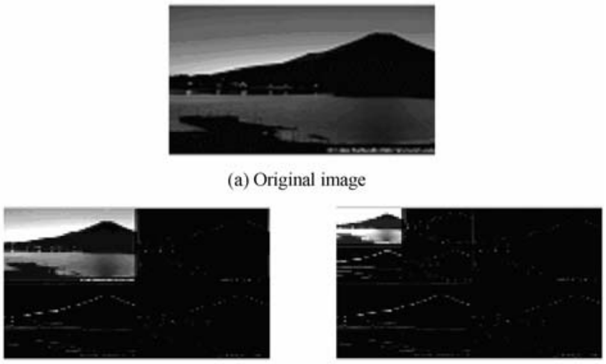


Fig.2 Radon transform drawing

III. Image Retrieval Based on Wavelet Decomposition and Radon Transform

After wavelet decomposition[8], most of image energy is integrated into its low-frequency component while the energy of edges and texture are localized in its high-frequency components. As far as human perception is concerned, the difference of the low-frequency component and the original image is quite small if small number of decomposition level is chosen. Passing through filter banks, an image will be decomposed into four components the approximation component LL and the detail components LH, HL, HH as shown in Fig.3.



(a) Original image

(b) One-level decomposition (c) Two-level decomposition

Fig.3 Wavelet decomposition

From Fig.3, we find that the components with different resolution are different from each other. Most pixels in the high-frequency component are zero. The higher the resolution, the more zeros appear. Most information of the image is focused on LL as can be seen from Fig.3(b). Considering that the second stage decomposition might lose too much color information, the low-frequency component of the first stage is directly processed by RT in our method. Fig.4 is the diagram of RT based retrieval scheme.

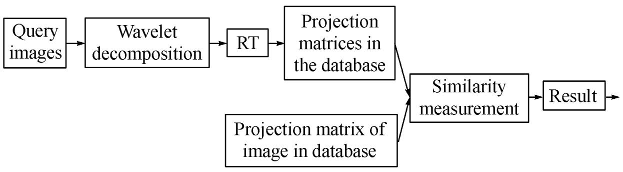


Fig.4 Diagram of the proposed retrieval method

Before image retrieval, each image in the database is processed by wavelet transform and RT. The feature matrixes are saved along with the images in database. During image retrieval process, the matrices of the query image and those of the images in the image database are taken out to get the similarity measurement. After comparing several similarity measurements in terms of their complexity and retrieval accuracy, we choose the E-distance[1] as that in RT based retrieval. Each pixel in RGB color space can be represented by a vector labeled $\boldsymbol{X}=[R_X, G_X, B_X]^{\mathrm{T}}$. Then the similarity between pixel x and pixel y is measured by

$$D(x,y)=\left[(R_x-R_y)^2+(G_x-G_y)^2+(B_x-B_y)^2\right]^{1/2} \tag{1}$$

Two sampling points are regarded similar to each other if the corresponding E-distance is small enough. Obviously, if the two points are the same, the distance is 0. In CBIR process, the system will show the most similar images to users according to the E-distance which is calculated from the query image and the images in the image database.

Indeed, how to choose the number of lines and the projectile directions in RT retrieval method is another problem. Too many lines would gain a detailed color feature of an image, but it also needs much more memory storage and slows down the speed of retrieval. Illogical projection directions may make the feature matrix contain too much information and do not meet the requirement of retrieval result corresponding to the visual sensation of human beings. After repetitious tests, we find that when $\Delta\theta=45^\circ$ and $M\approx\mathrm{int}\left[\sqrt{a^2+b^2}/4\right]$ (a, b are the sizes of the original image (by pixels)), the retrieval result approaches to the optimum and the amount of data of feature matrices is small enough. That is, the number of lines approximates to the number of pixels on the diagonal. In this way, significant color information can be kept and insignificant ones can be ignored.

The traditional color histogram, due to its statistical nature, can only index the content of images in a limited way. It does not take into consideration the spatial distribution information of color. Because each histogram bin represents a local color range in the given color space, color histogram represents coarsely distribution of the colors in images. Two similar colors will be treated as identical provided that they are allocated into the same histogram bin. On the other hand, two colors will be considered totally different if they fall into two different bins even though they might be very similar to each other. This makes color histograms sensitive to noisy interference such as illumination changes and quantization errors. The above disadvantages are the reason why so many people commit themselves to the investigation of ameliorating the color space to make the similitude of the colorful images more match human perception. The method that we put forward does not change the spatial distribution of the color and the method of feature exaction is simple. In our image retrieval process, all the system needs to do is to read the moment feature matrices of the images from the database and making similarity measurement. For a small image, the size of its projection matrix is very small (usually much smaller than the size of color histogram), so the speed of image retrieval is very fast. In existing color-spatial feature based retrieval methods, the process of color feature exaction is usually very complex. In regard to Ref.[4], they firstly divides the image into pieces, takes out the color feature from each piece and then compares the color feature of the corresponding pieces of two images. This method needs much memory storage and the amount of arithmetic operation increases with the number of image pieces. Although, comparatively, our RT-based method takes up more memory storage of the system, it improves both the retrieval speed and accuracy.

IV. Experimental Results

Diverse tests were preformed on experimental database consisting of 3000 varieties of color images, whose contents are all flowers. We designed the test on example-based query manner. A sample image, which is used to retrieve similar images from the entire database, is randomly selected from the database. The size of the images in the database is 72×108 (by pixels). After wavelet decomposition, we choose M=30 and N=4 as projection parameters and apply RT to the low-frequency component. The moment feature matrix is obtained with size of 30×4, approximately as large as 1.5% of the original image. Because of the small size of the matrix, RT-based image retrieval uses much less time than color histogram-based method. Fig.5 and Fig.6 are the retrieval results which are obtained by the RT method and by the color histogram method respectively. They are sorted from left to right and top to bottom. The first image of Fig.5 or Fig.6 is the query image. The spatial similarity is calculated based on the E-distance and the system shows the top 23 images which are the most similar to the query image according to the E-distance. There are only two images which are visually similar to query image in Fig.6 while similar images in Fig.5 are much more. The method proposed in this paper considers the projection density of the image color in several directions. Projection matrix produced by integral, unlike the quantization of the color histogram, keeps most information of color in the projection, which makes the retrieval results near to human perception.

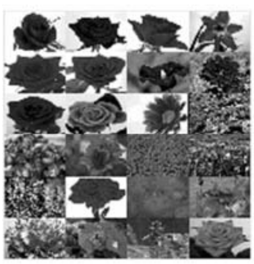


Fig.5 RT- based retrieval result

Fig.6 Color histogram-based retrieval result

To compare the projection matrix and the color histogram, we choose the query image and the second image in Fig.5. Figs.7~9 are comparisons of RT and color histogram in R, G, B space of two images. These two images are similar to our perception, but the difference between their histograms is visually larger than that of corresponding RT

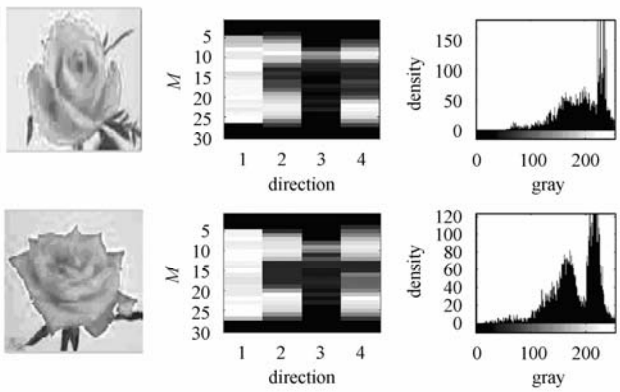


Fig.7 Comparison of color histogram and RT of R component

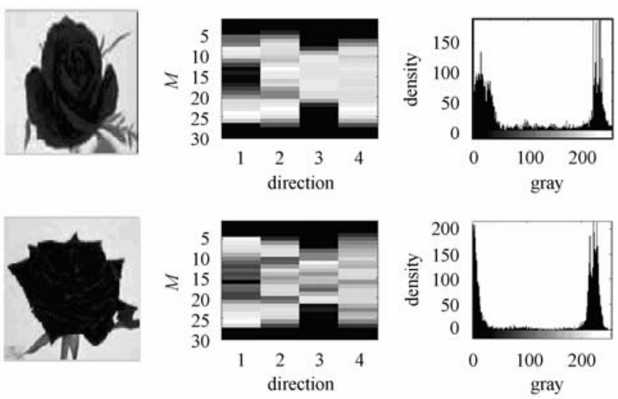


Fig.8 Comparison of color histogram and RT of G component

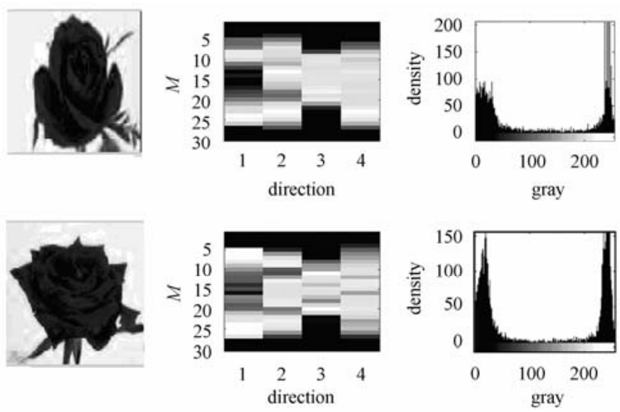


Fig.9 Comparison of color histogram and RT of B component

One of performances of an image retrieval system is the retrieval precision which is the percentage of the retrieved images that are relevant in the retrieved results. Precision can be defined as

$$\text{Precision}=N' / N \tag{2}$$

where N' represents the number of the relevant images and N represents the number of the retrieved images. We choose conventional color histogram-based retrieval method in Ref.[1], color-spatial based retrieval method in Ref.[5] and dominant color region based indexing in Ref.[3] to compare with our approach to see how we can improve the retrieval performances in terms of precision.

In our experiments, the top 50 images which are most similar to the query images are returned, that is N=50. We design five kinds of image retrieval processes, in which the query images are chosen yellow flowers, red flowers, white flowers, blue flowers and green leaves, respectively. For each retrieval process, ten images of each kind are arbitrarily chosen out and used as query images. The average precision of retrieval processes for the ten query images is calculated and taken as the precision of that kind. The precisions of the four kinds of retrievals are shown in Tab.1.

Tab.1 Comparison of four methods in terms of precision (%)

Retrieval process	Yellow flowers	Red flowers	White flowers	Blue flowers	Green leaves
RT-based	53.9	54.3	30.2	22.4	57.8
Color-spatial based	37.6	35.8	29.0	20.6	46.7
Dominant color-based	51.7	27.0	27.0	17.3	38.3
Histogram-based	35.6	25.6	27.0	17.0	41.1

Compared with other three methods, our RT method improves greatly in precision as shown in Tab.1.

Besides, RT-based method also makes improvement in speed. The system is written in MATLAB 6.5 and running on Windows XP platform. The configuration of our computer is 1.7GHz CPU, 256M RAM and 80G HD. RT-based method averagely costs 3.5(s) in each image retrieval process while histogram-based averagely costs 15.5(s).

V. Conclusions

Aiming at the disadvantage that the conventional color histogram-based image retrieval is not able to reflect the spatial distribution information of the color, we propose a novel and effective image retrieval approach based on RT. Experimental results show that this method can improve not only the retrieval accuracy but also the speed, which are very important performances in retrieval of larger image databases. However, using color feature only in image retrieval is sometimes not enough to represent completely images. In the future, we will investigate several other aspects related to CBIR systems, such as additional metadata extraction (e.g. shape, texture). As RT accentuates linear features and nowadays, it has been applied to detection and enhancement problems for images with linear features. We will also apply it in shape and texture feature exaction to improve the precision of image retrieval systems. How to save more storage space to make the method suitable to even larger image databases is another issue that we are studying.

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