國立交通大學

多媒體工程研究所

碩 士 論 文

一 個 基 於 花 與 葉 片 之 植 物 辨 識 系 統

A Plant Recognition System Based on Leaf and Flower

研 究 生：楊志鴻

指導教授：陳玲慧 教授

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摘要

本篇論文中我們提出一個基於花與葉片之植物辨識系統，針對台中都會公園的植物，利用照相手機所拍攝的花朵影像及葉片影像進行辨識。辨識系統共分為三大部分。第一部分為花朵辨識系統，總共使用了花朵的十四種特徵，包含三種外型以及十一種顏色的特徵。為了從複雜的背景中擷取出花朵的部分，我們提出了一個快速自動化切割物體的方法，並藉由使用者互動方式擷取出花朵部分。第二部份為葉片辨識系統，共使用了葉片的五個外型特徵。葉片自動辨識系統分為兩個階段，第一階段先將與輸入影像差異大的種類刪除，而第二階段依據第一階段過濾後的數種名單進行最後的辨識動作。系統的第三部份為針對開花植物中結合花朵以及葉片的辨識系統。首先，分別先將花朵以及葉片進行辨識。接著，我們提出了一個有效結合花朵以及葉片資訊的辨識方法，進行進一步的辨識，可有效提高辨識的準確率。

A Plant Recognition System Based on Leaf and Flower

Student: Chih-Hung Yang Advisor: Dr. Ling-Hwei Chen

Institute of Multimedia Engineering

National Chiao Tung University

Abstract

In this thesis, we propose a plant recognition system based on leaf and flower images. The images are taken in the Taichung Metropolitan Park by the camera mobile phone. There are three parts in the recognition system: flower, leaf, and combination of flower and leaf. In the flower recognition part, 14 features of flowers, including 3 shape features and 11 color features, are used. We propose a fast and automatic object segmentation method and combine user's interaction to extract the flower region. In the leaf recognition part, 5 shape features are extracted. A two-stage approach is provided for automatic leaf recognition. Firstly, some impossible species are pruned according to the first three features. Next, the remaining species are tested to do recognition based on all five features. In the combining recognition part, a pair of leaf and flower images are recognized respectively. Then, an effective method is presented to do recognition by combining the recognition results of leaf and flower. According to experimental results, the combining recognition part can improve the recognition rate effectively.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Motivation

When wandering around the field or park, we can find out many plants. If there are no signs for the plants, we can not know their names on the instant. Although we can try to identify the names of plants by looking up guide books for plant, or browsing web pages on the Internet through keywords searching, it is inconvenient and difficult to look for the name of specific plant. Since the camera mobile phone has been widely used for most people, it would be very useful and convenient if we can use the plant recognition system to identify the plants directly based on photograph by camera mobile phone.

1.2 Previous work

Plants are basically classified according to their shapes, colors and structures of their leaves and flowers. It is very difficult for us to recognize the plant without any knowledge of botany. In this thesis, we proposed a plant recognition system based on a photograph. It is a necessary step to extract a flower region or a leaf region of interest from the background for recognition. However, it is more difficult to achieve perfect segmentation from a complex background (e.g. natural scene).

To avoid this difficulty, Saitoh and Kaneko [1, 2] used a piece of black cloth (or black paper) under the flower and leaf when they took photographs. To separate the background, they used K-means algorithm [3] for clustering in RGB space and then removed the background region. Then, they proposed 21 features, including 10 features of flower and 11 features of leaf in recognition phase, and received a high accuracy rate above 95%. Nevertheless, it is inconvenient and laborious to photograph flowers and leaves with a piece of back cloth and the direction of leaf should be fixed.

Chen [4] proposed an automatic segmentation algorithm for natural images. Considering from human vision, they transformed RGB color space into CIELab color space [5-6]. Then, they also used K-means algorithm [3] to classify all colors in the image and proposed a two-stage method to segment regions by colors. However, the segmentation takes a lot of time and is impractical.

Zou and Nagy [7] used the rose curve which was defined by the Italian mathematician Guido Grandi for segmentation. Firstly, they used a rose curve model fitting on the initial segmented flower region and allowed interactive adjusting by user to fit the real flower region. When adjusting the curve of the flower, the system would receive features at the same time and would refresh the Top-3 candidate images. They used 2 shape features and 6 color features within rose curve for flower recognition. Obviously, the system needs a lot of user's adjustment to get high accuracy.

Saitoh et al. [8] proposed an automatic method for extracting flower region and recognition. For extracting the flower boundary, they used the well-known method proposed by Mortensen and Barrett called Intelligent Scissors (IS) [9]. Pictures were taken with macro mode setting F value from F2.8 to F3.5. They used 10 features for flower recognition and received high accuracy above 90%. However, there are some limitations such as the position of the flower must be in the center of the photograph and be well focused, with background defocused.

Wang et al. [10] proposed a two-stage approach for leaf image retrieval by using shape features such as centroid-contour distance (CCD) curve, eccentricity, and angle code histogram (ACH). The two-stage approach can achieve a performance comparable to an exhaustive search, but with a much reduced computational complexity. The average recall rate is 38.1% for 20 return images.

Lee and Chen [11] proposed a classification method for leaf images. They proposed 5 region-base features for leaf recognition. The accuracy rate is 82.33% and the recall rate is 48.2% for 10 return images. However, the leaf should be put on the light panel and the direction of leaf must be fixed when taking picture of leaf. It is also inconvenient for users to get leaf image by this way.

In this thesis, we propose three methods in our recognition system, including flower recognition, leaf recognition and combining recognition. Firstly, an interactive method is provided for flower segmentation which utilizes user's interaction to eliminate the limitations of photographs and to get a correct flower region of interest. Then, we adopt 14 various features including 3 for shapes and 11 for colors for recognition. Secondly, a two-stage automatic region-base method is used for leaf recognition. We use some techniques to remove noises and to solve rotation problem. Then, we can get the leaf region of interest and adopt 5 shape features for recognition. Thirdly, we propose a combining recognition method based on a pair of images of flower and leaf. The features of flower and leaf are extracted respectively by the steps described above. Then, we combine the features of flower and leaf for recognition. Experimental results show that the combining recognition method can get higher accuracy rate than using only flower or leaf.

1.3 Organization of the Thesis

This thesis is composed of five chapters. In Chapter 1, the motivation and previous works are introduced. Chapter 2 describes the database images including flower and leaf images used in the study. The proposed recognition method is presented in Chapter 3. Experimental results and discussions are given in Chapter 4. The final chapter gives conclusions.

CHAPTER 2

IMAGE DATABASE

The image database consists of flower images and leaf images taken in the Taichung Metropolitan Park by camera mobile phone. Pictures were taken with macro mode and an aperture value 2.8F. Camera mobile phone used is Nokia N82. All images are re-scaled to the same size, 320x240 pixels, before recognition.

2.1 Flower Image Database

The flower image database consists of 684 flower images with 24 species. Each of the flower images will be selected as the testing data, and the remaining 683 images are then used for database. There are at least 20 images for each species and the images are taken from natural scene by camera mobile phone. Fig. 1 shows 24 species of flowers in our database. Several images contain multiple, tiny, overlapping flowers. Some flowers have different colors in the same species as shown in Fig. 2. For robustness, the images of the same species were taken from different flowers.

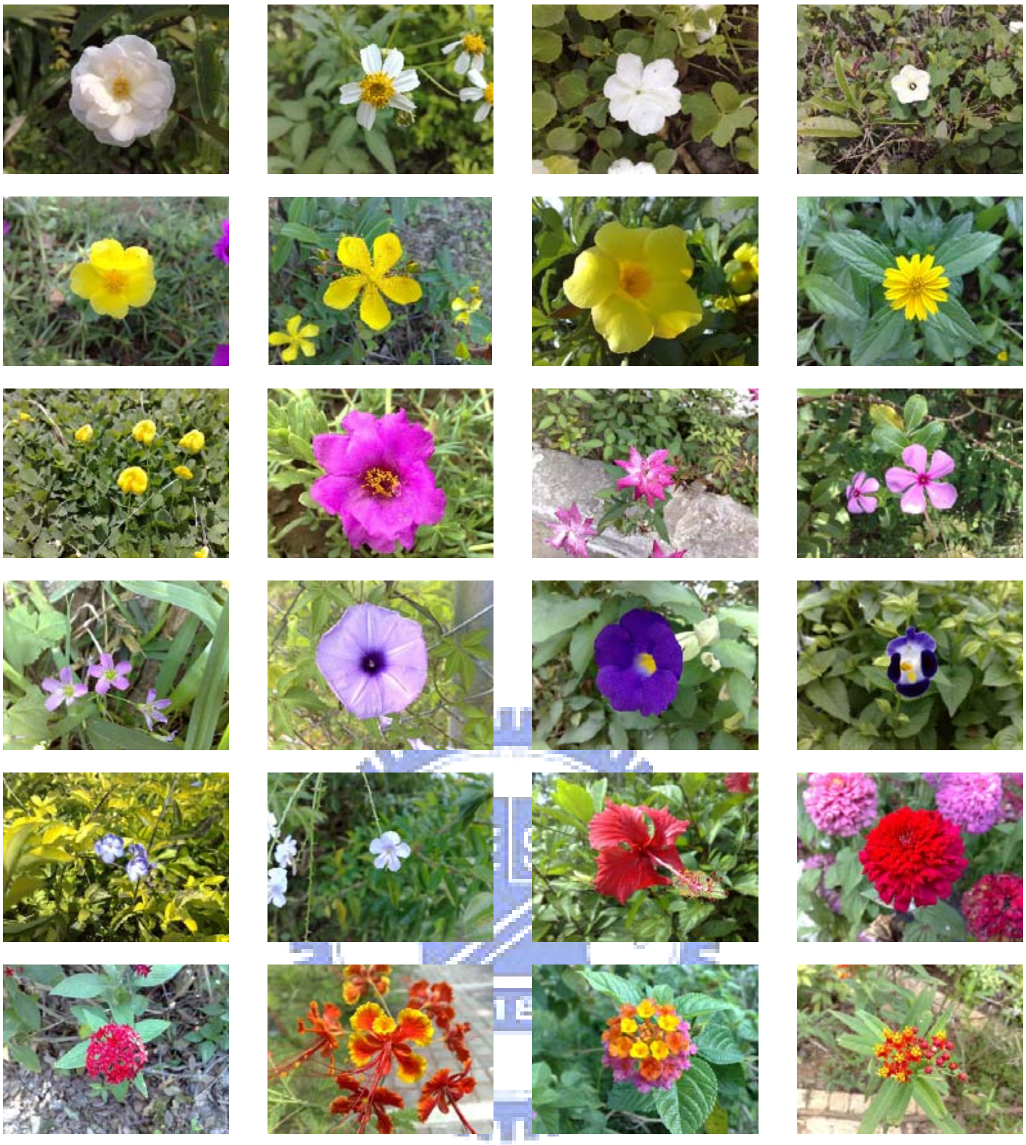


Fig. 1 Images of 24 distinct flowers.

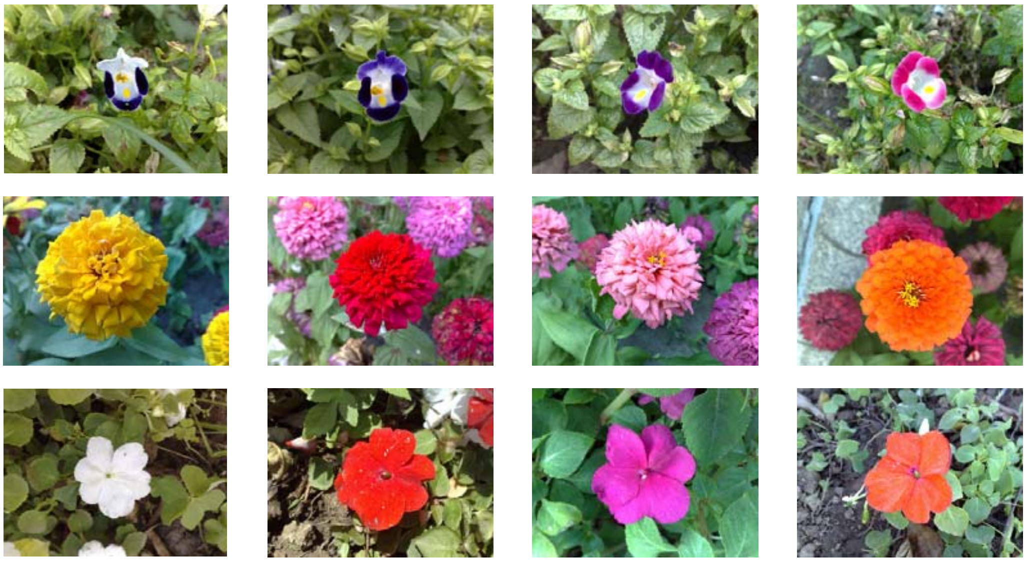


Fig. 2 Some examples of flowers with different colors in the same species.

2.2 Leaf Image Database

Leaves are usually clustered, so it is difficult to extract a leaf automatically from a natural image. As a result, we plucked a leaf and put it on a piece of white paper, and took the picture of the leaf with camera mobile phone. Thus, leaf images can be obtained without complex background.

The leaf image database consists of 1920 leaf images from 48 species. Each species includes 40 images; the 20 images of them are used for database images and the others are used for testing images. Fig. 3 shows the 24 species of the leaves, which have corresponding blooming flowers shown in Fig. 1. For the other 24 species, we only collect the leaves as shown in Fig. 4. For robustness, we plucked 15 to 20 leaves for each species and took pictures for each leaf from different directions.

Fig. 3 24 distinct leaves corresponding to the blooming flowers shown in Fig. 1.

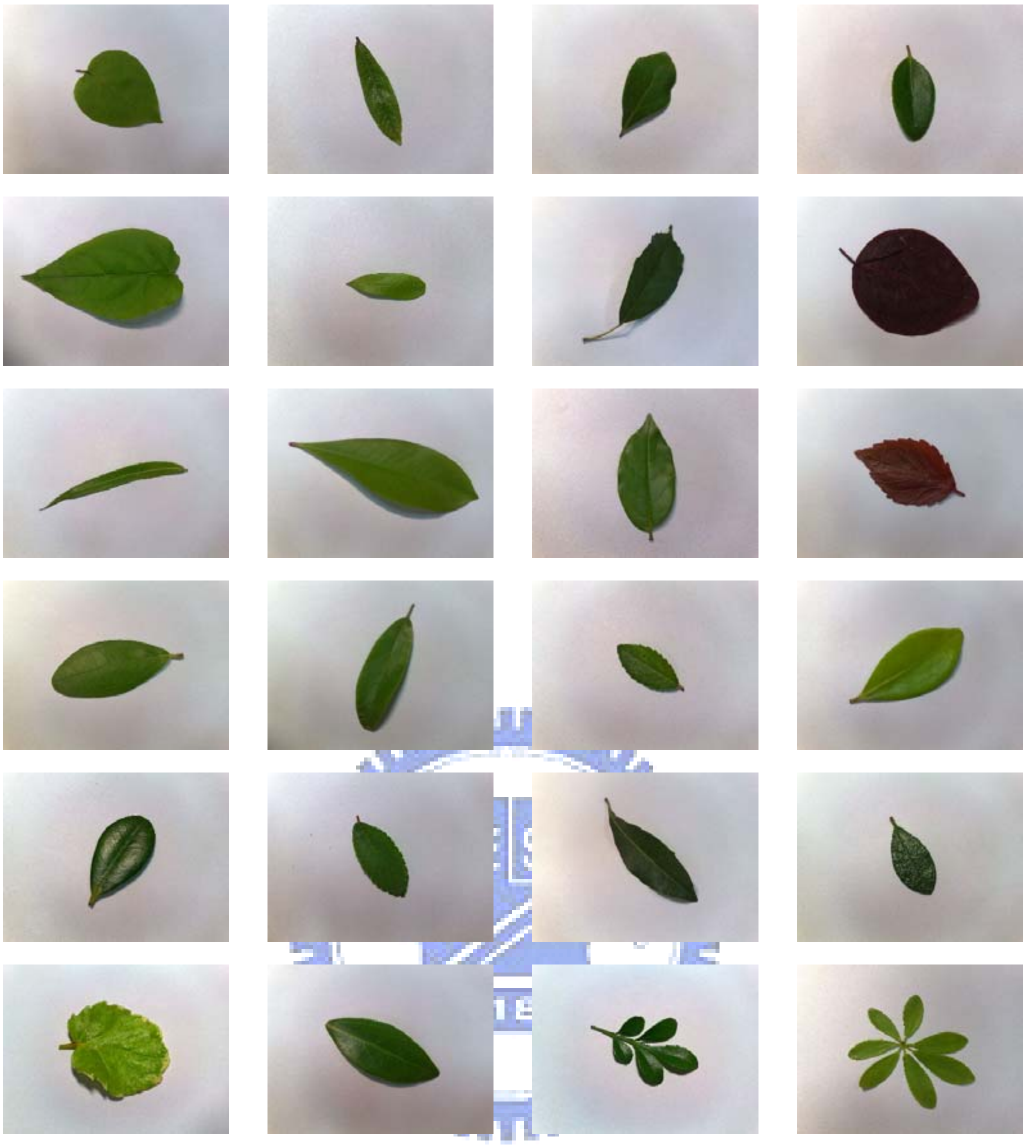


Fig. 4 Other 24 species collected with leaves only.

CHAPTER 3

PROPOSED SYSTEM

In this thesis, we propose a recognition system for plants. The plant recognition system has three functions which are flower recognition, leaf recognition and combining recognition. When a user only input a flower image or a leaf image, this system can recognize the query image and return the possible species to the user. When the user input a pair of images including the flower and the leaf, this system can get better result than only using a flower image or a leaf image. Details will be described in the following sections.

3.1 Flower Recognition Method

Fig. 5 shows the flow chart of the proposed method for flower recognition. The whole process consists of three major phases: preprocessing, feature extraction, and recognition. In the preprocessing phase, the proposed method provides a semi-automatic technique to find out the flower region. In the feature extraction phase, 3 shape features and 11 color features are extracted for recognition. In the recognition phase, a similarity measure based on the extracted features is provided. Based on the measure the most similar flower images to the query image in the database are determined.

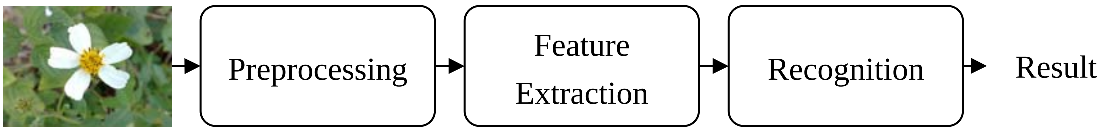


Fig. 5 The flow chart of the proposed method for flower recognition.

3.1.1 Preprocessing for Flower

Extracting a flower region from the background is a necessary step for flower recognition. In order to extract the flower region as correctly as possible, the proposed method provides a semi-automatic technique to locate the flower area. Because the flower always has the significant color distinct from the leaves, we can use color information to segment the region of the flower. Here the K-means algorithm is used to find the dominant colors of the flower image. According to the statistics, there are averagely fifty thousand colors in each flower image of our database. It costs extensive computation time to extract the dominant colors form fifty thousand colors by K-means. In order to speed up the process time, we first gather the nearby pixels with the similar colors and merge them into small regions. After that, we can reduce the colors of a flower image from fifty thousand to hundreds. Next, we use an automatically segment method proposed in [4] to determine the dominant colors by K-means and then replace the colors of small regions with the dominant colors. Then, the region growing technique is applied to merge those neighboring small regions of the same color. Finally, the flower region can be extracted by user selection based on the segmentation results. Fig. 6 shows the flow chart of the preprocessing steps.

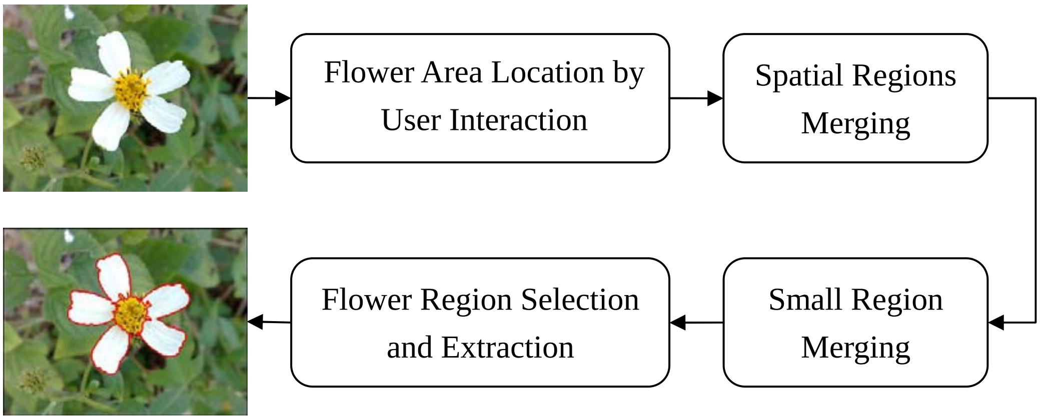


Fig. 6 The flow chart of the preprocessing steps of flower recognition.

3.1.1.1 Flower Area Location by User Interaction

In order to reduce the limitations of input images and to extract the correct flower region, an interactive method is provided. At first, a rectangle is drawn by user's mouse click to bind an interested flower. Fig. 7 shows an example of determining flower area location by user interaction. We called the region within the rectangle as the object region. After the flower area is located, we present a semi-automatic segment method to extract the flower region. The details are described in the following subsections.

(a) (b)

Fig. 7 An example of determining flower area location by user interaction. (a) Original image. (b) The rectangle is drawn by user.

3.1.1.2 Spatial Regions Merging

Most of flowers have the significant color distinct from leaves, therefore the color information is used to do segmentation and then we can extract the flower region by user interaction. To reduce the number of colors in the image without losing the important spatial information of colors, we first gather the nearby pixels with similar colors in the object region into a small region. Note that the differences of nearby pixels are below a threshold, we called them have the similar colors. The threshold is determined by edge detection described as following:

To estimate edge points in the object region, we apply Sobel operators (see Fig. 8). The gradient magnitude G for pixel (x, y) with color value $P_{x,y}$ is defined as

$$G = \sqrt{G_x^{\ 2} + G_y^{\ 2}}\ ,$$
$$\text{where } G_x = \left(P_{x+1,y-1} + 2P_{x+1,y} + P_{x+1,y+1}\right) - \left(P_{x-1,y-1} + 2P_{x-1,y} + P_{x-1,y+1}\right)$$
$$\text{and } G_y = \left(P_{x-1,y+1} + 2P_{x,y+1} + P_{x+1,y+1}\right) - \left(P_{x-1,y-1} + 2P_{x,y-1} + P_{x+1,y-1}\right), \qquad (1)$$

G_x is the magnitude of horizontal gradient and G_y is the magnitude of vertical one.

-1	0	1
-2	0	2
-1	0	1

G_x

-1	-2	-1
0	0	0
1	2	1

G_y

Fig. 8 Two Sobel operators for G_x and G_y

We compute the gradient magnitudes for R, G, and B channels. Next, we take the maximum value of three gradient magnitudes for each pixel to form another image. And then the Otsu's method [12] is applied to the image to get a binary image. Finally, we can get all edge points from the binary image easily.

According to the edge detection result, the percentage of edge points and smooth areas can be estimated. Then, we define four color differences: (i) the difference of R channel, (ii) the difference of G channel, (iii) the difference of B channel, (iv) the total difference of R, G and B channels which is defined as $diff = \sqrt{(r_1 - r_2)^2 + (g_1 - g_2)^2 + (b_1 - b_2)^2}$. We calculate the four differences to the 8 neighbors for each pixel in the object region. After that, we compute the four accumulated histograms and calculate the cumulative distribution function (CDF), respectively. In each CDF, the difference value at the same percentage as the smooth areas percentage is considered as threshold. Based on this threshold, we can get all connected components with similar colors. The details are described as follows:

Firstly, a pixel is taken as a starting point of a component, and the representative color of the component is decided by the average color of all pixels in the component. Each time when the component meets a new point, the four color differences between the average color of the component and the new point will be calculated. If one of these differences exceeds the threshold, the new point will be regarded as a starting of a new component; otherwise, it will be included to the component and the process will continue. After the process, there will be hundreds of connected component regions with different sizes. Since most of the connected components are small, we should merge those small regions. Thus, the next process will be used to merge small regions. It will first find the dominant colors for these regions based on K-means and replace the colors of these regions with those found dominant colors. The step is used to speed up the merging process.

3.1.1.3 Small Regions Merging

In this section, we will apply a modified K-means method to merge small regions. Before describing this method, we will introduce the used color space. Since the RGB color space is perceptually non-linear to human vision system, the RGB color space will be transformed into CIELab color space [5-6] based on ITU-R Recommendation BT.709 with the D65 white point reference:

$$\begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}, \tag{2}$$

$$\begin{cases} X = X'/0.950456 \\ Y = Y'/1.000000 \\ Z = Z'/1.088754 \end{cases}, \tag{3}$$

$$\begin{aligned} L^* &= 116 \cdot f(Y) - 16 \\ a^* &= 500 \cdot [f(X) - f(Y)], \\ b^* &= 200 \cdot [f(Y) - f(Z)] \end{aligned} \tag{4}$$

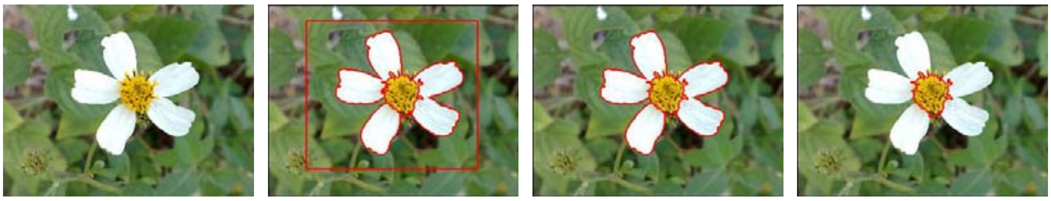
where

$$f(t) = \begin{cases} t^{1/3}, & \text{if} \quad t > (6/29)^3 \\ \frac{1}{3}(\frac{29}{6})^2 t + \frac{4}{29}, & \text{otherwise.} \end{cases} \tag{5}$$

After transforming the average color of each component to CIELab color space, the modified K-means method is conducted. There is a significant drawback with the traditional K-means algorithm; the K value cannot be adjusted after decided. Hence, we use the concept from [4], that is, an “error threshold” is provided to decide the suitable K. The average error after applying K-means method is defined as the average color difference among the original colors and the colors of the results by K-means. Firstly, we set K=2, and then the K-means method is applied. When the average error is larger than the error threshold, K is increased and K-means method is applied again. The process will finish when the average error is under the threshold, then the result K colors are used to represent the dominant colors of original colors. In our method, the error threshold is defined as 10% of the Lab color bandwidth. After the step, the color of each pixel in the object region will be transformed to the nearest dominant color. Then all neighboring pixels with the same dominant color are merged into a region.

3.1.1.4 Flower Region Selection and Extraction

Based on the merging results, the object region can be segmented by dominant colors as shown in Fig. 9(b). Since the system cannot automatically identify the flower regions from these segment results, a way of utilizing the user interaction is proposed. From Fig. 9(b), we can find that a flower is segmented to several regions. To acquire the complete flower region, users can use mouse click to point out the regions of the petal and stamen. After that, a flower region including the petal and stamen regions can be extracted as shown in Figs. 9(c) and 9(d). Sometimes the stamen color is so similar to the petal color, that the stamen region can not be extracted. To treat this case, the stamen region is defined as the rectangular window with the flower center as its center, and its area being 1/9 of the flower bounding box. Fig. 10 shows an example of the preprocessing results with the colors of petals and stamens similar.



(a) (b) (c) (d)

Fig. 9 An example of the preprocessing results. (a) The original image. (b) The segmentation results. (c) The petal and stamen region selected by user. (d) The stamen region.

(a) (b) (c) (d)

Fig. 10 An example of the preprocessing results with the colors of petals and stamens similar. (a) The original image. (b) The segmentation results. (c) The flower region selected by user. (d) The stamen region.

3.1.2 Feature Extraction for Flowers

Color and shape are the most widely-used features for describing flowers. In this thesis, 3 shape features and 11 color features are used for flower recognition. Parts of these features were proposed by Hsu [13].

3.1.2.1 Shape Information

Firstly, the gravity center (g_x, g_y) of the flower region is computed as follows:

$$g_x = \frac{1}{N}\sum_{i=1}^{N} x_i,$$
$$g_y = \frac{1}{N}\sum_{i=1}^{N} y_i, \tag{6}$$

where N is the number of pixels in the flower region, x_i and y_i are the coordinates of the i^{th} pixel in the flower region. The distance between the flower center and each pixel in the flower region is computed as follows:

$$d_i = \sqrt{(x_i - g_x)^2 + (y_i - g_y)^2}, 1 \le i \le N. \tag{7}$$

Without loss of generality, we let d_i be sorted in an increasing order. That is, $d_i \le d_{i+1}$, $1 \le i \le N-1$. The CDD [10] is a set of distances from those points in the contour to the shape center. Then the three shape features are described as follows:

F(1): Sharpness. A ratio indicates the relevance sharpness of the petals to the flower. It is computed as

$$F(1) = \frac{CCD_{10}}{CCD_{90}}, \tag{8}$$

where CCD_{10} represents the average of the top one-tenth of the shortest CCD and the and CCD_{90} represents the average of the top one-tenth of the largest CCD.

F(2): It represents the average of normalized distances computed from the flower center to every point in the flower region. It is computed as

$$F(2) = \frac{1}{N}\sum_{i=1}^{N} D_i, \tag{9}$$

where D_i is the normalized distance defined as

$$D_i = \begin{cases} 1, & d_i \ge R_{90} \\ \dfrac{d_i - R_{10}}{R_{90} - R_{10}}, & R_{10} < d_i < R_{90}, \\ 0, & d_i \le R_{10} \end{cases} \tag{10}$$

and R_{10} represents the average distance computed from the pixels with d_i in the first 10% of d_j and R_{90} is computed from the pixels with d_i in the last 10% d_j:

$$R_{10} = \frac{1}{0.1\times N}\sum_{j=1}^{0.1\times N} d_j,$$
$$R_{90} = \frac{1}{0.1\times N}\sum_{j=0.9\times N}^{N} d_j, \tag{11}$$

F(3): Roundness. The roundness represents the similarity between the shape of petals and a circle. It is computed as

$$F(3) = \frac{4\pi S}{L^2}, \tag{12}$$

where L is the perimeter of the flower and S is the area of the flower with $0 < F(3) \le 1$. When $F(3)$ is approximating to 1, it means that the shape of flower is near a circle.

3.1.2.2 Color Information

The flower images are represented in the RGB model. Because flower images are taken in different days and under various kinds of weather, the RGB values are converted into the HSV (hue, saturation and value) values [14] in order to reduce the illumination variation. Our features are taken by the primary, secondary and thirdly flower colors and the stamen color. Firstly, the H value is divided into 12 partitions and the S value is divided into 6 partitions and there are totally 72 cells represented by C_i, i=1,2,…,72. (see Fig. 11). For each flower image, its color distribution corresponding to divided cells is computed. Let DC_1, DC_2, and DC_3 denote the first three dominant color cells appearing in the flower region. Then, the color features can be summarized as

$F(4)$: the h value of the color cell DC_1,

$F(5)$: the s value of the color cell DC_1,

$F(6)$: the probability of the color cell DC_1,

$F(7)$: the h value of the color cell DC_2,

$F(8)$: the s value of the color cell DC_2,

$F(9)$: the probability of the color cell DC_2,

$F(10)$: the h value of the color cell DC_3,

$F(11)$: the s value of the color cell DC_3,

$F(12)$: the probability of the color cell DC_3,

Since the color of the stamen is also an important characteristic, we will compute the dominant color of the stamen region. Let SC denote the dominant color cell in the stamen region, then the color features of the stamen are defined as

$F(13)$: the h value of the color cell SC.

$F(14)$: the s value of the color cell SC.

Note that we have used the following equations to normalize the H and S values into h and s values.

$$h=\begin{cases}1, & if\ H\in[0,\ 30)\\ 2, & if\ H\in[30,\ 60)\\ 3, & if\ H\in[60,\ 90)\\ 4, & if\ H\in[90,\ 120)\\ 5, & if\ H\in[120,\ 150)\\ 6, & if\ H\in[150,\ 180)\\ 7, & if\ H\in[180,\ 210)\\ 8, & if\ H\in[210,\ 240)\\ 9, & if\ H\in[240,\ 270)\\ 10, & if\ H\in[270,\ 300)\\ 11, & if\ H\in[300,\ 330)\\ 12, & if\ H\in[330,\ 360)\end{cases}\qquad s=\begin{cases}1, & if\ S\in[0,\ 0.17)\\ 2, & if\ S\in[0.17,\ 0.34)\\ 3, & if\ S\in[0.34,\ 0.51)\\ 4, & if\ S\in[0.51,\ 0.68)\\ 5, & if\ S\in[0.68,\ 0.85)\\ 6, & if\ S\in[0.85,\ 1]\end{cases}\qquad (13)$$

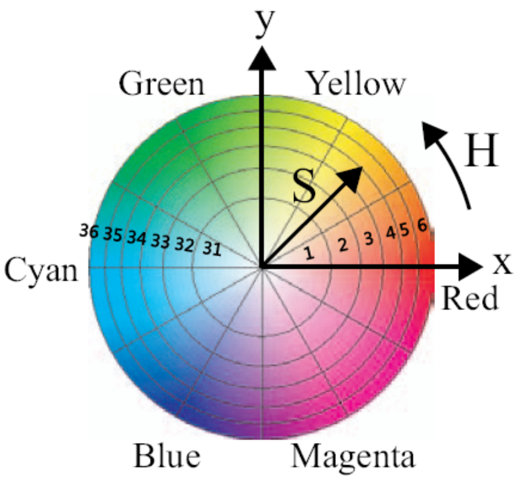


Fig. 11 The HS space divided into 12x6 cells.

3.1.3 Flower Recognition

Before recognition, all features, $F(i)$, are normalized to [0, 1] and represented by $f(i)$. In the recognition phase, we calculate the distances between the query image and all flower images in the database. The distance $dist_i$, which is between the query image and the i-th image in the database, is measured by

$$dist_i=\sum_{k=1}^{14}\left|f_i(k)-f(k)\right|,$$

where $f_i(k)$ denotes the k-th feature value of the i-th database image, $f(k)$ denotes the k-th feature value of the query image. Then, flower recognition is accomplished using the k-nearest neighbor algorithm. After that, the recognition system ranks the distances and returns the Top-20 nearest neighbors. Then, the system gives scores to each rank such as $1^{st} = 20$, $2^{nd} = 19$ …, respectively. Next, we sum up the scores of the same species and compute the similarity. Finally, we rank the similarity and return the flower images of possible species.

3.2 Leaf Recognition Method

The leaf recognition method is originally proposed by Huang [15]. Based on the method, we do some improvement in leaf extraction and recognition rate. Fig. 12 shows the flow chart of the proposed method for leaf recognition. The whole process consists of three major phases: preprocessing, feature extraction and recognition. In preprocessing phase, we use some techniques to extract the leaf object. In the feature extraction phase, five shape features are extracted for recognition. Then, we apply a two-stage recognition based on the extracted features. The impossible species can be pruned in the first stage. The second stage uses a similarity measure for the remaining species.

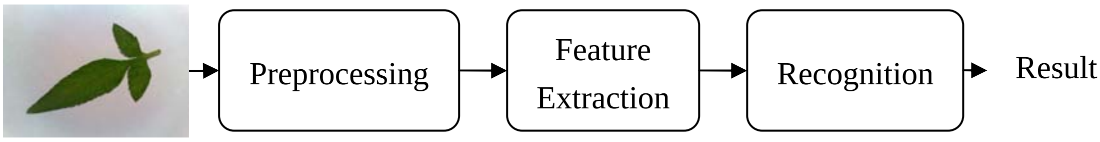


Fig. 12 The flow chart of the proposed method for leaf recognition.

3.2.1 Preprocessing of Leaf

When we take picture of the leaf image, there could be some distortion (including rotation, translation and scaling) and unbalanced light condition. Therefore, we have to overcome these problems according to following five steps as shown in Fig. 13. After that, the leaf object can be extracted and be normalized.

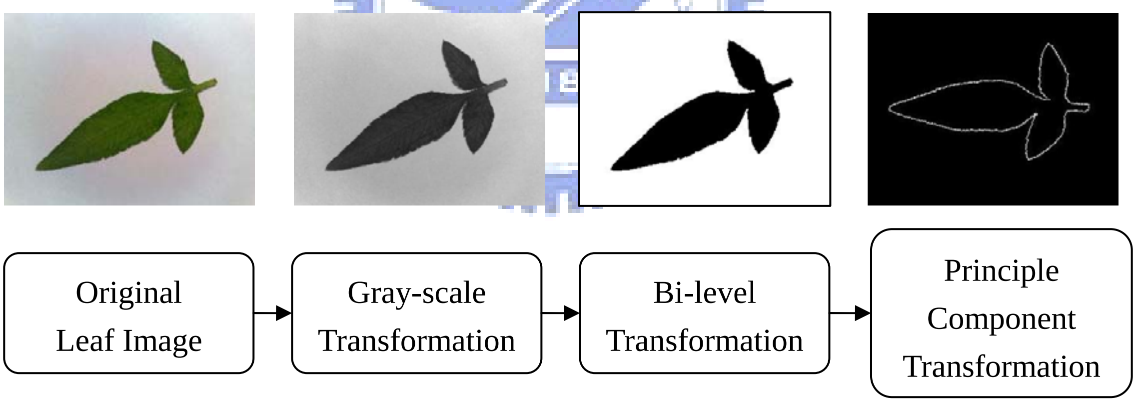


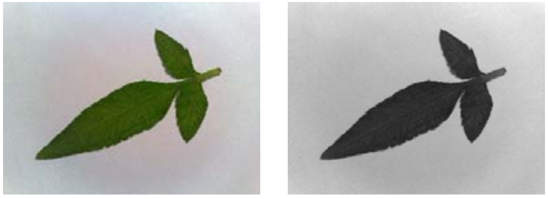
Fig. 13 The flow chart of the preprocessing steps of leaf recognition.

3.2.1.1 Gray-scale Transformation

Generally, most leaves are green. However, shades and the variety of environments reduce reliability of color features. For the reason, we transfer the color image to a gray-level image. Each pixel is computed from the original image by

$$gray(i, j) = \frac{R(i, j) + G(i, j) + B(i, j)}{3}, \tag{14}$$

where $R(i, j)$, $G(i, j)$ and $B(i, j)$ denote the red value, green value and blue value at pixel $P_{i, j}$. An example of gray-level transformation is shown in Fig. 14.



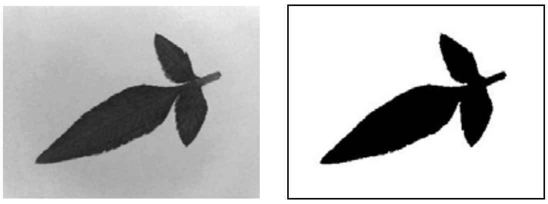
(a) (b)

Fig. 14 An example of gray-level transformation. (a) Original image. (b) Gray-level image.

3.2.1.2 Bi-level Transformation

To simplify the cost of computation, we transform the gray-level image to bi-level image. Otsu's method [12] is a classical method, which binarizes a gray-level image to a binary image. The algorithm assumes that an image contains two classes of pixels. It finds the optimum threshold separating the two classes so that their within-class variance is minimal.

After using Otsu's method to find the optimum threshold, the pixels are separated into background area and leaf object area. The pixel with gray value in the gray-level image larger than the threshold t be considered as background and set its gray value to 255; otherwise, it is regarded as the leaf object and set its gray value to 0. An example of bi-level transformation is shown in Fig. 15.



(a) (b)

Fig. 15 An example of bi-level transformation. (a) Gray-level image. (b) Bi-level image.

By the above steps, we can extract the leaf objects correctly from most of the leaf images. Some species of the leaf images can not be extracted successfully, because the size of the leaf is too small or the color of the leaf is too light. Hence, the following steps will solve this problem on the bi-level image (See Fig. 15(b)). Firstly, the positions of the black pixels in the bi-level image are recorded. Next, we preserve the pixels in the gray-level image according to the positions. Then, the Otsu's method is applied to these pixels on the gray-level image to do bi-level transformation. Fig. 16 is an example of this case. After bi-level transform, we can get a binary image. Based on the binary image, we can get the boundary points of leaf easily.

(a) (b) (c)

Fig. 16 A special case of bi-level transformation. (a) A gray-level image. (b) The result of first thresholding. (c) The result of second thresholding.

3.2.1.3 Principle Component Transformation

We face another issue that the direction of the leaf images are various during feature extraction. To solve this problem, we use the principle component to align the image with the direction of maximum variance.

Let

$X_k = (x_k, y_k)$ be the position of the k-th boundary point of a leaf pixel,

n = the number of boundary pixels.

We present the steps of principle component transformation as follows:

1. Compute the center point m_x of the boundary pixels by

$$m_x = \frac{1}{n}\sum_{k=1}^{n} X_k, \tag{15}$$

2. Compute the covariance matrix

$$C_x = \frac{1}{n}\sum_{k=1}^{n} X_k X_k^T - m_k m_k^T, \tag{16}$$

3. Let $\mathbf{V} = (e_i, e_j)$ be the normalized associated eigenvector of the max eigenvalue of C_x, and the angle between it and x-axis is θ. Note that $\mathbf{V}$ is the principle

component of the boundary points.

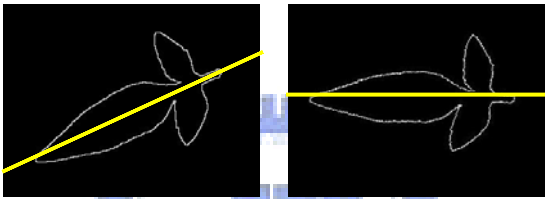
4. Let the transformation matrix **A** be $\begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix}$.

5. Rotate the leaf with θ degree according to

$$Y_k = A(X_k - m_x), \tag{17}$$

such that the principle component of the boundary points will coincide with the *x*-axis.

Fig. 17 shows an example of principle component transformation.



(a) (b)

Fig. 17 An example of principle component transformation. (a) The boundary of a leaf image and its principle component. (b) The transformed boundary of a leaf image.

3.2.2 Feature Extraction for Leaf

Note that most leaves have green color, the color information is improper for recognition. According to the theory of plant taxonomy [16], external leaf characteristics are important for identifying plant species. Thus, we use the shape information of leaf for recognition. In this section, 5 shape features are used. We use a rectangle enclosing the leaf, and call it as a bounding box, *B*, shown in Fig. 18.

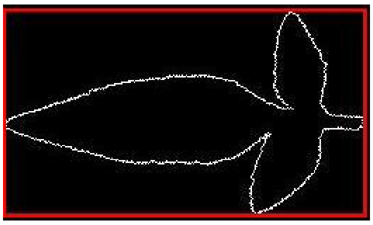


Fig. 18 The bounding box of a leaf.

3.2.2.1 Shape Information

$L(1)$: Aspect Ratio (AR). The AR represents the ratio of the vertical length (height) to horizontal length (width) of B. It is computed as

$$L(1) = \frac{height\ of\ B}{width\ of\ B}. \tag{18}$$

$L(2)$: Rectangularity Ratio (RR). The RR represents the ratio of the area of the leaf to the area of B. It is computed as

$$L(2) = \frac{the\ area\ of\ leaf}{the\ area\ of\ B}. \tag{19}$$

$L(3)$: Sharpness Ratio (SR). The SR represents the ratio of the average of the top one-tenth of the shortest CCD to the average of the top one-tenth of the largest CCD. It is computed as

$$L(3) = \frac{CCD_{10}}{CCD_{90}}. \tag{20}$$

$L(4)$: UpAndDown Ratio (UDR). The UDR represents the ratio of the area of the upper part to the area of lower part of the leaf. It is computed as

$$L(4) = \frac{area_{upper}\ of\ the\ leaf}{area_{lower}\ of\ the\ leaf}. \tag{21}$$

$L(5)$: LeftAndRight Ratio (LRR). The LRR represents the ratio of the area of the left part to the area of the right part of the leaf. It is computed as

$$L(5) = \frac{area_{left}\ of\ the\ leaf}{area_{right}\ of\ the\ leaf}. \tag{22}$$

3.2.3 Leaf Recognition

Fig. 19 is the flow chart of leaf recognition method. The proposed method contains two stages: preliminary and essential. The preliminary phase is to prune some impossible species based on three features. The essential phase is to recognize the query image based on five features.

Fig. 19 The flow chart of leaf recognition method.

3.2.3.1 Preliminary Stage

Since each plant species has its own specific shape, we can use the shape characteristics to prune impossible species. Here, we take *AR*, *RR*, and *SR* as features. The steps of the preliminary stage are listed as follows:

1. Let $range_i(AR)$, $range_i(RR)$ and $range_i(SR)$ be the ranges of *AR*, *RR* and *SR* of the

i-th plant specie in database.

2. Let $range_i = \{range_i(AR), range_i(RR), range_i(SR)\}$.

3. Consider each plant species in database as a candidate if all the features *AR*, *RR*, and *SR* of the query image fall in the range of this plant species.

Table 1 and Fig. 20 show the ranges of AR, RR and SR of all plant species in our database.

Table 1 The ranges of *AR*, *RR* and *SR* of every plant species in our database. (continued)

Plant Species		AR		RR		SR	
		Min	Max	Min	Max	Min	Max
S1		0.500005	0.773026	0.313155	0.430668	0.141353	0.306348
S2		0.490891	0.835501	0.655937	0.739268	0.470754	0.728605
S3		0.364929	0.475650	0.561458	0.638728	0.371395	0.477601
S4		0.289997	0.518000	0.591908	0.693873	0.229458	0.425193
S5		0.393013	0.584269	0.566454	0.618049	0.396798	0.573008

Table 1 The ranges of *AR*, *RR* and *SR* of every plant species in our database. (continued)

Plant Species		AR		RR		SR	
		Min	Max	Min	Max	Min	Max
S6		0.646994	0.957895	0.483377	0.650202	0.446093	0.579906
S7		0.342713	0.453393	0.592032	0.687368	0.348970	0.452622
S8		0.369100	0.659794	0.684117	0.744928	0.345730	0.555043
S9		0.850267	0.966887	0.341329	0.524770	0.232662	0.405166
S10		0.373110	0.571885	0.467892	0.542941	0.348888	0.466524
S11		0.613636	0.910714	0.324896	0.534139	0.089039	0.461601
S12		0.696098	0.961259	0.463078	0.643130	0.197574	0.579269
S13		0.459647	0.570677	0.536333	0.599083	0.450049	0.554795

Table 1 The ranges of *AR*, *RR* and *SR* of every plant species in our database. (continued)

Plant Species		AR		RR		SR	
		Min	Max	Min	Max	Min	Max
S14		0.300813	0.484314	0.482751	0.618298	0.219108	0.420216
S15		0.490697	0.655044	0.580597	0.658235	0.397417	0.586286
S16		0.350489	0.501208	0.594031	0.732827	0.250404	0.408398
S17		0.149356	0.521739	0.311594	0.722101	0.126961	0.180075
S18		0.403383	0.915913	0.534473	0.743730	0.354658	0.523828
S19		0.481512	0.731455	0.501748	0.666173	0.470612	0.699087
S20		0.127660	0.197935	0.515042	0.721839	0.142460	0.169629
S21		0.577416	0.757615	0.561470	0.642953	0.549425	0.709965

Table 1 The ranges of *AR*, *RR* and *SR* of every plant species in our database. (continued)

Plant Species		AR		RR		SR	
		Min	Max	Min	Max	Min	Max
S22		0.376590	0.589474	0.556220	0.688156	0.371869	0.487669
S23		0.268229	0.408092	0.638544	0.743659	0.262652	0.397760
S24		0.838626	0.978536	0.644065	0.706955	0.525970	0.725693
S25		0.566434	0.915295	0.549771	0.709073	0.523594	0.748094
S26		0.264264	0.447305	0.603989	0.761816	0.259365	0.423183
S27		0.508361	0.743867	0.598305	0.703685	0.462139	0.684671
S28		0.433658	0.732143	0.635302	0.708608	0.397673	0.715808
S29		0.481578	0.645731	0.630086	0.719904	0.415729	0.600762

Table 1 The ranges of *AR*, *RR* and *SR* of every plant species in our database. (continued)

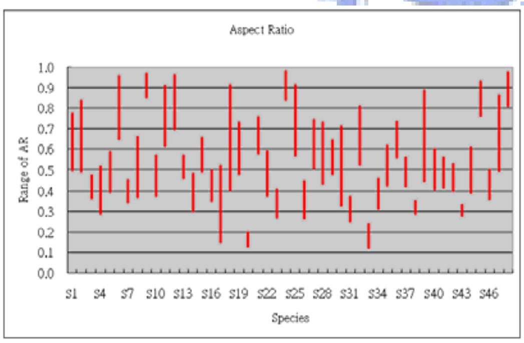
Plant Species		AR		RR		SR	
		Min	Max	Min	Max	Min	Max
S30		0.328562	0.709290	0.619182	0.747966	0.280579	0.567571
S31		0.251634	0.372642	0.470335	0.628621	0.245393	0.371333
S32		0.525510	0.810164	0.526402	0.671394	0.464076	0.746022
S33		0.119326	0.237569	0.346524	0.661944	0.110767	0.136062
S34		0.310665	0.460616	0.579032	0.725554	0.262772	0.444621
S35		0.426464	0.618236	0.628875	0.731921	0.409101	0.607532
S36		0.557103	0.735288	0.569495	0.648156	0.488965	0.678543
S37		0.420440	0.559009	0.636115	0.732630	0.387697	0.545420

Table 1 The ranges of *AR*, *RR* and *SR* of every plant species in our database. (continued)

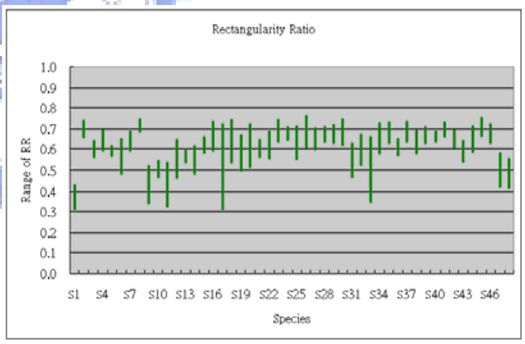
Plant Species		AR		RR		SR	
		Min	Max	Min	Max	Min	Max
S38		0.287793	0.352576	0.579252	0.692514	0.246174	0.352030
S39		0.445313	0.886624	0.630633	0.708960	0.445922	0.582450
S40		0.406164	0.601597	0.635243	0.687023	0.377741	0.549532
S41		0.412806	0.559542	0.658390	0.731062	0.371005	0.516199
S42		0.398457	0.533146	0.606449	0.696520	0.393285	0.524849
S43		0.276878	0.331878	0.538492	0.639607	0.211772	0.310246
S44		0.392135	0.610905	0.584610	0.710791	0.337063	0.553846
S45		0.763015	0.928887	0.665981	0.753122	0.557193	0.787315

Table 1 The ranges of *AR*, *RR* and *SR* of every plant species in our database. (continued)

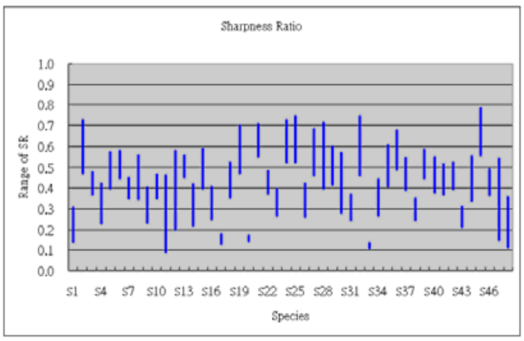
Plant Species		AR		RR		SR	
		Min	Max	Min	Max	Min	Max
S46		0.360243	0.503852	0.630388	0.724279	0.364011	0.492582
S47		0.497874	0.864877	0.421029	0.583044	0.147642	0.541633
S48		0.808081	0.978102	0.412950	0.552835	0.111141	0.357392



(a)



(b)



(c)

Fig. 20 The ranges of three features. (a) The ranges of AR. (b) The ranges of RR. (c) The ranges of SR.

3.2.3.2 Essential Stage

After the preliminary stage, some candidate species have been selected. Then, we calculate the distances between the query image and the candidate images in the database. The distance $dist_i$, which is between the query image and the i-th image in the database, is measured by

$$dist_i = \sum_{k=1}^{5} \left| L_i(k) - L(k) \right|,$$

where the $L_i(k)$ denotes the k-th feature value of the i-th database image, $L(k)$ denotes the k-th feature value of the query image. Leaf recognition is accomplished using the k-nearest neighbor algorithm. After that, the recognition system ranks the distances and returns the Top-20 nearest neighbors. Then, we give scores to each rank such as $1^{st} = 20$, $2^{nd} = 19$ …, respectively. Next, we sum up the scores of the same species as the similarity value. Finally, we rank the similarity value and return the leaf images of possible species.

3.3 Combining Recognition Method

Although the recognition method has good recognition rate using only the single flower image or leaf image, the information is not enough to distinguish from varieties of plants. In addition, it is also a difficult task for botanist to recognize a plant only by flower images or leaf images. Therefore, we proposed a recognition system combining the flower and leaf information to improve recognition rate. Fig. 21 shows the flow chart of the proposed method for combining recognition.

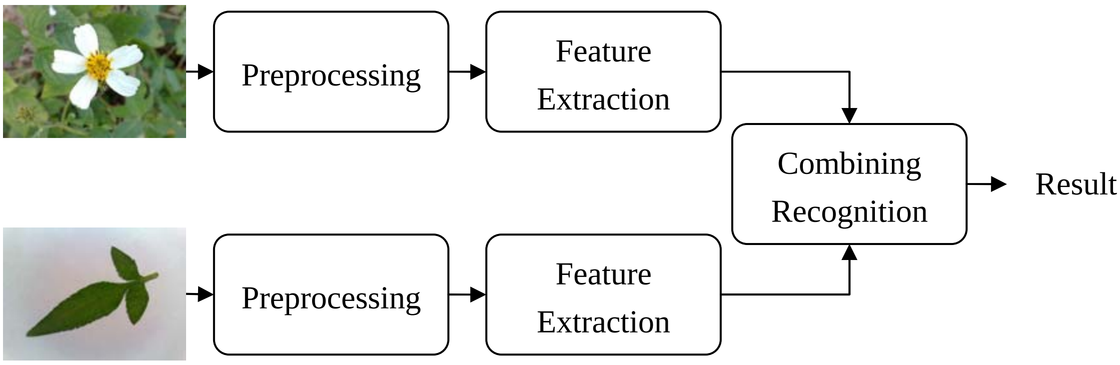


Fig. 21 The flow chart of the proposed method for combining recognition.

3.3.1 Combining Recognition

In the combining recognition phase, the flower and leaf images of a particular plant were obtained. Then, the features of the flower and leaf are extracted by the steps described in sections 3.1 and 3.2. After that, the distances between the query image and all images in the database are calculated and then the distances are ranked. The steps are listed below:

1. Get the Top-40 nearest neighbors for the flower and give scores to each rank such as $1^{st} = 40$, $2^{nd} = 39$ …, respectively. Next, sum up the scores of the same species.
2. Get the Top-40 nearest neighbors for the leaf and give scores to each rank such as

$1^{st} = 40$, $2^{nd} = 39$ …, respectively. Next, sum up the scores of the same species.

3. Preserve the species appearing both in step1 and step2. Sum up the scores of the same species in step1 and step2 as the similarity measure.
4. Rank the similarity measure and return the possible species.

Finally, we can get the most similar species of the query images and the results are better than using only flower or leaf image.

CHAPTER 4

EXPERIMENTAL RESULTS

In this chapter, experiments are conducted to evaluate the performance of the proposed method. Firstly, the recognition results of flowers are presented based on two databases. One is our database of 684 flower images consisting of 24 species and the other is Zou-Nagy's [7] database of 612 flower images with 102 species. The performance of our system in flower recognition will be compared with Zou-Nagy's method. Secondly, the recognition results of leaves are presented based on two databases. One is our database of 960 leaf images consisting of 48 species. The other is Lee-Chen's [11] database of 600 leaf images with 60 species. We will compare the performance between our method and Lee-Chen's method. Thirdly, the recognition results of combining system are presented based on two databases. One is our database consisting of 16 species, including 320 flower images and 320 leaf images. The other is Saitoh-Kaneko's [1] database containing 16 species with 320 flower images and 320 leaf images. The performance of our system will be compared with Saitoh-Kaneko's method. Finally, we will compare the performance between our three recognition methods.

Each flower image in our database is re-scaled to 320x240 pixels. We pick out one flower image in our database as our query image and consider the remaining 683 flower images as the training data. The results are shown in Table 2. The first row of Table 2 is measured by returning the Top-5 most similar images to the query image of the flower recognition method. The second row of Table 2 is measured by returning the Top-5 most similar species to the query image of the flower recognition method.

Table 2 Performance on our flower database.

	Recognition rate (%)					Number of images	Number of species
	Top-1	Top-2	Top-3	Top-4	Top-5		
Similar images	81.43	89.33	92.25	94.44	96.35	684	24
Similar species	76.9	93.12	98.25	99.12	99.71	684	24

We also conduct the proposed method on Zou-Nagy's [7] database collected from [17]. All images in Zou-Nagy's database have the same size of 320x240. There are six images for each species. Some pictures are quite out of focus and the objects are too small and overlapping. The results are shown in Table 3. We can see that the processing time of our method is faster than Zou-Nagy's and the Top-3 recognition rate (87.6%) is much higher than Zou-Nagy's (79%) with 8.5 seconds by user's rose-curve adjustments before labeling the flower to the class. Although Zou-Nagy's method with human help can achieve 93%, it cost much time (10 seconds per flower). Moreover, we also can get high recognition rate by returning the Top-5 most similar species (93.5%) and our process time is twice faster than Zou-Nagy's.

Table 3 Performance comparison between our method and Zou-Nagy's method using Zou-Nagy's database.

	Time (s)	Recognition rate (%)				
		Top-1	Top-2	Top-3	Top-4	Top-5
Our method (similar images)	4.3	76.1	83.8	87.6	90.5	91.3
Our method (similar species)	4.3	67.3	84.2	92.2	93	93.5
Zou-Nagy's method (before labeling)	8.5	52	-	79	-	-
Zou-Nagy's method (labeling)	10.7	93	-	-	-	-

In our leaf recognition method, each species of leaf includes 40 images; 20 of them are selected as database images and the remaining are used for testing data. The results are shown in Table 4 and Table 5. The results of Table 4 are measured by returning the Top-5 most similar images, and the results of Table 5 are measured by returning the Top-5 most similar species. The first row of Table 4 and Table 5 is the performance of the leaves having blooming flowers. The second row of Table 4 and Table 5 is the performance of the other leaves. The third row of Table 4 and Table 5 is the performance of all leaves in our database.

Table 4 Performance on our leaf database by returning Top-5 images.

No.	Recognition rate (%)					Number of images	Number of species
	Top-1	Top-2	Top-3	Top-4	Top-5		
1	74.8	86.7	91.5	94	95.8	480	24
2	62.1	76	83.3	87.3	91.3	480	24
3	58.1	71.5	79.9	84.7	87.9	960	48

Table 5 Performance on our leaf database by returning Top-5 species.

No.	Recognition rate (%)					Number of images	Number of species
	Top-1	Top-2	Top-3	Top-4	Top-5		
1.	68.5	90.4	96	98.3	99.4	480	24
2	60	79	88.3	94.6	96.9	480	24
3	52.6	73.1	82.1	89.1	93.2	960	48

We also conduct the proposed method on Lee-Chen's [4] database. Each image size of Lee-Chen's database is 640x480 pixels. Each species in their database includes 15 images; 10 of them are database images and the others are used for testing data. The results are shown in Table 6. We can see that the recall rate of our method (51.4%) is much higher than Lee-Chen's (48.2%) from Table 6. However, Lee and Chen tuned the weights of features to achieve the optimal recognition rate. Hence, our recognition rate (70%) is lower than Lee-Chen's (82.33%) by returning the most similar image. Nevertheless, our recognition rate can achieve 94.33% by returning the Top-5 most similar species and it is higher than Lee-Chen's.

Table 6 Performance comparison between our method and Lee-Chen’s method using Lee-Chen’s database.

	Recognition rate (%)					Recall rate (%)
	Top-1	Top-2	Top-3	Top-4	Top-5	
Our method (similar images)	70	77.67	84.33	88.67	91.67	51.4
Our method (similar species)	65	82	88.33	93	94.33	51.4
Lee-Chen’s method	82.33	-	-	-	-	48.2

In order to compare the performance with Saitoh-Kaneko’s [1] method, we collected the same numbers of species and images with Saitoh-Kaneko’s database, the reason is that we can not get their database. The recognition results are listed in Table 7. We can see that the recognition rate of our method is much higher than Saitoh-Kaneko’s method.

Table 7 Performance comparison between our method and Saitoh-Kaneko’s method using the same numbers of Saitoh-Kaneko’s database.

	Recognition rate (%)		
	Top-1	Top-2	Top-3
Our method	97.5	100	100
Saitoh-Kaneko’s method	96.03	99.26	99.26

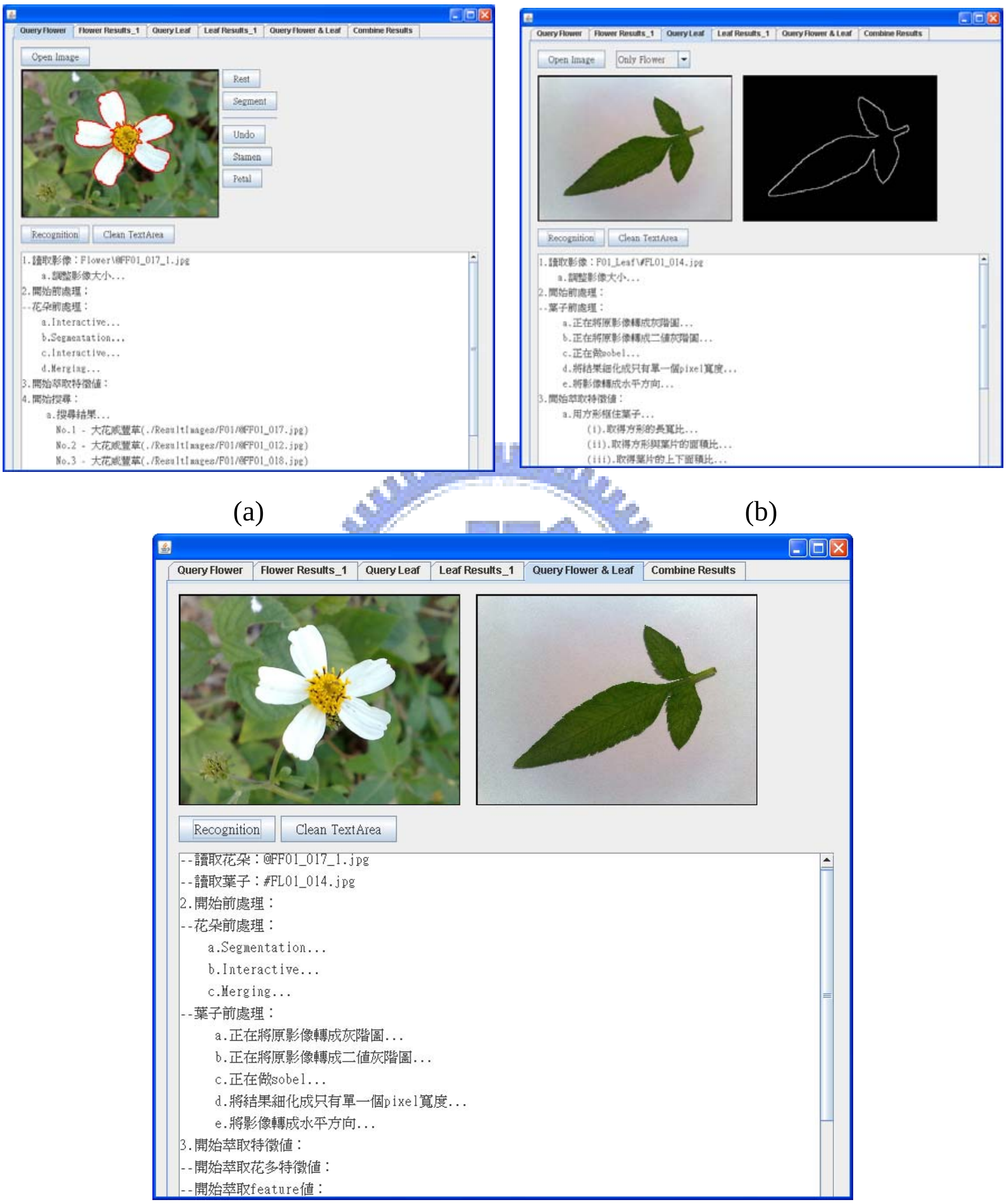
Finally, we compare the performance of our recognition methods: flower, leaf and combining method. The recognition rate is calculated by three sets of images: (i)

Only flower images of 24 species; (ii) Only leaf images of 24 species which correspond to (i); (iii) A pair of flower and leaf images of 24 species. Table 8 shows the performance results. From Table 8, we can see that the combining method get higher recognition rate than those using only flower or leaf image. Hence, the combining recognition method is more effective and can provide better results to user.

Table 8 Performance comparison.

Method	Recognition rate (%)					Number of images	Number of species
	Top-1	Top-2	Top-3	Top-4	Top-5		
Our method (Flower)	76.9	93.1	98.3	99.1	99.7	684	24
Our method (Leaf)	68.5	90.4	96	98.3	99.4	480	24
Our method (Combining)	94.4	99.7	100	100	100	684	24

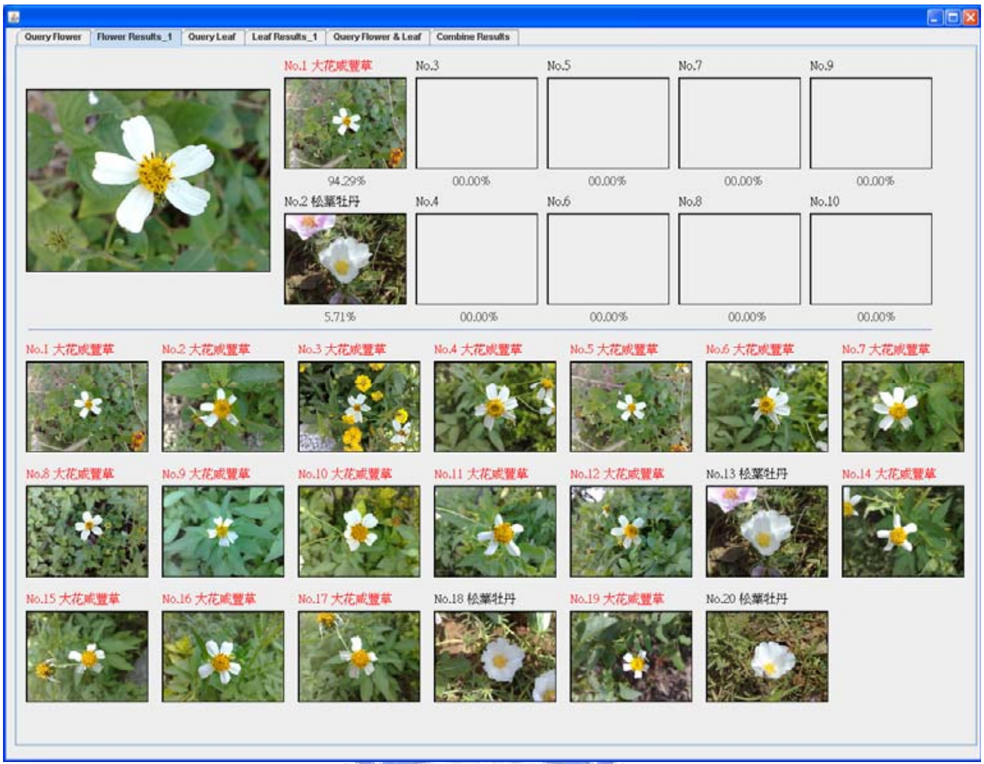
We have built a plant recognition system written in Java language on a PC. Figs. 22(a), 22(b) and 22(c) are the interfaces for the flower, leaf and combining recognition systems, respectively. Figs. 23(a), 23(b) and 23(d) are the interface for recognition results of flower, leaf and combining recognition systems respectively. After we retrieved the candidate images, users can click on the image to get the information about the plant (name, scientific name and other relative species information, see Fig. 23(c)). Therefore, users can easily make use of the recognition system to know the species of the plant which they did not know before.



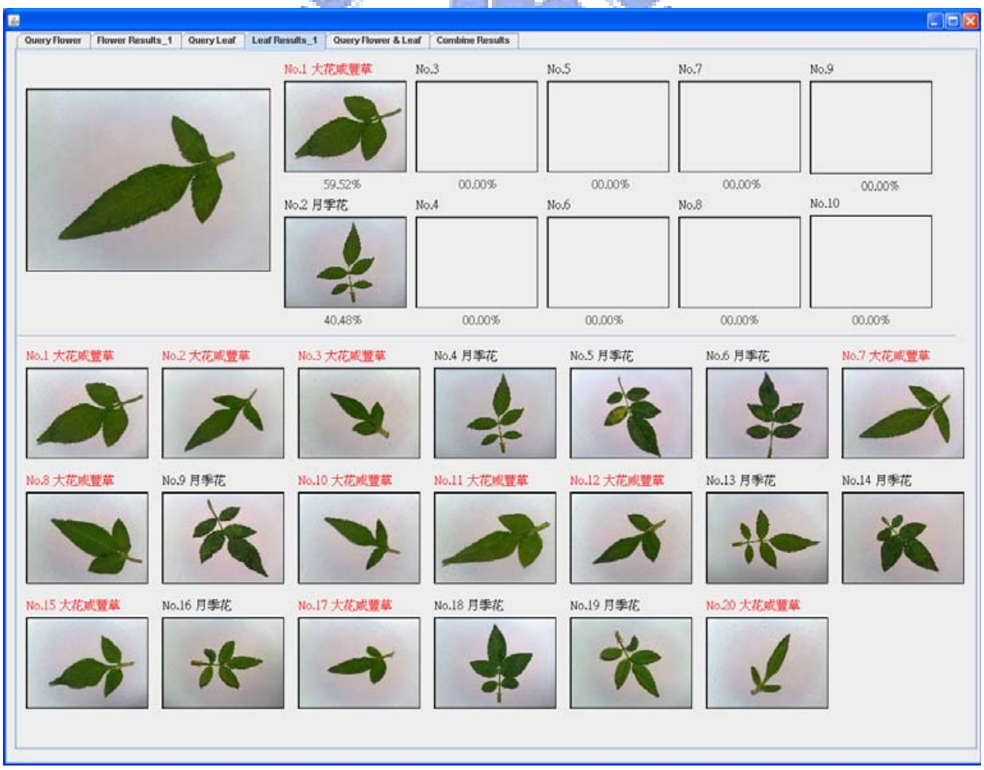
(a) (b)

(c)

Fig. 22 Interfaces of recognition system. (a) Flower recognition system. (b) Leaf recognition system. (c) Combining recognition system.



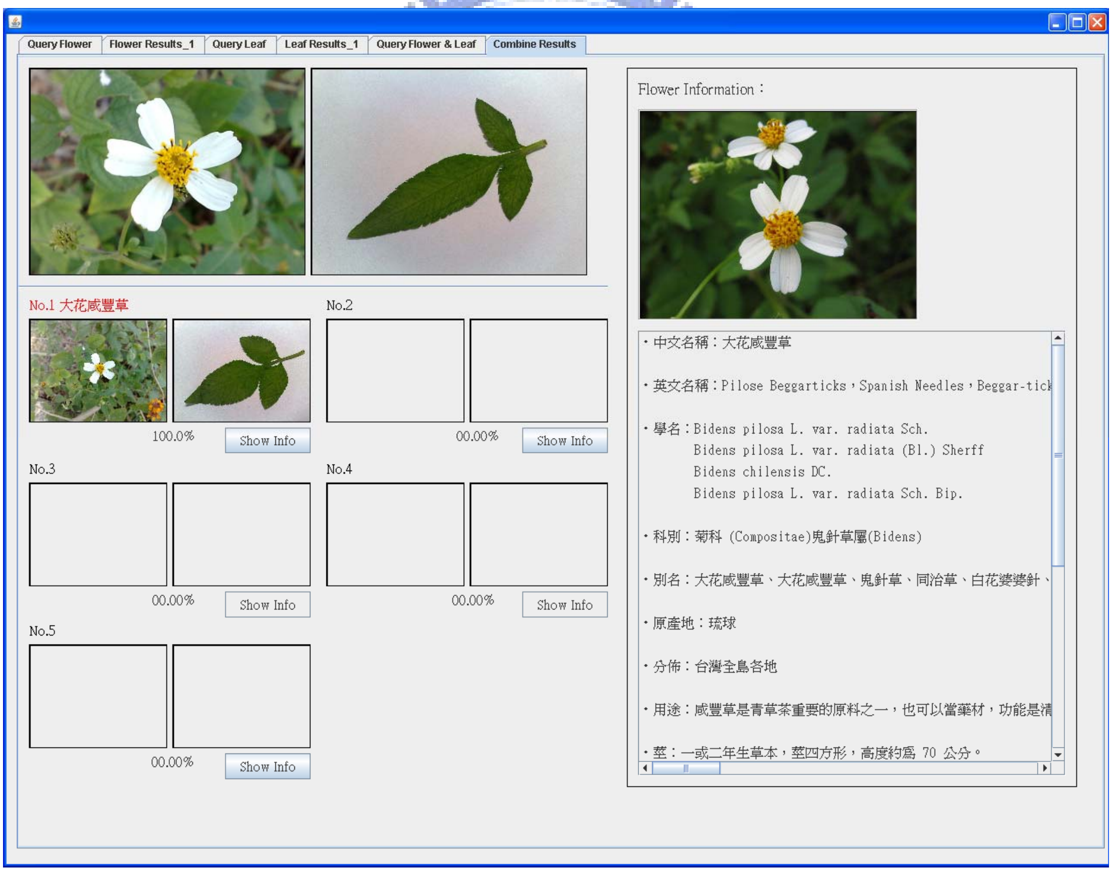
(a)



(b)

Fig. 23 Interfaces for recognition results. (a) Flower recognition results. (b) Leaf recognition results. (c) The retrieved information of the query image. (d) Combining recognition results. (continued)

(c)



(d)

Fig. 23 Interfaces for recognition results. (a) Flower recognition results. (b) Leaf recognition results. (c) The retrieved information of the query image. (d) Combining recognition results.

CHAPTER 5

CONCLUSION

In this thesis, we have proposed a plant recognition system based on leaf and flower. In the flower recognition system, we use an automatic segmentation based on human visual system. Then, a simple and interactive user interface is applied. According to the shape and color features of the flower, 14 features are extracted from the segmented flower image. Finally, a similarity measure is provided to do recognition.

In the leaf recognition system, we also proposed an automatic segmentation method and a solution to treat rotation problem. Next, we extract 5 features according to the characteristics of the leaf shapes. Then, we preserve possible species and find out the similar images from leaf image database by similarity distance.

In the combining recognition system, a new method has been proposed for recognizing plants based on leaf and flower. Firstly, the features of the leaf and flower are extracted. Next, we calculate the similarity between the query image and database images of leaf and flower and then combine the results of leaf and flower. Finally, the system can find out the most similar species.

On average, the accuracy rate for Top-5 of flower recognition system is 99.71%, and the accuracy rate for leaf is 93.22%; it can achieve 100% for Top-3 in combining recognition system. This means that our combining recognition system can get higher accuracy rate than the single recognition system.

1896

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