An Implementation of Leaf Recognition System using Leaf Vein and Shape

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Abstract

In this paper, we propose and implement a leaf recognition system using the leaf vein and shape that can be used for plant classification. The proposed approach uses major main vein and frequency domain data by using Fast Fourier Transform (hereinafter, FFT) methods with distance between contour and centroid on the detected leaf image. Total 21 leaf features were extracted for the leaf recognition, which they include ① the distance feature between centroid and all points on the leaf contour, ② frequency domain data by FFT that was performed using the distances. In summary, 10 features of all the 21 leaf features were extracted using distance, FFT magnitude, and phase, the other 10 features were extracted using t the digital morphological features using four basic geometric features and five vein features, and the last 1 feature was extracted using the convex hull. To verify the validity of the approach, images of 1907 leaves apply to classify 32 kinds of plants. In the experimental results, the proposed leaf recognition system showed an average recognition rate of 97.19%, and we can confirm that the recognition rate of the proposed leaf recognition system was better than that of the existed leaf recognition method.

Keywords: *Intelligent Scissor (IS) algorithm, Leaf Contour Extraction, Edge Point, color gradient magnitude*

1. Introduction

Approximately 350,000 species of plants exist on earth, and they share a very close relationship to human beings. Plants play a major role in various areas, such as food, medical science, industry, and the environment. However, many species of plants are endangered because of environmental pollution due to the rapid development of human society. Therefore, it is very important to study automatic plant classification and recognition for plant protection.

Leaf recognition technology plays an important role in plant classification and its key issue lies in whether selected features are stable and have good ability to discriminate different kinds of leaves.

Many recent studies exist on plant classification and recognition based on plant components such as flowers, leaves, and barks. To handle such volumes of information, realization of a quick and efficient classification method has become an area of active study [1-9]. In particular, it is well known that the correct way to extract plant features involves plant recognition based on leaf images. Two features, which are widely used for plant recognition based on leaf image, are color and shape [1], [6-9]. In the color-based conventional study, a simple color similarity between two images can be measured by comparing their color histogram. Also in the shape based-conventional study, they used region and contour-based simple features and features could be considered time domain data.

However, the recognition performance was limited due to leaf color was affected by the seasons and there is a problem that user to directly specify both ends of the leaves.

Consequently, in this paper, we propose a leaf recognition system for plant classification based on the leaf vein and shape. One of the notable points is that we can decide leaf direction using leaf vein, and then use frequency domain data by using FFT on distance between contour and centroid in the given leaf image. Figure 1 shows the flowchart for the proposed leaf recognition system.

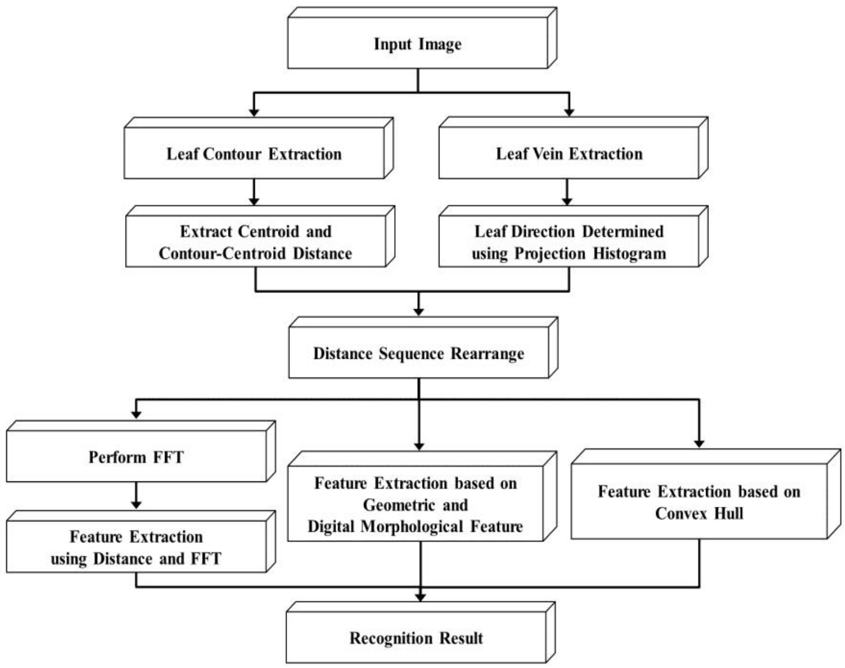


Figure 1. Flowchart for the proposed leaf recognition system

The remainder of this paper is organized as follows: Section 2 describes leaf contour extraction from the input image, and we describe main vein extraction and leaf direction decision method in Section 3. Section 4 describes the extraction of the 21 leaf features, and Section 5 describes the proposed leaf recognition system. The experimental results are presented in Section 6, and concluded in Section 7.

2. Leaf contour extraction

We describe on the leaf contour extraction in the given leaf image. Most leaves have generally green color, while the color of leaves is changed by season or environmental factors. The color change of leaf image can cause decline of recognition performance or non-recognized problem. The color converting process on input image is the first step for leaf contour extraction, and it can set foundation to improve recognition performance irrelevant to the leaf color change.

Therefore, we convert the input color leaf image to gray scale image as follows:

$$Gray = 0.299 * R + 0.587 * G + 0.114 * B \quad (1)$$

The converted gray scale leaf image is converted to a binary image once again. The threshold conversion is performed as follows:

$$B(x,y) = \begin{cases} 0 & if \quad f(x,y) \le T \\ 255 & if \quad f(x,y) > T \end{cases} \tag{2}$$

Where, $B(x,y)$ and $f(x,y)$ are the intensity values of the gray scale image and the binary image, respectively, at position (x,y), and T is the threshold value [10]. Figure 2 shows an example of leaf contour extraction.

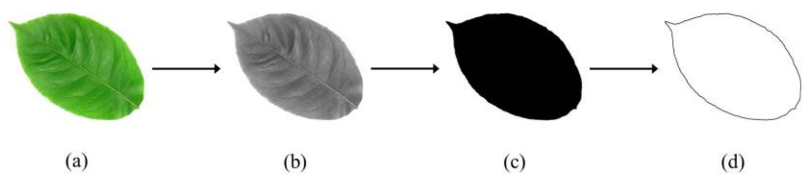


Figure 2. Example of leaf contour extraction: (a) input image, (b) gray scale image, (c) binary image, (d) extracted leaf contour

3. Leaf direction decision using main vein

3.1. Leaf vein extraction

We convert the input leaf image to a gray scale image and then perform opening operations [1]. In other words, erosion operations are performed after dilation operations are performed. We are obtained difference image of gray scale image and image of performed opening operation. Then, we are obtained leaf vein image by convert the difference image to binary image. Figure 3 shows an example of leaf vein extraction.

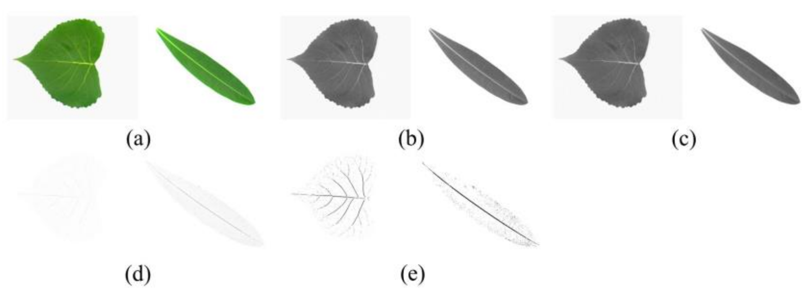


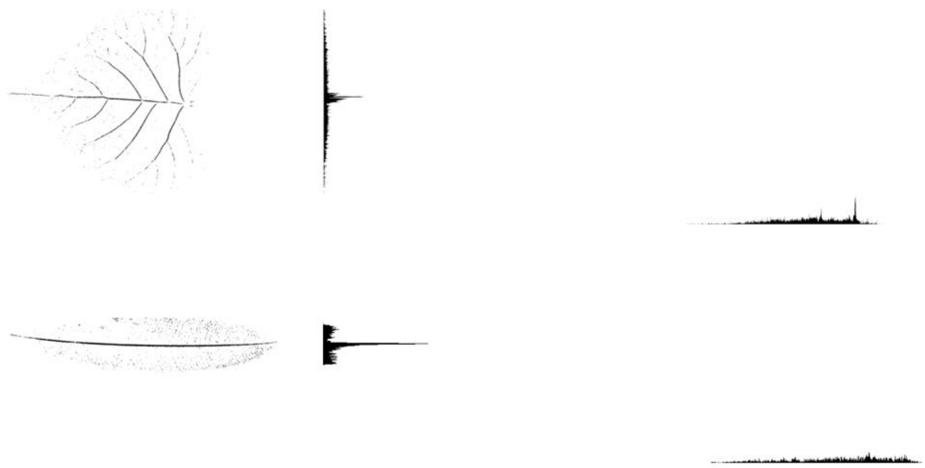
Figure 3. Example of leaf vein extraction: (a) input image, (b) gray scale image, (c) performed opening operations, (d) difference image of b and c, (e) leaf vein image

3.2. Main vein extraction and leaf direction decision

We describe on the method of main vein extraction and leaf direction decision from leaf vein image, using projection histogram in the horizontal and vertical directions, in order to measure the distribution of the leaf vein.

In the first step, we extract main vein of leaf using projections in the horizontal. We decide the main vein to the point of maximum of the histogram while leaf vein image rotated 180 degrees. After extracting the main vein, we decided the direction of the leaf through the projections in the vertical direction.

Figure 4 shows an example of main vein extraction and leaf direction determined. In Figure 4(c), when the image is divided in half, we can confirm that the histogram distribution of the leafstalk region is larger than leaf apex region.



(a) (b) (c)

Figure 4. Example of main vein extraction and leaf direction decision: (a) leaf vein image, (b) projections in the horizontal direction, (c) projection in the vertical direction

4. Leaf feature extraction

Total 21 leaf features were extracted for the leaf recognition, which they include ① the distance feature between centroid and all points on the leaf contour, ② frequency domain data by FFT that was performed using the distances. In summary, 10 features of all the 21 leaf features were extracted using distance, FFT magnitude, and phase [2], the other 10 features were extracted using t the digital morphological features using four basic geometric features and five vein features [1], and the last 1 feature was extracted using the convex hull.

4.1. Leaf feature (1): Distance and FFT-based frequency domain analysis

The centroid of the detected leaf region was found as follows:

$$C(x,y) = C(\frac{1}{N}\sum_{n=1}^{N} x_n,\ \frac{1}{N}\sum_{n=1}^{N} y_n) \quad (3)$$

Where, $C(x,y)$ is the centroid coordinate of leaf region image and N is the number of pixels on the detected leaf region.

The distance is calculated by measuring the centroid of the leaf region to all points on the leaf contour as follows:

$$D(i) = \sqrt{\left|C_x - E(i)_x\right|^2 + \left|C_y - E(i)_y\right|^2} \quad (4)$$

Where, $D(i)$ is the distance between the centroid of the leaf region and the i^{th} leaf contour pixel. C_x, C_y are the coordinates of the centroid of the leaf region, and, $E(i)_x$, $E(i)_y$ are the coordinates of i^{th} leaf contour pixel.

FFT is then performed using calculated distance values. The distance is acquired by measuring the longest distance point from the centroid in a clockwise direction. 10 features were then extracted based on the distance, FFT magnitude, and phase. The 10 features are as follows: average of the distance, standard deviation of the distance, Zero Crossing Rate (ZCR) of the distance from the average of the distance, average of the FFT magnitude, standard deviation of the FFT magnitude, number of peaks higher than the average of the FFT magnitude, the priority of the top ten peaks of the FFT magnitude, average of the FFT phase, standard deviation of the FFT phase, and ZCR of the FFT phase from the average of the FFT phase.

4.2. Leaf feature (2): Geometric and digital morphological features

We describe geometric and digital morphological features in order to leaf feature extraction.

We extract four basic geometric features as leaf length, leaf width, leaf area, leaf perimeter. The leaf length is defined as the longest distance between the centroid and the two ends on the margin of the leaf on opposite sides of the centroid. It is denoted by LL. The leaf width is defined as the distance between the intersection point with LL at the centroid and its opposite side on the margin of the leaf. It is denoted by LW. Figure 5 shows the procedure for obtaining LL and LW. The leaf area is the number of pixels in the leaf region. It is denoted by LA. The leaf perimeter is the number of pixels in the leaf contour. It is denoted by LP.

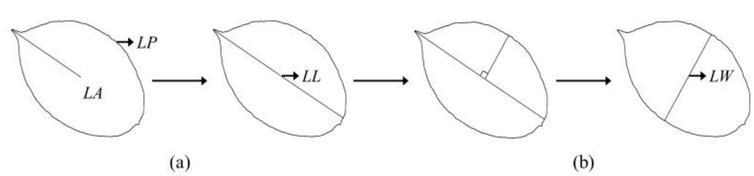


Figure 5. Procedure for Obtaining Leaf Length and Leaf Width: (a) leaf length, (b) leaf width

We extract ten features based on digital morphological features using four basic geometric features and the study conducted by S. G. Wu, *et al.*, [1] as aspect ratio, form factor, rectangularity, perimeter ratio of the leaf length, perimeter ratio of the leaf length and leaf width, and five vein features. The aspect ratio is calculated using the leaf length LL and leaf width LW. It is defined as LL/LW. The form factor is used to describe the difference between a leaf and a circle. It is defined as $4\pi LA/LP^2$, where LA is the leaf area and LP is the perimeter of the leaf margin. The rectangularity describes the similarity between a leaf and a rectangle. It is defined as $LL \cdot LW/LA$, where LL is the leaf length, LW is the leaf width and LA is the leaf area. The ratio of perimeter to leaf length, representing the ratio of the leaf perimeter LP and leaf length LL, is calculated by LL/LP. The perimeter ratio of the leaf length and leaf width is defined as the ratio of the leaf perimeter LP and the sum of the leaf length LL and leaf width LW, thus $LP/(LL+LW)$. The Vein features have been extracted using the methods proposed by S. G. Wu, *et al.*, [1] and the morphological openings on the gray scale images [11]. The five features are as follows: L_v1/A, L_v2/A, L_v3/A, L_v4/A, L_v4/L_v1.

4.3. Leaf feature (3): Convex hull

In mathematics, the convex hull of a set X of points in the Euclidean plane or Euclidean space is the smallest convex set that contains X. For instance, when X is a bounded subset of the plane, the convex hull may be visualized as the shape formed by a rubber band stretched around X [12]. In this paper, we use convex hull in order to reflect the complexity of the leaf contour. We compute the rate of extent of original image and convex hull image in order to extract leaf feature. Figure 6 shows an example of original image and convex hull image for extract leaf feature.

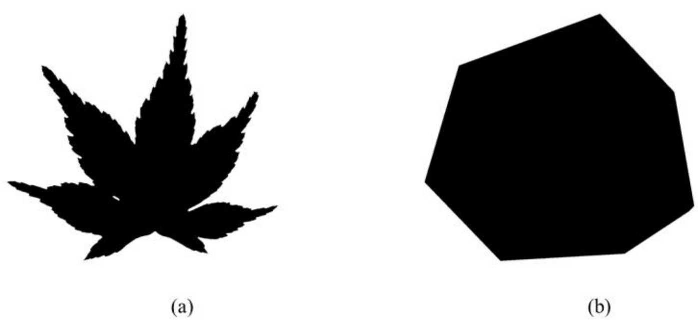


Figure 6. Example of convex hull image: (a) input image, (b) convex hull image.

5. Leaf recognition system

In this paper, we go through 20 steps in the plant classification process, and 3 steps in the leaf recognition process, using the extracted 21 leaf features. When only the plant of 1 species is classified after the 20 steps of the plant classification process, the recognition results are shown.

Three steps in the leaf recognition process using 10 peaks of the FFT magnitude procedure is as follows: ① The priority of the top 10 peaks of the FFT magnitude, ② If priorities of the top 10 peaks have the same score, we count the number of peaks with the same number, ③ If the same number also exists, we count the number of peaks with matching numbers and position. The score was calculated using the priority of the top 10 peaks. An example is shown in Figure 7, and Table 1 shows an example of the leaf classification and recognition process.

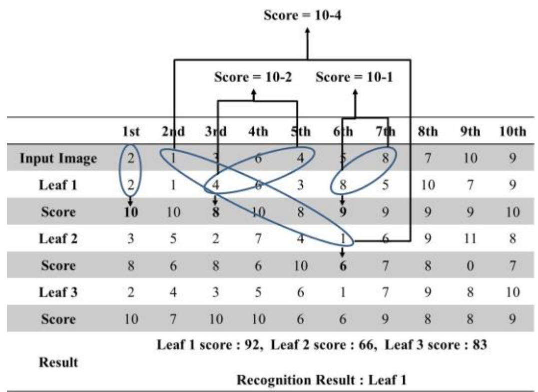


Figure 7. Example of how the score is calculated

Table 1. Example of the leaf classification and recognition process

Input : 2	Corresponding image									
Step 1	2	3	6	13	15	19	22	25	29	32
Step 2	2	6	13	15	25	29	32			
Step 3	2	6	13	15	25	32				
Step 4	2	6	13	15	25	32				
Step 5	2	6	15	25	32					
Step 6	2	6	15	25	32					
Step 7	2	6	15	25	32					
Step 8	2	6	15	25	32					
Step 9	2	15	25	32						
Step 10	2	15	25	32						
Step 11	2	15	25							
Step 12	2	15	25							
Step 13	2	15	25							
Step 14	2	15	25							
Step 15	2	15	25							
Step 16	2	15	25							
Step 17	2	15	25							
Step 18	2	15	25							
Step 19	2	15	25							
Step 20	2	15	25							
Step 21				2 : 86,		15 : 79,	25 : 86			
Step 22					2 : 9,	25 : 9				
Step 23					2 : 7,	25 : 5				
Recognition Result : 2										

As shown in Figure 7, we give 10 points when match number and position, and we give 9 points when 1 space difference of number and position of priority of the top 10 peaks of the FFT magnitude of input image and recognition models. The total score is calculated by summing the points of each position.

In Table 1, step 1~20 are plant classification process, and step 21~23 are leaf recognition process, and corresponding image shows classification and recognition result of each steps.

6. Experiments and results

In this paper, we used 1907 leaf images of 32 species collected by Wu et al. [1]. Each plant species has a minimum of 50 to a maximum of 77 sample leaves.

The proposed system was implemented using Microsoft Visual C++ 6.0 and the Intel OpenCV library. Because the leaf image size and position of the dataset is not constant, we normalized to the leaf image.

To evaluate the performance of the proposed leaf recognition system, a recognition model was created using a range of values with twenty-one features for each plant species. To each kind of plant, 10 pieces of leaves from testing sets are used to test. Table 2 shows the experimental results for the proposed leaf recognition system, and Figure 8 shows the example of leaf recognition system. The average recognition accuracy of proposed system is 97.19%.

Table 2. Experimental result for proposed leaf recognition system

Recognition system	Number of Leaf Image	Number of Incorrect recognition	Recognition rate
Existing system [1]	1800	31	90.31%
Existing system [2]	1907	15	95.31%
Proposed system	1907	9	97.19%

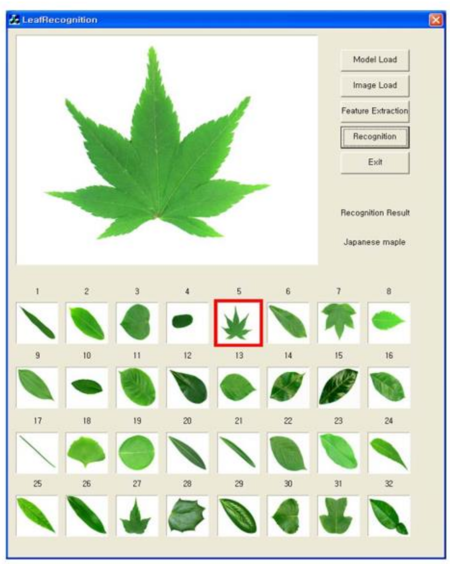


Figure 8. Example of leaf recognition system

7. Conclusions

In this paper, we proposed and implemented of leaf recognition system based on the leaf vein and shape for plant classification. We extract main vein from the input image, and leaf direction is determined using projection histograms of extracted main vein image. We were extracted twenty-one leaf features as distance, FFT, and convex hull for the leaf recognition.

In the experimental results, the proposed leaf recognition system showed a performance of 97.19%. From the experimental results, we can confirm that the recognition rate of the proposed advanced leaf recognition system was better than that of the existing leaf recognition system.

In future work, we improve the proposed system and further improve its recognition performance. In addition, we are continuing to research to find a correct leaf contour extraction method in the complex background.

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References

[1] S. G. F. Wu, S. Bao, E. Y. Y. Xu, X. Y. Wang, F. Chang and Q. L. Xiang, "A Leaf Recognition Algorithm for Plant Classification using Probabilistic Neural Network", The 7th IEEE International Symposium on Signal Processing and Information Technology, **(2007)** Cairo, Egypt.

[2] K. B. Lee and K. S. Hong, "Advanced Leaf Recognition based on Leaf Contour and Centroid for Plant Classification", The 2012 International Conference on Information Science and Technology, **(2012)** Shanghai, China.

[3] J. H. Kim, R. G. Huang, S. H. Jin and K. S. Hong, "Mobile-based flower recognition system", 2009 Third International Symposium on Intelligent Information Technology Application , **(2009)**, NanChang, China.

[4] T. H. Hsu, C. H. Lee and L. H. Chen, "An interactive flower image recognition system", Multimed. Tools Appl., vol. 53, no. 1, **(2011)**.

[5] S. J. Kim, B. W. Kim and D. P. Kim, "Tree Recognition for Landscape Using by Combination of Features of its Leaf, Flower and Bark", The SICE Annual Conference 2012, **(2011)** Tokyo, Japan.

[6] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta and R. Jain, "Content-based image retrieval at the end of the early years", IEEE Trans. Pattern Anal. Mach., vol. 22, **(2000)**.

[7] X. Wang, D. Huang, J. Dua, H. Xu and L. Heutte, "Classification of plant leaf images with complicated background", Appl. Math. Comput., vol. 205, **(2008)**.

[8] J. Du, D. Huang, X. Wang and X. Gu, "Computer-aided plant species identification (CAPSI) based on leaf shape matching technique", Trans. Inst. Meas. Control, vol. 23, **(2006)**.

[9] S. Zhang and Y. K. Lei, "Modified locally linear discriminant embedding for plant leaf recognition", Neurocomputing, vol. 74, **(2011)**.

[10] R. C. Gonzalez and R. E. Woods, "Digital Image Processing", Addison Wesley, Boston, **(1992)**.

[11] R. C. Gonzalez, R. E. Woods and S. L. Eddins, "Digital Image Processing Using MATLAB", Prentice Hall, New Jersey, **(2004)**.

[12] M. Berg, O. Cheong, M. Kreveld and M. Overmars, "Computational Geometry: Algorithms and Applications", Springer-Verlag Press, New York, **(2000)**.

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