Recognition of Leaf Based on Its Tip and Base using Centroid Contour Gradient

Mei Fern Bong[1], Ghazali bin Sulong[2] and Mohd Shafry Mohd Rahim[3]

**[1] Faculty of Computing, Universiti Teknologi Malaysia
Skudai, 81310 Johor, Malaysia**

**[2] Faculty of Computing, Universiti Teknologi Malaysia
Skudai, 81310 Johor, Malaysia**

**[3] Faculty of Computing, Universiti Teknologi Malaysia
Skudai, 81310 Johor, Malaysia**

Abstract

This paper suggests normalization of the tip and base of leaf as both of them incline to one direction which is able to influence data extraction process. The extraction method we used is Centroid Contour Gradient (CCG) which calculates the gradient between pairs of boundary points corresponding to interval angle. CCG had outperformed its competitor which is Centroid Contours Distance (CCD), as it successfully captures the curvature of the tip and base of leaf. The accuracy in classifying the tip of leaf using CCG is 99.47%, but CCD is only 80.30%. For accuracy of leaf base classification, CCG (98%) also outperforms CCD (88%). The average accuracy for recognizing the 5 classes of plant is 96.6% for CCG and 74.4% for CCD. In this research, we utilized the Feed-forward Back-propagation as our classifier.

Keywords: *Leaf Recognition, Centroid Contour Distance, Centroid Contour Gradient, Leaf Tip, Leaf Base.*

1. Introduction

Although humans can recognize plant based on botanical and biological methods, both methods are not efficient and expensive. It is difficult to get an expert to identify plants. Therefore, it is necessary to programme the computer to identify plants, and besides, it is helpful to those who are not experts but are still able to differentiate plants by using computer device. Currently, many researchers recognize plants by their flowers, leaves, bark, seedling and morph; but leaves have become popular features as they are almost 2D. According to Wang[1], leaves of tree are considered as the most useful and direct basic feature for identifying plants. There are many ways by which a leaf can be described: leaf shape, leaf margin, leaf venation, leaf texture, leaf vein, leaf color, leaf base and leaf tip. The selected features should be stable and unique[2]; otherwise it may affect the accuracy in plant's recognition.

This research was performed extensively by many experts. A lot of frameworks were investigated to extract the features of tree leaf. In previous researches, the common features extracted from leaf are usually leaf vein[3,4,24,26], leaf shape[4,5,6,7,9,10,11,12,13], leaf texture[4,10,16], leaf skeleton[8], color[10,13,17,18] and leaf edge[19]; however, researchers are rarely seen extracting leaf tip and leaf base. There are some popular methods used to extract the information of leaf which include Digital Morphology[10,13,17,20,21,22], Centroid Contour Distance[11,12,14,15,28] or also known as Centroid-Radii Model, Moment Invariant[14,15,20,24,25] and Polar Fourier Transform[10,17]. In the latest research on this field done in 2011, Kadir[28] used many different features of leaf to classify plant which include shape, vein, color and texture. This algorithm produces a good result in the experiment; it had 93.75% accuracy in recognizing the species of plant. From this statement, we can conclude that, the increasing recognition accuracy is proportional to the rise of the number and the significance of features used in the algorithm. Thus, in this paper we propose this method to get information on tip and base of leaf and we strongly believe that these two features are able to improve the recognition result.

Based on the traditional plant morphology, botanist are able to distinguish between plants by the external structures of leaf which include leaf shape, leaf tip, leaf base, leaf margin, leaf color, leaf surface and leaf hairiness. Although the tip and base of leaf are considered as one of the features to identify plants, research on them is still in the infant stage. The main reason why so many researchers ignore their study is because both of them may deform in one direction according to the environment. In fact, they are naturally imperfect symmetry. Therefore, we first normalize them to make them perfect symmetry and then get information on their shape.

2. Pre-Processing

Before information can be extracted from the leaf image, it is necessary that it undergoes a series of pre-processing to ensure information on its boundary is accurate and free of noise. This is because feature extraction is extraordinarily sensitive to unclear boundary. First, the image is converted to binary as in this research only information on leaf contour is needed. Therefore, the complicated RGB image is not required. After converting the image to binary image, it was noticed that the scar of the leaf left some hole. Hence, the hole was filled before edge detection method was used. In this research, it was observed that canny edge detection is more suitable for use. After canny edge detection process, thinning approach was applied to ensure the leaf boundary is in single pixel thickness and redundant data were removed. It also simplified the feature extraction work. Finally, a normalization process for the leaf tip and base was done as shown below.

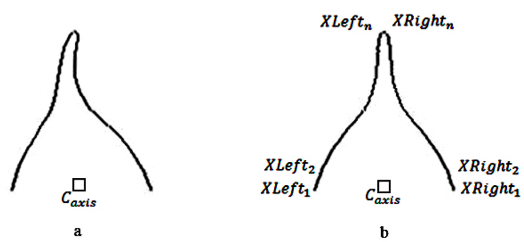

Fig. 1 Normalization: (a) Original image (b).Normalized image

Figure 1(a) clearly shows that the leaf is inclining to one direction naturally. Hence, it is necessary to normalize its tip and base to make them perfect symmetry as shown in Figure 1(b). This normalization process idealizes the leaf tip and base in order to produce standard shape information. The followings are the steps for normalizing the leaf tip:

a.) First, the leaf boundary points are separated into two parts, left and right as $XLeft_i$ and $XRight_i$, (i = 1,…, n).

b.) Then, it is assumed the bottom of the leaf tip does not deform much, the centre of this two bottom boundary point ($XLeft_1$ and $XRight_1$) is obtained and it is named as centre axis (c_{axis}) using the equation (1),

$$c_{axis} = \frac{XLeft_1 + XRight_1}{2} \tag{1}$$

c.) Move $XLeft_i$ and $XRight_i$ until their centre point is parallel to the centre axis (c_{axis}); this describes step d to step f.

d.) Find the centre point for the following $XLeft_i$ and $XRight_i$ using the equation (2),

$$c_i = \frac{XLeft_i + XRight_i}{2} \tag{2}$$

e.) Calculate the distance between c_i and c_{axis} using equation (3),

$$\text{Distance}_i = C_{axis} - C_i \tag{3}$$

e.) Add the $Distance_i$ to $XLeft_i$ and $XRight_i$ (as shown in equations 4 and 5) to make their centre parallel to centre axis, so the centre of the new located $XLeft_i$ and $XRight_i$ should be same with the centre axis (c_{axis}).

$$XLeft\_new_i = distance_i + XLeft_i \tag{4}$$

$$XRight\_new_i = distance_i + XRight_i \tag{5}$$

3. Feature Extraction

The feature extraction method proposed here is Centroid Contour Gradient (CCG) used to calculate the gradient between pairs of pixels in leaf boundary corresponding to the interval angle, θ. This method successfully obtains the details of the leaf curvature.

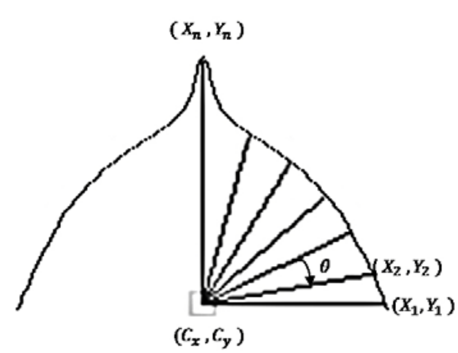

Fig. 2 Centroid Contour Gradient Approach.

Although there is a series of boundary points, only the right boundary points by interval angle, θ were chosen. As after normalization both right and left should be symmetry, only right boundary points were adopted. The selected boundary points are noted as (X_i, Y_i) and (i =1,2,…,n-1,n). Here, n represents the number of intervals that are given by $n = (90/\theta)+1$.

For example, 15° was chosen as default angle; which implies that we need to obtain the pixels on the leaf contour at a different angle set θ={0, 15, 30, 45, 60, 75, 90}. The boundary points will be selected if they fit into equation (6),

$$Y_i = [\tan(\theta) * (X_i - C_x)] + C_y \tag{6}$$

Co-ordinate (C_x , C_y) represents the centroid point of the leaf tip. After obtaining the boundary points which intersect with the respective angle, the gradients between pairs of pixels, that is, (X_2,Y_2) and (X_1,Y_1) and (X_3,Y_3) and (X_2,Y_2), …, (X_{i+1},Y_{i+1}) and (X_i,Y_i) were calculated using equation (7).

$$G_i = \left| \frac{Y_{i+1} - Y_i}{X_{i+1} - X_i} \right|, i = 1,2,3,...,n-1 \tag{7}$$

This method is derived from Centroid Contour Distance (CCD) approach. The difference between these two approaches are: Centroid Contour Distance (CCD) is used to find out the distance between centroid point and the pixels on the leaf's contour point, but Centroid Contour Gradient is used in calculating the gradient between two pixels on the leaf's contour corresponding to the interval angle. In this paper, CCG was used to extract information on leaf tip and base.

4. Experimental Results

In this paper, CCG was used to extract information on leaf tip and base. In this paper, a total of 250 samples of leaves from five classes were utilized; they were collected from Universiti Teknologi Malaysia. Every class consists of 50 images. 125 images were used as testing set. In these 5 classes, the leaf tip of Class A and D is acuminate, class B is cuspidate, class C is obtuse and class E is acute. Figure 3 below shows the samples of plant leaves that were used.

Fig. 3 Samples of 5 classes' plant leaves.

CCG approach was compared with CCD approach based on regular angle. In order to optimize the result, 2-tier recognition system was used. In the first-tier, the leaf was classified based on its tip and in the second tier, the class of the tree was identified by the leaf base as shown in Figure 4.

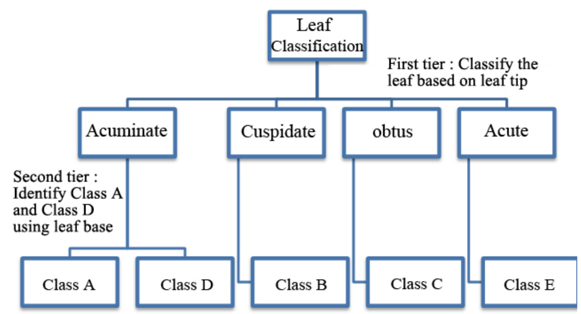

Fig. 4 2-tier recognition system.

Table 1 shows the result of classification of leaf tip using CCG and CCD (1-tier recognition). Here, there are 4 types of leaf tips, which are acuminate, cuspidate, obtuse and acute and can be separated into Class B, Class C and Class E. In addition, Class A and Class D are in the same group as both of them possess the same tip type which is acuminate. Therefore, both of them will be further distinguished based on their leaf base using CCG and CCD, which can be referred to as the 2-tier recognition system.

Table 1 shows that CCG yielded better result in differentiating the class based on their leaf tip. CCG achieved 99.47% accuracy in classifying the different leaves based on their tip, but its competitors (CCD) only had 80.30% accuracy.

Table 2 shows the result of second tier recognition, which used leaf base to differentiate between Class A and Class

D. CCG and CCD obtained higher accuracy when they were in 10°, which is 98% and 88% in recognition accuracy, respectively. The first-tier result will influence the second tier recognition.

Tables 3 and 4 show the results for each leaf class after it has undergone first tier classification and second tier recognition. Class C obviously had lower accuracy as this class had the high variance among its class. CCD fails to recognize Class C where each angle was tested for; their recognition accuracy did not increase more than 40%. On the other hand, CCG still performed well in recognizing class C, and it achieved accuracy of 96%. On average, CCG achieved 96.6% recognition accuracy, but CCD approach had 22.2% less than CCG.

Table 1: The result of leaf tip classification using CCD VS CCG

Angle (°)	*CCD (%)*	*CCG (%)*
18.00	68.30	90.70
15.00	77.30	94.40
11.25	77.10	88.27
10.00	79.70	99.47
9.00	80.30	86.90

Table 2: The result of differentiating between class A VS Class D using CCD and CCG

Angle (°)	*CCD (%)*	*CCG (%)*
18.00	86.00	96.00
15.00	78.00	92.00
11.25	78.00	92.00
10.00	88.00	98.00
9.00	82.00	88.00

Table 3: The accuracy for each class using CCD.

Angle(°) / Class	*18.00*	*15.00*	*11.25*	*10.00*	*9.00*
A	88.0	80.0	76.0	84.0	84.0
B	76.0	68.0	76.0	80.0	84.0
C	20.0	40.0	20.0	28.0	32.0
D	84.0	76.0	80.0	92.0	80.0
E	16.0	76.0	88.0	88.0	72.0
Avg.	56.8	68.0	68.0	74.4	70.4

Table 4: The accuracy for each class using CCG.

Angle (°) / Class	*18.00*	*15.00*	*11.25*	*10.00*	*9.00*
A	96.0	92.0	92.0	99.0	92.0
B	96.0	88.0	96.0	96.0	88.0
C	56.0	76.0	60.0	96.0	80.0
D	96.0	92.0	92.0	96.0	84.0
E	96.0	99.0	99.0	96.0	96.0
Avg.	88.0	89.4	87.8	96.6	88.0

4. Conclusions

This research has achieved its objective by using a novel framework, which is the Centroid Contour Gradient (CCG) after normalizing the tip and base of leaf. This framework outperformed its competitor, the Centroid Contour Distance (CCD). Experimental results indicated that this framework had higher accuracy compared to CCD method in classification of the various classes of leaf. The highest accuracy for CCD in first tier recognition is 80.30%, but CCG was able to get 99.47%. On average, CCG achieved a better result which is 96.6% accuracy, but CCD method was only able to achieve accuracy of 74.4%. Therefore, the performance of CCG has been proved in leaf recognition using leaf tip and base.

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Bong Mei Fern obtained her B Comp. Sc. (Hons) in Graphic and Multimedia in 2012 from Universiti Teknologi Malaysia (UTM), Johor Bahru, Malaysia. Currently, she pursues her Ph.D. degree in the same university. Her current research interests are image processing, computer vision and object recognition.

Ghazali Bin Sulong received his BSc degree in statistic from National University of Malaysia, in 1979, and MSc and PhD in computing from University of Wales, Cardiff, United Kingdom, in 1982 and 1989, respectively. He is currently professor at Faculty of Computing, Universiti Teknologi Malaysia. His research interest includes Biometric - fingerprint identification, face recognition, iris verification, ear recognition, handwritten recognition, and writer identification; object recognition; image enhancement and restoration; medical imaging; human activities recognition; data hiding - digital watermarking, steganography and image encryption; image fusion; image mining; object detection, segmentation and tracking.

Mohd Shafry bin Mohd Rahim is an Associate Professor of Computer Graphic and Image Processing at Universiti Technologi Malaysia. He received his B. Sc. (Hons.) in Computer Science (1999) and his MSc. in Computer Science (2002) from Universiti Teknologi Malaysia. Then, he obtained his Ph. D. in Spatial

Modelling from Universiti Putra Malaysia at 2008. The rapid development in the field of Computer Graphics caused him eagerly want to share his acquired knowledge. To realize his desire, he has started his career as a lecturer at CITI College, Taiping, Perak in early 1999 and continued his work at Universiti Teknologi Malaysia. He was appointed as a Senior Lecturer at the age 32 years during his early involvement with UTM and as an Associate Professor 4 years later. Now, he focused his research together with his research group, UTM ViCube Lab under Faculty of Computing, UTM. He is expert in research area of computer graphic and image processing. His passionate with his research area make him published more than 70 papers for journals and conferences. Currently, he has appointed to be Deputy Director of Centre for Joint Programme, UTMSPACE. In addition, he experienced as ICIDM 2012 conference's chair and has appointed as Chief Editor for International Journal in Interactive Digital Media.