REGION-OF-INTEREST BASED FLOWER IMAGES RETRIEVAL

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ABSTRACT

Flower image retrieval is a very important step for computer-aided plant species identification. 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 show that our flower region extraction approach based on color clustering and domain knowledge can achieve accurate flower regions. The retrieval results on a database of 885 flower images collected from 14 plant species show that our Region-Of-Interest (ROI) based retrieval approach can perform better than the Swain's method based on global color histogram.

1. INTRODUCTION

There are 250,000 named species of flowering plants and more plant species that have not been classified and named. Plant classification and identification is a very old field. In flowering plant taxonomy, one of the first documented efforts to systematize a local flora was that of the Theophrastus (370-285 B.C.), a Greek student of Plato and successor to Aristotle as director of Lyceum and its botanical garden [1]. So far, this time-consuming process has mainly been carried out by taxonomists and/or botanists. A significant improvement can be excepted 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* [2], development by the Center for Pest Information Technology and Transfer (CPITT) at University of Queenland, *UConn* [3] the University of Connecticut Plant Database, and *CalFlora* [4] hosted by the UC Berkeley Digital Library Project. But none of these systems supports image processing and intelligent content-based search techniques. With advancing information technology and computer vision techniques, a computer-aided plant identification system is becoming feasible.

Content-based image retrieval uses the visual contents of an image like color, shape, texture, and the spatial layout to represent and index images, such as IBM's QBIC, Photobook, VisualSEEK *etc.* Most retrieval algorithms have targeted a general images database that may contain diverse types of images. However, there is a growing number of large images database which are dedicated to specific types and subjects, such as flower images [5], trademark images [6] 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 images retrieval. In our approach, an efficient segmentation method based on color clustering and domain knowledge is used to extract flower regions from flower images. The contour of a flower is then extracted by using an edge detection algorithm. Three feature sets are extracted for flower image retrieval. The feature sets used are (1) the color histogram of a flower region for characterizing the color feature of flower, (2) Centroid-Contour-Distance (CCD) and (3) Angle Code Histogram (ACH) for characterizing the shape features of a flower contour.

2. RELATED WORK

For flower images identification and retrieval, we need to segment the flower regions from the background before we can accurately describe flowers. But it is a rather difficult problem to perform a perfect segmentation in a color image. Although many color image segmentation algorithms have been proposed during the past few decades [7] [8]. But for flower images, those segmentation algorithms are not very effective since no domain-specific knowledge is considered. Knowledge-based image segmentation and/or interpretation have been investigated by a number of researchers. Zhang *et al.* proposed a knowledge-guided image segmentation and labeling system (KGSL) [9]. As the KGSL system makes use of multiple classifiers and integrates different image processing algorithms under the guidance of a knowledge base, it outperforms the segmentation methods based on simple strategies. Maddirakshi *et al.* [5] developed an automatic iterative segmentation algorithm with knowledge-driven feedback to isolate a flower region from the background. They used a natural language color classification derived from the *ISSC-NBS* color system to provide perceptually correct retrieval and allow natural lingual queries.

3. 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. The pixels corresponding to a flower are normally clustered spatially and have a certain shape. So we can utilize this knowledge to segment flower regions from the background. Each pixel of the image can be represented as a point in a 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. We select the *CIE L*a*b** [10] which is a perceptual *uniformity* color space. Clustering is a fundamental approach in pattern recognition. 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.

   2.1 Compute the color distance of each pixel from the existing color clusters. If no color clusters exist, then a new color cluster is created. The color distance is given by $\sqrt{(\Delta L)^2 + (\Delta a)^2 + (\Delta b)^2}$.

   2.2 If the minimum color distance is less than the pre-set threshold value, then a match is found. Otherwise, a new color cluster is created.

   2.3 For each match, the L , a , b values and the population of the clusters are updated. The new representative color of the cluster is the weighted average of the original cluster and the current pixel's color.
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.

Each pixel is assigned to one cluster. We consider each cluster as an image layer. As we have mentioned, 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. In our approach, we used a table of 25 colors [11] among which 10 colors are flower colors.

The procedure below maps all image layers to flower colors or background colors according to the color distance between an image layer' color and the color look-up table, C_d , which is defined as:

$$C_d = \min_{i=1}^{25} \sqrt{(C_L - T_{iL})^2 + (a_L - T_{ia})^2 + (b_L - T_{ib})^2} \quad (1)$$

If the layer's color belongs to a background color, we discard the whole layer. In some cases, all the color clusters may be regarded as the background layers due to the problem with illumination, failing detecting any flower regions. To solve this problem, we will consider the layer which including the largest cluster as a flower color layer. In doing this, some non-flower regions may be kept. Considering the normal situation in which a flower region will appear near the center of the image, we can remove those clustering regions near the borders whose areas are smaller than 1/10 of the area of the whole image. The flower region candidates will be considered as noise blocks and be removed if they have a size of smaller the 1/5 of that of the largest candidate. Morphological operations (dilation followed by erosion) are carried out to fill the holes in flower regions resulting in from removing noise blocks. In the flower layers, those pixels forming small inlands based on 4-connection or 8-connection are discard.

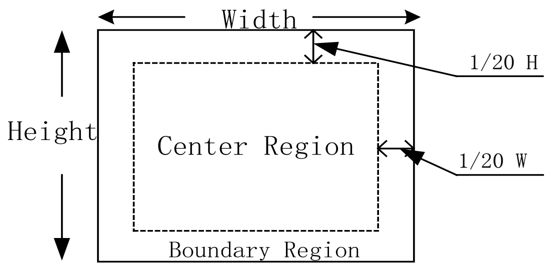

Figure 1: Definition of Image regions.

After the above-mentioned processing, we can obtain flower region(s). To extract the shape features, the contour of a flower region is determined based on the segmentation. There may be several flower regions in a flower image. We only keep the longest contour. The segmentation result and the contour of a flower are shown in Fig. 2.

Figure 2: Flower image segmentation and contour extraction.

4. SHAPE FEATRUES

Shape feature is one of the most important features for characterizing an object. Many investigations on shape representation such as chain codes, centroid-contour distance (CCD) curve, medial axis transform (MAT), Fourier descriptors (FDs), moment invariants, and deformable templates, have been carried out. All of them perform well for some specific applications. An important riterion for shape representation is that the representation has to be invariant to rotation, scaling, and translation. In this paper, we use two shape feature sets, CCD and Angle Code Histogram (ACH).

4.1 Centroid-Contour Distance (CCD)

CCD can reflect the global character of the shape, but the CCD curve is neither scaling nor rotation invariant, and change object size will affect the number of the edge points, Consequently, the number of its CCD curve sample points and the amplitude of its CCD curve will change. Based on the maximal and minimal CCD curve values we can normalize the CCD curve values to range [0,1] make it scaling invariant. As to the number of the edge points, we can down-sampling the CCD curve of more sample points to make the sample points of two CCD curve equal. The key for 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, when we insert the data to the database we set the farthest point from the centroid as the start point. In retrieving image with a query image, we select several points farthest 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 distances of two object contours at the i-th point and n is the total number of the contour points.

4.2 Angle Code Histogram (ACH)

It is observed that the CCD curve cannot represent local features effectively. However, local features are very important for the identification of flower shapes. Peng *et al.* [6] proposed angle codes. 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 angle code string. However flower images are quite different from artificially generated graphics which have ideal lines or arcs. Following the idea of the angle code, we compute the angle for each 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 features of a flower image. If the distributions of the angle codes of two contours are similar, they will have similar local features. 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. Weight summation and fuzzy integral, can be applied to combining 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.

5. EXPERIMENTAL RESULTS AND DISCUSSION

The histogram of a flower region is used to characterize the flower colors. Our approach has been thoroughly evaluated on our flower image database. The database contains 885 flower images. Several experiments were conducted using (1) color feature, (2) shape feature, (3) combined color and shape features to retrieve flower images. The results were compared with those achieved using the Swain's method [12].

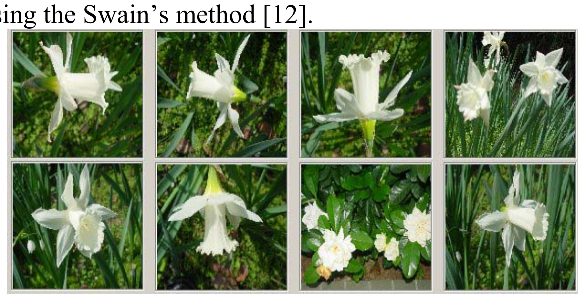

Figure 3: Retrieval result using the color histogram of ROI.

Figure 4: Retrieval result using the shape feature.

Figure 5: Retrieval result using combined color and shape features.

Figure 6: Retrieval result using the Swain's method.

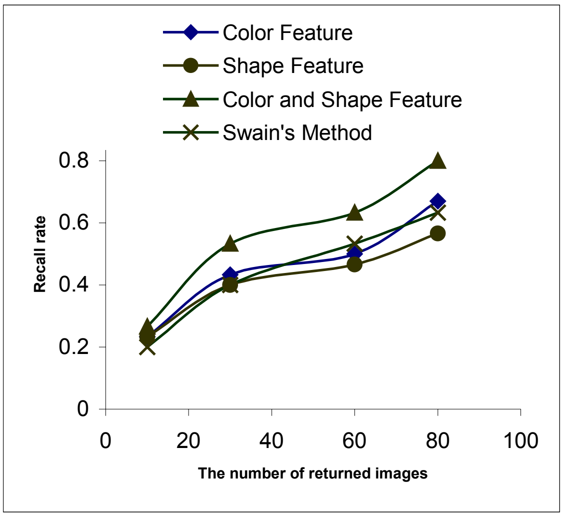

Figure 7 A comparison of the retrieval performance

Figure 7 shows the average recall rate. It is observed that the retrieval performance is improved by using combined color and shape features. We can find that the retrieval results of our ROI-based approach are better than those of the Swain's method.

6. CONCLUSION

In this paper, we first present an effective method to segment the flower region from the background based on color clustering and domain knowledge. We then discuss the flower image retrieval based on three feature sets: the color histogram of ROI, 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 show that our approach perform well and is compared favorably with the Swain's method in terms of recall rate.

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