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A flower image retrieval method based on ROI feature*

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Abstract: Flower image retrieval is a very important step for computer-aided plant species recognition. In this paper, we propose an efficient segmentation method based on color clustering and domain knowledge to extract flower regions from flower images. For flower retrieval, we use the color histogram of a flower region to characterize the color features of flower and two shape-based features sets, Centroid-Contour Distance (CCD) and Angle Code Histogram (ACH), to characterize the shape features of a flower contour. Experimental results showed that our flower region extraction method based on color clustering and domain knowledge can produce accurate flower regions. Flower retrieval results on a database of 885 flower images collected from 14 plant species showed that our Region-of-Interest (ROI) based retrieval approach using both color and shape features can perform better than a method based on the global color histogram proposed by Swain and Ballard (1991) and a method based on domain knowledge-driven segmentation and color names proposed by Das *et al.*(1999).

Key words: Flower image retrieval, Knowledge-driven segmentation, Flower image characterization, Region-of-Interest (ROI), Color features, Shape features
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INTRODUCTION

There are about 250000 named species of flowering plants and many plant species that have not been classified and named. Plant classification and identification is a very old field. So far, this time-consuming process has mainly been carried out by taxonomists and/or botanists. A significant improvement can be expected if the plant identification can be carried out by a computer automatically or semi-automatically with the aid of image processing and computer vision techniques, and various data management techniques. Several systems have been developed for plant identification and plant data management. The typical systems include Lucid, development by the Center for Pest Information Technology and Transfer (CPITT) at University of Queensland, Uconn, the University of Connecticut Plant Database, and CalFlora hosted by the UC Berkeley Digital Library Project. But none of these systems support image processing and intelligent content-based search techniques. With advancing information technology and computer vision techniques, a computer-aided plant identification system is becoming more and more

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feasible.

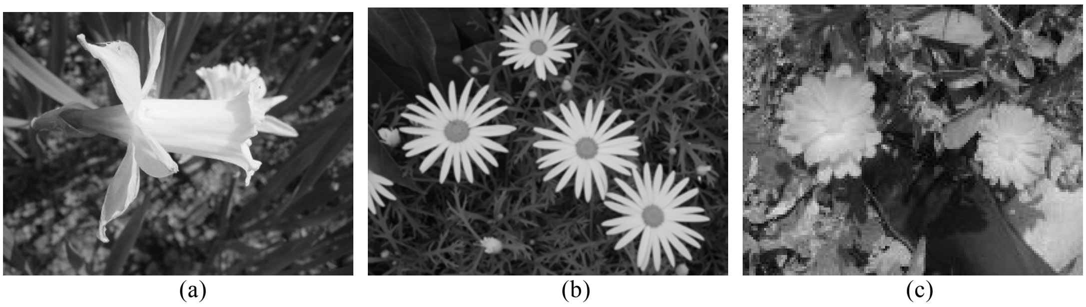
Content-based image retrieval (Smeulders *et al.*, 2000) uses the visual content of an image like color, shape, texture, and the spatial layout to represent and index image, such as IBM's QBIC (Flickner *et al.*, 1995), Photobook (Pentland *et al.*, 1996). Most retrieval algorithms targeted at general images databases that may contain diverse types of images. However, there is a growing number of large image databases that are dedicated to specific types of images and subjects, such as medical images (Sonka *et al.*, 1996), flower images (Das *et al.*, 1998; 1999; Saitoh and Kaneko, 2000), trademark images (Peng and Chen, 1997) and so on. When general-purpose retrieval strategies are applied to these databases, the domain characteristics of a database may not be considered. In this paper, we focus our discussion on flower image retrieval. In our approach, an effective segmentation method based on color clustering and domain knowledge is proposed to extract flower regions from flower images. Three feature sets are extracted for the similarity measure in flower image retrieval. The feature sets include (1) the color histogram of a flower region for characterizing the color feature of flowers; (2) Centroid-Contour-Distance (CCD) curve and (3) Angle Code Histogram (ACH) for characterizing the shape feature of a flower contour.

RELATED WORK

A flower image may have one or more flower regions as shown in Fig.1. For flower image identification and retrieval, we need to segment the flower regions from the background before we can accurately describe flowers. Image segmentation is a necessary step to achieve this. However, it is very difficult to achieve perfect segmentation in most gray-scale and color images. Due to their importance, many color image segmentation algorithms had been proposed in the past few decades (Ma and Manjunath, 1997; Zhong and Yan, 2000; Zhang *et al.*, 2002). Zhong and Yan (2000) proposed a color image segmentation method based on fuzzy clustering. Yining *et al.*(1999) proposed a color image segmentation method called JSEG that defined a measure J to find the distance between different classes. Chien and Cheng (2002) defined a set of fuzzy colors in the HLS color coordinate space, and proposed a new image segmentation method based on fuzzy color similarity measure. The above mentioned methods failed to achieve good results when they were applied to our flower image segmentation because no domain-specific knowledge is considered. Knowledge-driven image segmentation and/or interpretation were investigated by several researchers (Ezquerra and Mullick, 1996; Sonka *et al.*, 1996; Zhang *et al.*, 2002). Das *et al.* (1998; 1999) developed an automatic iterative segmentation algorithm with knowledge-driven feedback to isolate flower regions from the background.

FLOWER REGION EXTRACTION

Flowers are rarely green, black, gray or brown in color and background regions are usually visible along the periphery of the image (Das *et al.*, 1999). The pixels corresponding to a flower are normally clustered spatially and have a certain shape. So we



(a) (b) (c)

Fig.1 Examples of flower images
(a) asteraceae; (b) amaryllidaceae; (c) violaceae

can utilize the knowledge on flowers to segment flower regions from the background. Each pixel of the image can be represented as a point in 3-D color space. Commonly used color spaces for image retrieval include RGB, Munsell, CIE L*a*b*, CIE L*u*v*, HSV (or HSL, HSB), and the opponent color space. It is difficult to determine which color space is the best for tackling the problem. However, one of the desirable characteristics of an appropriate color space for image retrieval is its perceptual uniformity. Perceptual uniformity means that two colors that have the same similarity distance to the same reference color in a color space are perceived as equal by viewers. In other words, the measured proximity among colors must be directly related to the psychological similarity among them. We select the CIE L*a*b* (Albuz *et al.*, 2000) which is a color space of perceptual uniformity.

Clustering is a fundamental approach in pattern recognition. One of the clustering methods is the fuzzy clustering method (FCM) (Zhong and Yan, 2000; Chien and Cheng, 2002), which produces a set of c class centroids and allows examples to partially belong to each one. Kankanhalli *et al.*(1999) proposed a color clustering method. The color clustering algorithm that we adopted is described as follows:

(1) Obtain the RGB components of an image and transform them to the CIE L*a*b* system.

(2) Find all color clusters.

(i) Compute the color distance of each pixel from the existing color clusters. If no color clusters exist, then set the first pixel as a new cluster. The color distance is given by:

$$\sqrt{(\Delta L)^2+(\Delta a)^2+(\Delta b)^2}\ .$$

(ii) If the minimum color distance is less than the pre-set threshold, then a match is found. Otherwise, a new color cluster is generated, and set the unmached pixel as the new cluster.

(iii) For each match, the L, a, b values and the population of the cluster are updated. The new representative color of the cluster is the weighted average of the original cluster and the color of the current pixel.

(3) Compute the population of every cluster. The clusters with a population of less than a threshold are discarded.

(4) For each pixel, compute the color distance to different clusters. Assign the pixel to the cluster to which the color distance is minimum.

We consider each cluster as an image layer and each pixel is assigned to one image layer. Fig.2 shows the image layers of the flower image shown in Fig.1a.

As mentioned above, flowers are rarely green, black, gray or brown in color, so we can define a color look-up table in which some are flower's colors and the other are background colors. We use a table of 25 colors (Ravishankar *et al.*, 1999) and assign the first 15 colors to background colors and the remaining colors to flower colors.

Each of image layers will be mapped to either a flower color or a background color according to the color distance between the color of the image layer and a color in the look-up table, C_d, which is defined as:

$$C_d=\min_{1\le i\le 25}\sqrt{(L_c-L_{iT})^2+(a_c-a_{iT})^2+(b_c-b_{iT})^2} \qquad (1)$$

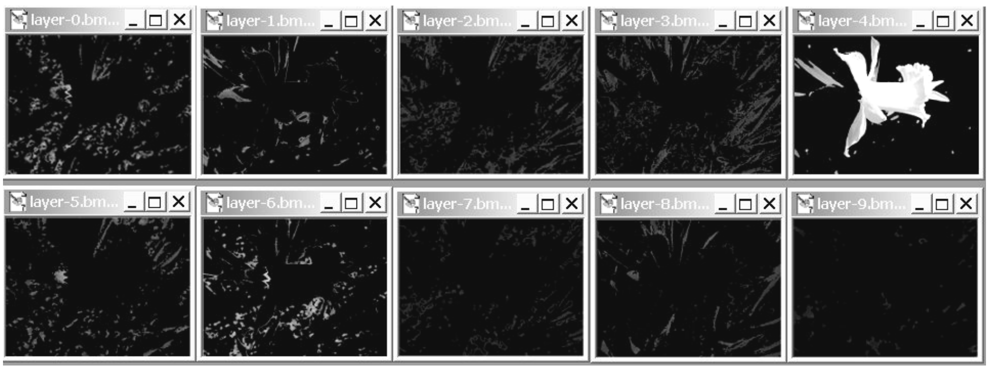


Fig.2 Image layers after color clustering

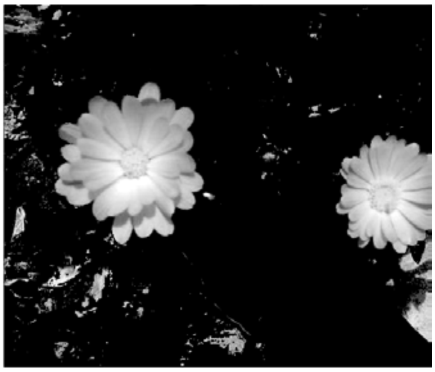
where L_c, a_c, b_c are the L, a, b values of the color layer, and L_{iT}, a_{iT}, b_{iT} are the L, a, b values of the i-th color in the color table (i=1,2,…,25).

If the layer's color belongs to a background color, we discard the whole layer. Due to diversities of flowers, different illumination conditions, and noise introduced in acquiring the image, we have to consider the following three situations:

1) There is no flower region remained. We will bring back the largest cluster and label it as a flower region. Normally, flowers should dominate the image and hence it is quite safe to assume that the largest cluster is a flower region.

2) Some background regions are kept as flower regions as shown in Fig.3a. In general, there are no flower regions spread on the narrow peripheral zone (Fig.4). The clusters locating in the narrow peripheral area will be considered as background regions and removed (Das *et al.*, 1999).

3) There are small noise blocks in the flower region. Those small blocks in a flower layer with size of small than a pre-set threshold (1/10 of size of the largest flower region in the layer) will be removed. Fig.3b shows the flower regions after removing background blocks at steps 2 and 3.



(a)

(b)

Fig.3 Flower regions obtained after (a) clustering; (b) removing background blocks

After removing the background layers and noise blocks, there will be some holes in the flower layers. We use dilation and erosion, two mathematical morphology operations (Xu, 2001) to remove these holes, resulting in more accurate flower region(s). To extract the shape features, the contour of a flower region is extracted based on the segmentation. Fig.5 shows the flowchart of our flower image segmentation approach based on clustering and domain knowledge. There may be several flower regions in a flower image. We keep only the longest contour in flower shape analysis. The segmentation result and the contour of a flower in Fig.1 are shown in Fig.6.

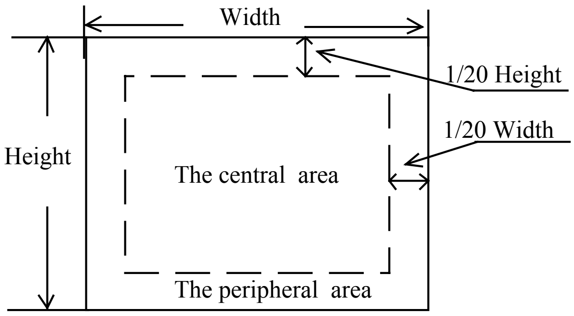


Fig.4 Definition of the central and peripheral areas of a flower image

SHAPE FEATURES

Shape is one of the most important features characterizing an object (Loncaric, 1988). Many investigations in shape representation such as chain codes, centroid-contour distance (CCD) curve, medial axis transform (MAT), Fourier descriptors (FDs), Wavelet descriptions, moment invariants, and deformable templates, had been carried out. All of these features perform well and have advantages for some applications. An important criterion for a good shape representation is that the representation has to be invariant to rotation, scaling, and translation. In this paper, we use two shape features, CCD and angle code histogram (ACH).

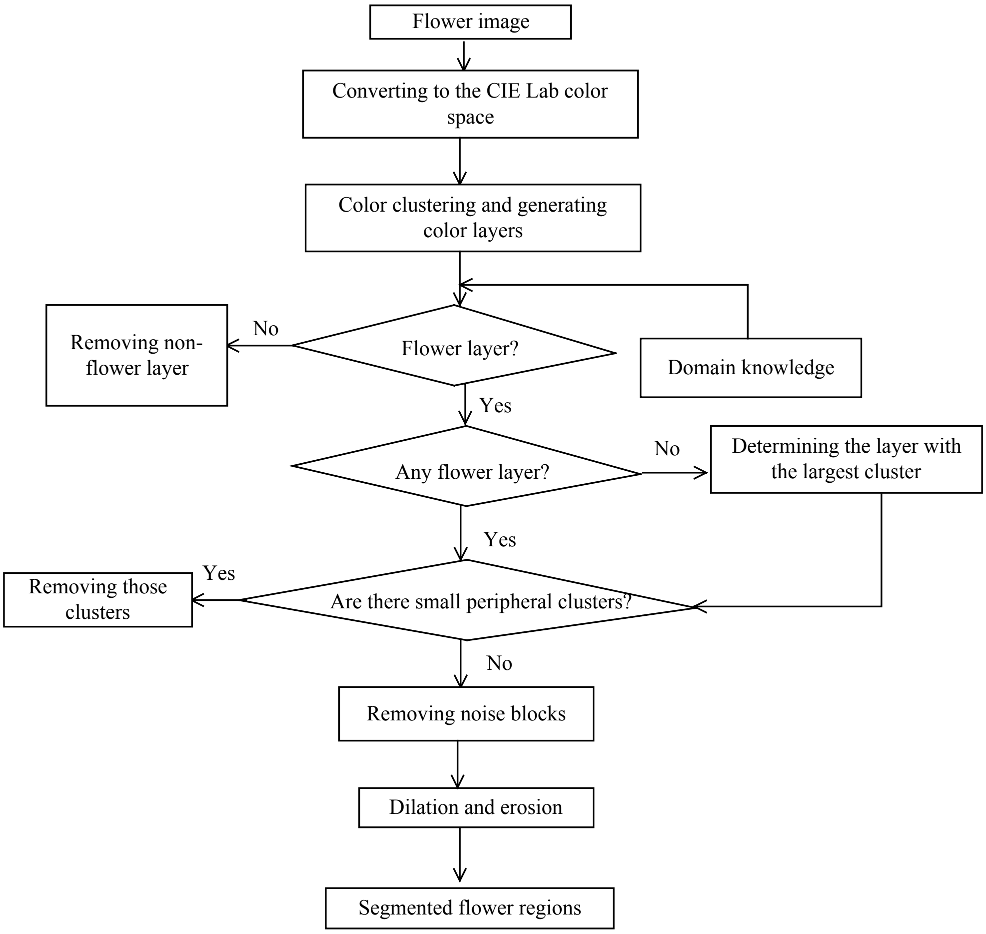


Fig.5 The flowchart of flower image segmentation based on clustering and domain knowledge

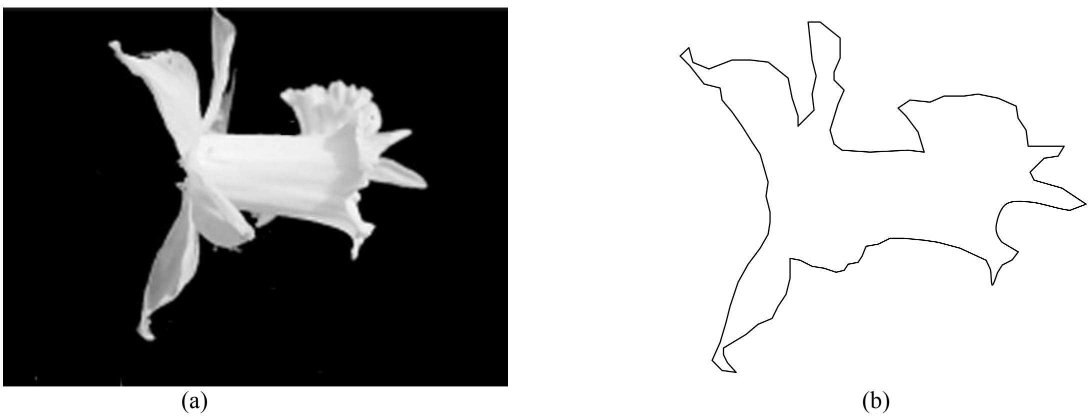


Fig.6 (a) Segmentation result and (b) the extracted flower contour of a flower image shown in Fig.1

Centroid-contour distance (CCD)

Centroid-contour distance (CCD) can reflect the global character of a shape, but the CCD curve is neither scaling nor rotation invariant. Fig.7 illustrates the definition of the centroid-contour distance curve. Actually, the number of contour points is dependent on the object size. Consequently, the number of CCD curve sample points and the amplitude of CCD samples will change if the scale of the object changes.

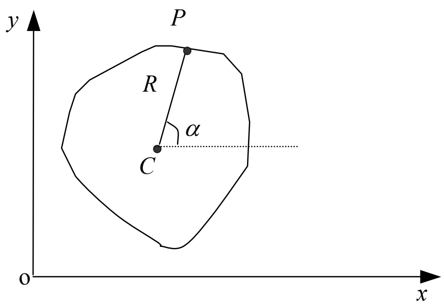


Fig.7 Illustration of the centroid-contour distance

Based on the maximal and minimal CCD curve values, we can normalize the CCD values to range [0,1] to make it scaling invariant. As to the number of the edge points, we can down-sample the CCD curve with more sample points to make the number of sample points of two CCD curves to be compared equal. The key for a similarity measure with CCD curves to be rotation invariant is to locate fixed starting point(s) of CCD curves. In order to solve this problem, we set the farthest point from the centroid as the start point for each data sample in the database. In retrieving image with a query image, we select several farthest points from the centroid as possible start points. The difference between two CCD curves is computed when a possible start point of an enquiry image is aligned with the start point of the database image. The smallest difference between two CCD curves among all possible start points is used to measure the dissimilarity of two contours. We define the distance function to measure the dissimilarity between two CCD curves as:

$$D_C = \sum_{i=1}^{n} \left| f_1(i) - f_2(i) \right| / n \tag{2}$$

where $f_1(i)$ and $f_2(i)$ are the CCD curves of two object contours at the ith point and n is the total number of the contour points.

Angle code histogram

It was observed that the CCD curve cannot characterize local properties of a contour effectively. However, local properties are very important for the identification of flower shapes. Peng and Chen (1997) proposed an angle code method for shape characterization. In their approach, each closed contour is represented by a sequence of line segments with two successive line segments forming an angle. The angles at contour points on each closed contour were computed and the resulting sequence of successive angles was used to characterize the contour. Angle code has been applied to image retrieval of trademarks and logs. The retrieval process was performed by matching the angle code string. However, flower images are quite different from artificially generated graphics that have ideal lines or arcs. Following the idea of the angle code, we computed the angle for each contour point based on two approximate line coming to and leaving the point. If the distributions of the angle codes of two closed contours are close, they will have similar local features. We propose to use an angle code histogram (ACH) to characterize the local properties of a flower image. If the distributions of the angle codes of two contours are similar, they will have similar local properties. The difference between two angle code histograms is defined as:

$$D_h(I,J) = \sum_{i=1}^{m} \left| H_i(I) - H_i(J) \right| \tag{3}$$

where m is the number of bins in which the angle code histogram is partitioned. The weight summation method can be applied to combine the similarity (dissimilarity) measures from the two sets of features:

$$D_s(I,J) = \frac{w_1 D_c(I,J) + w_2 D_h(I,J)}{w_1 + w_2} \tag{4}$$

where w_1 and w_2 are used to weight the relative importance of the two feature sets, which will be determined by simulation or tuned by the user.

EXPERIMENTAL RESULTS

Our approach has been evaluated on a flower image database containing 885 flower images, including 101 asteraceae images, 40 amaryllidaceae images, 62 brassicaceae images, 88 violaceae images, 94 malvaceae images, and 500 other flower images.

Several experiments were conducted. We used (1) the color histogram of a flower region (Fig.9a), (2) shape features (Fig.9b), (3) combined color and shape features (Fig.9c) to retrieve flower images, which are compared with the retrieval results using a method based on the global color histogram proposed by Swain and Ballard (1991) (Fig.10a) and a method based on domain knowledge-driven segmentation and color names proposed by Das *et al.*(1999) (Fig.10b).

Table 1 summarizes the average recall rate forthem and it was observed that it is useful to improve the retrieval performance by combining color and shape features.

The performance comparison of different methods is also illustrated in Fig.11. It was observ-

Fig.9 (a) Retrieval result using ROI color features; (b) Retrieval result using ROI shape features; (c) Retrieval result using both color and shape features

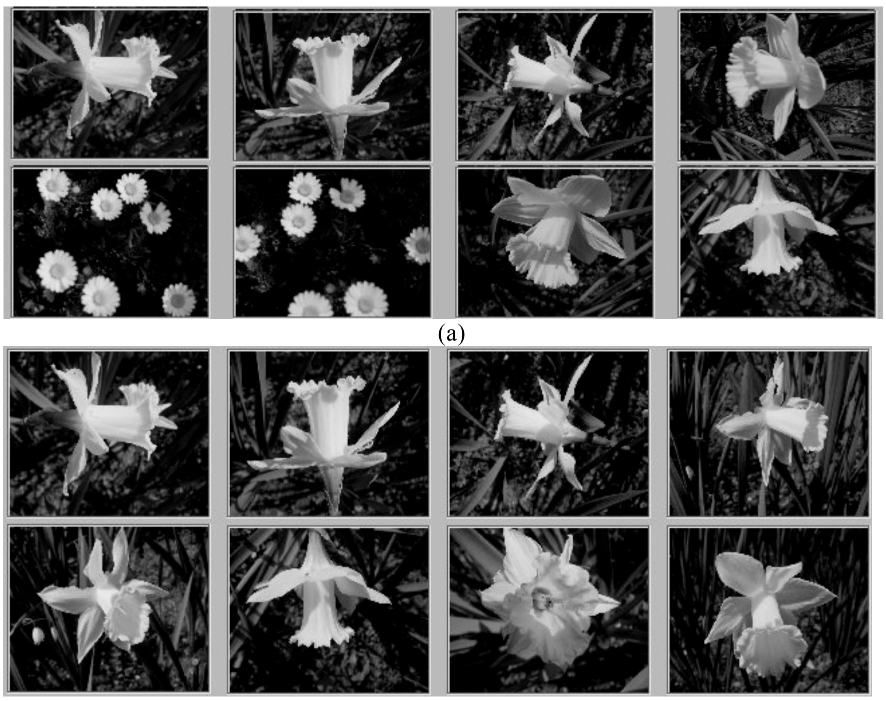
ed that combining color and shape features outperforms both color feature and shape feature used individually. We also observed that retrieval results of our ROI-based approach was better than those using the method proposed by Swain and Ballard (1991) and the method proposed by Das *et al.*(1999).

CONCLUSION

In this paper, we first present an effective method to segment flower regions from flower images based on color clustering and domain knowledge. We then discuss the flower image retrieval using three feature sets: the color histogram of the flower region (region-of-interest), the Centroid-Contour Distance (CCD) and the Angle Code Histogram (ACH) of the flower contour. Experimental results on 885 flower images from 14 plant species showed that our approach performs well and compared favorably with the Swain and Ballard's method and the Das *et al.*'s method in terms of recall rate.

Table 1 The recall rate of different features

Feature	Return images	Recall rate (%)
Color feature	10	0.233
	30	0.433
	60	0.5
	80	0.67
Shape feature	10	0.233
	30	0.4
	60	0.466
	80	0.566
Color and shape features	10	0.266
	30	0.533
	60	0.633
	80	0.8
Swain and Ballard's method	10	0.20
	30	0.4
	60	0.533
	80	0.633
Das *et al.*'s method	10	0.252
	30	0.482
	60	0.608
	80	0.76



(a)

(b)

Fig.10 (a) Retrieval result using the method proposed by Swain and Ballard; (b) Retrieval result using the method proposed by Das *et al.*

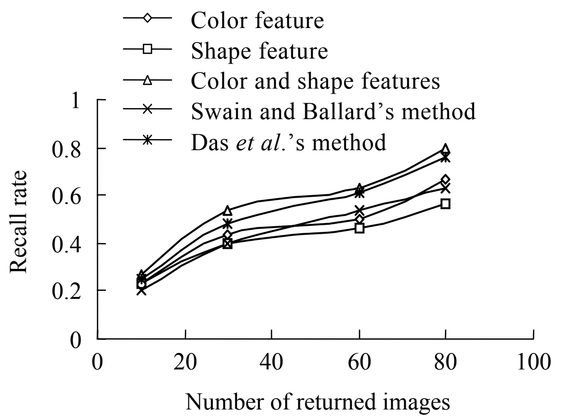


Fig.11 Comparison of the retrieval performance of different methods

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