LEAF IMAGE RETRIEVAL USING A SHAPE BASED METHOD

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Abstract: For content-based image retrieval, shape information is of great importance. This paper presents a shape descriptor of imaged leaf objects according to their boundaries for image retrieval. We take picture of leaves, exact the sketch from original images and produce a low dimensional feature vector to describe the shape. By comparing the similarity of the query image with those in database, a set of images with shape similarity are retrieved. The experiment shows that the method has high reliability and less time consuming.

Keywords: CBIR, shape, leaf image retrieval, image representation

1. INTRODUCTION

Chinese tradition medicine is becoming more and more popular all over the world. But it is difficult to identify and classify the herbal medicine. If a non-skilled doctor or a student wants to know the name of an unknown species of herbal medicine, a book about herbal medicine is needed. It would be useful if we take a picture of a sample, input it into a computer and a computer-aid process may help recognize it.

Most herbal medicine are plant leaves or flowers, leaves or flowers are usually distinguished by their shapes and colors, but the color of a leaf usually green, and shades and the background light always make the color feature low reliability. Therefore, we decided to research their shape feature based on 2D images for our purpose.

Klassen et al. [13] consider the shapes of continuous, closed curves. Shapes are often encoded by a set of sampled points of objects' boundaries. Our goal is to develop mathematical approach to represent the continuous boundaries of high accuracy and efficiency.

Some recent work has focused on shape feature extraction. [7][8][9] describe the shape of an object by contour points which are represented by their distance and angel to the centroid points. In some special applications, they show good results, but their process is often time consuming. [11][12] use the region-based feature to represent the shape. Consider their advantages and disadvantages, we propose an improved contour based algorithm that is more efficient and easily implemented.

An important step before shape representation is edge detection. We will assume that the boundary of the shape have been extracted from training images or using a standard edge detector. There are many robust edge detection methods such as Sobel operation, Roberts operation and Laplacian operation. In our prototype system, we choose Sobel operation to detect the edge of an object.

This paper is organized as follows: Section 2 describes in detail the methods we proposed, followed by the experiment we implemented in Section 3. Conclusions and future work is given in Section 4.

2. SHAPE REPRESENTATION

In this section, we introduce our shape descriptor which is invariant to translation, scaling and rotation and how to measure the similarity between images based on the shape descriptor. Global shape parameters are extracted from the entire image, like area, contour points, and shape feature are calculated like centroid, orientation and curvature. A combination of global features is used in our approach.

2.1 Centroid and Contour representation

The sketch extracted from an original image can be characterized by a sequence of points belonging to its boundary. The base idea is as follows:

(1) The centroid

The first step is to determine the centroid C of an object, its coordinates (x_0, y_0) is computed by:

$$x_0 = \frac{\sum_{\forall pixel \in image} x \cdot S(x,y)}{m}, \quad y_0 = \frac{\sum_{\forall pixel \in image} y \cdot S(x,y)}{m} \tag{1}$$

$$m = \sum_{\forall pixel \in image} S(x,y)$$

where

$$S(x,y) = \begin{cases} 1 & \cdots\cdots if \;\; pixel\,(x,y) \in contour \\ 0 & \qquad\quad\;\; pixel\,(x,y) \notin contour \end{cases}$$

(2) Boundary representation

Here, we have taken the centroid $C(x_0, y_0)$ of an object, and then the contour can be described by the following equations:

$$d = \sqrt{(x-x_0)^2 + (y-y_0)^2} \tag{2}$$

$$\theta = \begin{cases} \arctan(y - y_0/x - x_0) & y - y_0 > 0, x - x_0 > 0 \\ \pi/2 & y - y_0 > 0, x - x_0 = 0 \\ \pi + \arctan(y - y_0/\; x - x_0) & x - x_0 < 0 \\ 3\pi/2 & y - y_0 < 0, x - x_0 > 0 \\ 2\pi + \arctan(y - y_0/\; x - x_0) & y - y_0 < 0, x - x_0 > 0 \end{cases} \tag{3}$$

The value of θ ranges from 0 to 2 π.

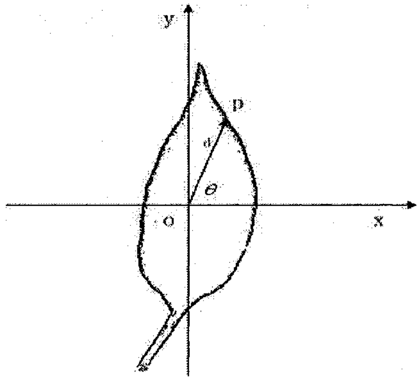

Figure 1

Consider the boundaries of the object as closed, the point P(x, y) on contour is determined by the centroid C(x_0, y_0), the distance *d* between C and P, and the angel θ of the two points. Obviously, it is translation invariant. Finally, we can describe the object by the vector < x_0, y_0, d_1, θ_1, d_2, θ_2······ d_n, θ_n>.

2.2 Feature vector

As the method mentioned above is neither scaling nor rotation invariant, it can not be used for image retrieval effectively. The essential of achieving rotation invariant is to find the start point of the curve. Generally, the shape of a leaf is usually symmetrical. We choose the $\max\{d_1, d_2 \cdots d_n\}$ as the start point.

In a content based image retrieval system, the shape matching process efficiency is very essential, so a low dimension feature vector is needed. We can select fixed *k* pixels on a contour as the feature vector of an image.

The procedure of the algorithm is as follows:

1. Select the d_{max} as the start point, the corresponding angel of d_{max} is θ_{max}.
2. let $\Delta\theta = 2\pi / k$
3. SV[0] = d_{max};
```
for(j=1; j<k; j++)
    SV[k] =0.0;
```
4. for(each (d_i, θ_i)) {
```
        for (j=1; j<=k; j++) {
         if(θi<θmax) {
           if((2π+θi-θmax-j·Δθ)<0.01) {
             if(SV[j]!=0)
               SV[j] = di;
```

```
            }
        }
        if(θi>θmax) {
            if((θi-θmax- j·Δθ)<0.01) {
                if(SV[j]!=0)
                SV[j] = di;
            }
        }
    }
}
```

To improve efficiency, we reduce the *k* vertices to a lower dimensional vector. The least important sample point is removed every time, the process is repeated unless we get the desired shape representation. The importance of a sample point *p* is determined by:

$$K_p = \left| \frac{k_1 - k_2}{1 + k_1 k_2} \right| \cdot \frac{l_1 l_2}{l_1 + l_2} \tag{4}$$

Let p_1, p_2 be the neighbor point of *p*. k_1 is the slope of curve p_1p, l_1 is the length of p_1p, k_2 is the slope of curve pp_2, l_2 is the length of pp_2. The lower of the value of K_p, the less the point is important to the shape. For a closed contour, this method can generate a set of sampled points with the value $\{d, \theta\}$ that represents the boundary.

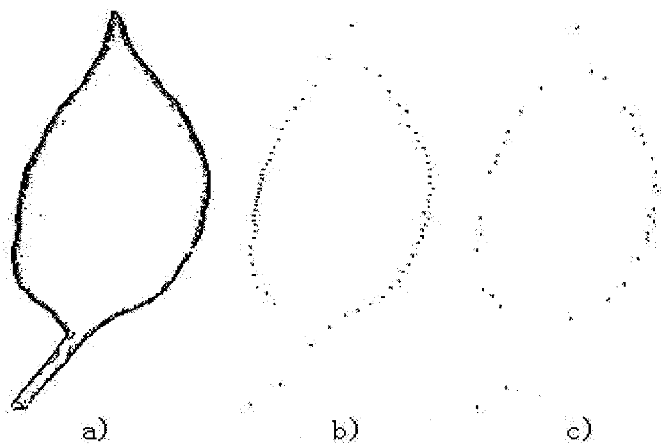

Figure 2: a) the original sketch image, b) 72 sample points, c) reduced to 36 points

2.3 Strategy before image matching

A query image Q and a database image D which is the same species of leaf may be different in size. We can normalize the curve value to range [0, 1] to make scaling invariant. The distance vector $SV[k]$ will be normalized to $SV'[k]$ by:

$$\mathrm{SV}'[\mathrm{i}] = \frac{\mathrm{SV}[\mathrm{i}]}{\max\{\mathrm{SV}[0], \mathrm{SV}[1] \cdots \mathrm{SV}[\mathrm{k}]\}} \qquad 1 \leq \mathrm{i} \leq \mathrm{k} \tag{5}$$

Because image matching is a time-consuming task, we can use some simple feature to index the database images to be compared.

We use a shape feature, the ratio of d_{max} over d_{min}. The feature is calculated by:

$$R = \frac{d_{\max}}{d_{\min}} \tag{6}$$

And the distance between image Q and D is computed by:

$$d_r(Q, D) = \left| R_Q - R_D \right| \tag{7}$$

It is easy to verify that the ratio is translation, scaling and rotation invariant. This method can be used to score the similarity before the matching process. By this method, the whole database can be pruned to a small candidate set. This can significantly improve the matching efficiency.

2.4 Shape matching

The similarity between two images can be defined as the distance between their feature vectors, so that we can use the Euclidean distance function to measure their similarity. The function is as follows:

$$d_c(Q, D) = \sqrt{\sum_{i=1}^{k} (SV_Q'[i] - SV_D'[i])^2} \tag{8}$$

where Q is the query image and D is the database image, k is the number of sample points.

But the method mentioned above does not guarantee if there is more than one maximum distance in the sample points. Motivated by the MCS method in [a study of shape-based image retrieval], we proposed a method to reduce this problem. The algorithm is described as follows:

1. select the top m maximum distances as the possible start points
2. calculate the $d_{ci}(Q,D)$, $1 \le i \le m$
3. the minimal distance $d_c = \min\{d_{c1}, d_{c2} \cdots d_{cm}\}$

3. EXPERIMENTS

We pluck leaves from plants, and then put a single leaf on a white panel and take photo of the leaf by a digital camera. In this way, the shape of a leaf will be presented and the background will be wiped off easily. Our image database includes 30 species, with 10 sample images in each species. Every image can be used as query. For every image, first the edge detector is adopted to get the sketch, then for every $2\pi/k$ (k = 72, 144, 216) orientation, k points on the contour are selected as the feature vector, finally the vector is reduced to a 36-dimentional vector by removing the unimportant points to the shape. Example is given in Figure 2.

For the image retrieval, give a query image and a value r of the number of the images to be ranked, let $r1$ be the number of images that are the same object with the query image and r_T be the number of images with same object in the database, the average precision is defined as $r/r1$, the average recall is defined as r/r_T. The system performs the similarity algorithm to recover the set of images that best match.

Fig.3 shows a good result with the query image at the left and the retrieved images at the right with 10 ranked images. Eight out of ten were the same with the query image.

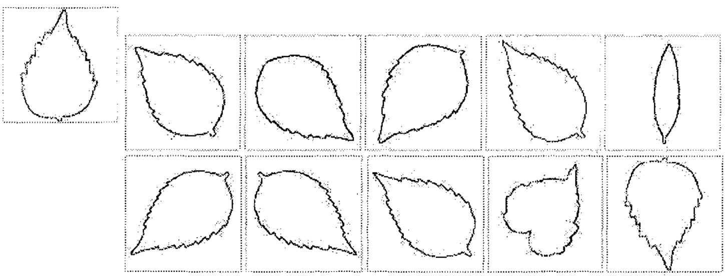

Figure 3

Table 1 lists the result compared with those of A. Hong in [9]. We can see that our proposed method is better. Table 2 shows the recall rate and precision with respect to different *k* sample points.

Table 1. Compared result

Feature	Return Images	Recall rate (%)
A.Hong's method	10	0.266
	30	0.533
Our Method	10	0.49
	30	0.65

Table 2. Recall rate and precision with different sample points

Number of Sample Points (10 return images)	Recall rate (%)	Precision (%)
72	0.43	0.72
144	0.51	0.74
216	0.54	0.78

4. CONCLUSIONS AND FUTURE WORK

This paper proposed a shape based method to retrieve leaf images. It discussed how to extract shape feature from sketch images and how to compare the feature vectors. The method is implemented and evaluated in order to analyze its effectiveness and efficiency.

Future work is to include more features to improve the performance of our method and extend our method to handle broken leaves.

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