

Hybrid Image Segmentation Algorithm for Leaf Recognition and Characterization

N.Valliammal^{#1}, Dr.S.N.Geethalakshmi^{#2}

*Assistant Professor, Department of Computer Science
Avinashilingam Deemed University for Women, Coimbatore-641043*

Email id: valli.p.2008@gmail.com. Mobile : 9944436253

*Associate Professor, Department of Computer Science
Avinashilingam Deemed University for Women, Coimbatore-641043*

Email id: sngethalakshmi@yahoo.com. Mobile : 9789774236

Abstract— Plants play an important role in both human life and other lives that exist on the earth. Due to environmental deterioration and lack of awareness, many rare plant species are at the margins of extinction. Despite the great advances made in botany, there are many plants yet to be discovered, classified, and utilized; unknown plants are treasures waiting to be found. Leaf classification and recognition for plant identification plays a vital role in all these endeavors. There has been little work reported on leaves, flower and fruit image processing and recognition. In recent years, several researchers have dedicated their work to leaf characterisation. As an inherent trait, leaf vein definitely contains the important information for plant species recognition despite its complex modality. A new approach that combines a thresholding method and H-maxima transformation based method is proposed to extract the leaf veins. A preliminary segmentation based on the intensity histogram of leaf images is first carried out to coarsely determine vein regions using thresholding. This is followed by a fine segmentation using H maxima transformation based method for object pixel as its inputs. Compared with other methods, experimental results show that this combined approach is capable of extracting more accurate venation modality of the leaf for the subsequent vein pattern classification. The approach can also reduce the computing time compared with other approach.

Keywords—Image segmentation, Thresholding, recognition, leaf characterization, plant identification, H-maxima transformation, Hybrid method and computation time.

I. INTRODUCTION

There are about 250 000 species of flowering plants that have been named and classified on earth. It is impossible for any botanist to know more than a tiny fraction of the total number of named species, which makes the further research on plants difficult. The advanced information technologies provide a potentially very attractive solution of building a computerised plant identification system for the central management of plant data. Several systems such as Lucid [1], Uconn [2] and CalFlora [3] have been developed for plant recognition and plant data management. These systems can

help user recognize plant species by using grayscale inputs, but neither of them support image processing as well as intelligent hybrid image segmentation techniques.

Segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels) (also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images[5,6,7]. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

This paper designs a new segmentation method, based on thresholding and H maxima transformation. First, a preliminary segmentation based on the intensity histogram of leaf images is first carried out to coarsely determine vein regions using thresholding. This is followed by a fine segmentation using a H maxima transformation based method for object pixel as its inputs.

The proposes method is organized as follows: Section I provided a brief introduction to the topic. Section II discusses the need for image segmentation. Section III presents the Image segmentation algorithm for leaf Image segmentation. The simulation results with different parameter evaluation are presented in section IV. Finally, conclusions are given in section V.

II. NEED FOR IMAGE SEGMENTATION

Leaf vein extraction is an important part of modeling plant organs. Assessing the appearance of plants is an important botanical skill, with many applications, ranging from plant recognition to health diagnosis. In identifying plant species, human beings will observe one or more of the following: the whole plant, leaves, flowers, stem and fruit. Plant leaf has an approximately two-dimensional nature. Therefore, it is most suitable for machine processing. As the shape of leaves is one of the most important features for characterizing various plants visually, the study of leaf segmentation will be an important stage for developing a plant recognition system.

III. IMAGE SEGMENTATION METHOD FOR LEAF RECOGNITION

Image segmentation is a fundamental task in computer vision. Although many methods are proposed, it is still difficult to accurately segment an arbitrary image by any method alone. In recent years, more and more attention has been paid to combining segmentation algorithms and information from multiple feature spaces (e.g. color, texture, and pattern) in order to improve segmentation results.

According to literature survey, segmentation algorithm is divided into categories using two properties such as, discontinuity and similarity. For this leaf recognition, basic standard segmentation algorithms are taken and are discussed in this section.

A. Edge Based Image Segmentation Method

In the first step, the canny edge detector is used to process the two parameter images and then the derived edges are added to derive the final edge detection results. After that local thresholding technique is applied.

The Canny edge detection operator [4] was developed by John F. Canny in 1986 and uses a multi-stage algorithm to detect a wide range of edges in images. It arises from the earlier work of Marr and Hildreth, who were concerned with modeling the early stages of human visual perception. His work is a gradient-based edge-finding algorithm that has become one of the most widely used edge detectors. This algorithm is known as the optimal edge detector. In this situation, an "optimal" edge detector is based on the following three criteria:

- Good detection: The algorithm should mark as many real edges in the image as possible.
- Good localization: Marked edges should be as close as possible to the edge in the real scene.
- Minimal response: A given edge in the image should only be marked once, and where possible, image noises should not create false edges.

Figure 1 shows an example of Canny edge based image segmentation for a leaf images.

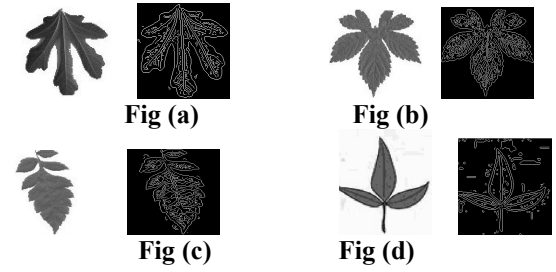


Figure 1 : Segmentation using canny edge detection

B) Adaptive Thresholding Method

Thresholding is called adaptive thresholding when different thresholds are used for different regions in the image. This may also be known as local or dynamic thresholding.

Consider a grayscale document image in which $g(x, y) \in [0, 255]$ be the intensity of a pixel at location (x, y) . In local adaptive thresholding techniques, the aim is to compute a threshold $t(x, y)$ for each pixel such that

$$O(x, y) = \begin{cases} 0, & \text{if } g(x, y) \leq t(x, y) \\ 255, & \text{otherwise} \end{cases} \quad (1)$$

In Sauvola's binarization method, the threshold $t(x, y)$ is computed using the mean $m(x, y)$ and standard deviation $s(x, y)$ of the pixel intensities in a $w \times w$ window centered around the pixel (x, y) as

$$t(x, y) = m(x, y) \left[1 + k \left(\frac{s(x, y)}{R} - 1 \right) \right] \quad (2)$$

where 'R' is the maximum value of the standard deviation ($R = 128$ for a grayscale document), and 'k' is a parameter which takes positive values in the range $[0.2, 0.5]$.

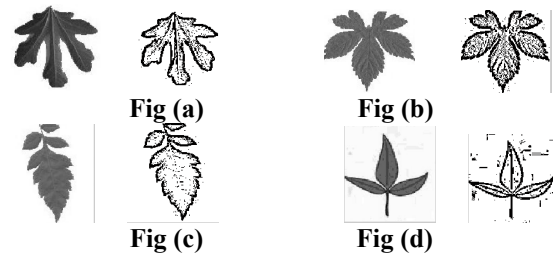


Figure-2 Segmentation using Adaptive Thresholding

The above figure 2 shows the image segmentation using adaptive thresholding method for different leaves. The original and segmented leaves are shown in Fig(a) to Fig (d).

C) Intensity Distribution

It can detect object boundaries with low gradient or reduce noise effect in gradient. However, an accurate and stable estimation of intensity distribution is difficult to get from a finite set of 3D image data. To reduce the "shrink" or "expand" effect on segmentation results, gradient information is used to calibrate the estimation of intensity distribution and overlapping of image gradient is computed with the boundaries determined by intensity distribution through introducing a probability offset to intensity distribution. The maximum overlap indicates the optimal boundaries of the interested objects. To restate the problem without losing generality, here it use a mixed Gaussian distribution model as in Eq(3)

$$P(u) = \sum_{k=1}^n \pi_k P(u | \lambda_k; \mu_k, \sigma_k), \quad (3)$$

where π_k is the prior probability of class λ_k with

$$\sum_{k=1}^n \pi_k = 1, \text{ and } \mu_k, \sigma_k \text{ are the mean and variance of the}$$

Gaussian distribution of the intensity. Intensity distribution inside the region Ω is in Eq (4)

$$P_{in}(u) = \sum_{k | \lambda_k \in \Omega} \pi_k P(u | \lambda_k; \mu_k, \sigma_k) \quad (4)$$

and the intensity distribution of the outside region Ω , P_{out} , can be obtained in a similar way. Normally for pixel x on region boundaries with $u = I(x)$, is shown in Eq (5).

$$P_{out}(I(x)) - P_{in}(I(x)) = 0 \quad (5)$$

Figure 3 shows the image segmentation using intensity distribution method for different leaves.

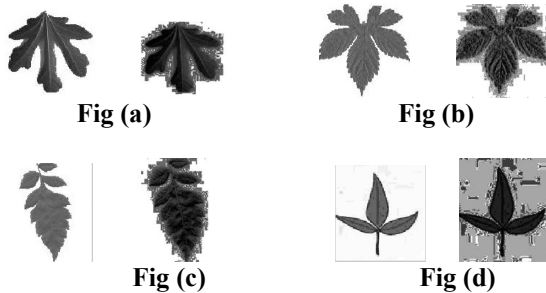


Figure-3 Segmentation using Intensity Distribution

The evolution of the boundary was controlled by a speed function based on the gradient and intensity distribution.

D. Hybrid Image Segmentation

This paper explains a new segmentation method, based on thresholding and H maxima transformation. First, a

preliminary segmentation based on the intensity histogram of leaf images is first carried out to coarsely determine vein regions using thresholding. This is followed by a fine segmentation using a H maxima transformation based method for object pixel as its inputs. The algorithms are explained in this section.

1) Collecting datasets :

The data acquisition is done by digital camera. The acquisition rate is varied between 4 fps and 30 fps. The light source was a conventional He-Ne laser, with beam power of 10 mW.

2) Pre-processing the leaf images

The pictures are saved in JPG format. They are converted into grayscale images and then the leaf region of each image is segmented by using a simple thresholding process. As the background is almost white, a pre-defined threshold works well in this process.

3) Preliminary segmentation result using the thresholding method

A simple preliminary segmentation based on thresholding is carried out to determine the coarse regions of vein pixels by eliminating those pixels that most likely belong to the background. The preliminary segmentation serves two purposes. It determines whether vein pixels as a whole are darker than the background. If so, reverse the intensity of the leaf image in order to make all the leaf images have vein pixels that are brighter than the background and therefore improve the performance of the classifiers. The second purpose of the preliminary segmentation is to determine the coarse vein regions by removing most background pixels. The main steps of this process are detailed below:

1. Compute the edge $d1$ of the whole leaf image I using the Sobel operator

$$d1(i, j) = \begin{cases} 1, & \text{if } I(i, j) \text{ edge pixel,} \\ 0, & \text{otherwise} \end{cases}$$

$$i, j \in \text{leafregion}$$

2. Compute the second-order derivative $d2$ of the pixels on both sides of the edge using the Laplacian operator. A positive second-order derivative indicates the pixel is on the brighter side of the edge whereas a negative second-order derivative indicates the pixel is on the darker side of the edge.

$$d2(i, j) = 8I(i, j) - \sum_{l=-1}^1 \sum_{m=-1}^1 I(i+l, j+m)$$

3. Extract the pixels on the brighter and the darker sides of the edge. Let

$$I1(i, j) = \begin{cases} I(i, j), & d2(i, j) > 0 \\ 0, & d2(i, j) \leq 0 \end{cases} \quad \text{and} \\ I2(i, j) = \begin{cases} I(i, j), & d2(i, j) < 0 \\ 0, & d2(i, j) \geq 0 \end{cases}$$

where $I1(i, j)$ denotes the pixels on the brighter side of the edge, and $I2(i, j)$ denotes the pixels on the darker side of the edge. Because vein pixels should be near the edge, that is, either on the brighter side or on the darker side of the edge, the intensities of $I1(i, j)$ and $I2(i, j)$ will be useful to detect the vein pixels.

4) Histogram of an image

Histogram equalization is done for enhancement of the leaf. The idea behind Histogram Equalization is that one can try to evenly distribute the occurrence of pixel intensities so that the entire range of intensities is used more fully. Each pixel intensity is given an equal opportunity, thus it is called equalization. Especially, for images with predominately low intensities, histograms will improve the contrasts in histogram equalization technique. It is the probability density function (pdf) that is being manipulated. To make it simple, histogram equalization technique changes the pdf of a given image into that of a uniform pdf that spreads out from the lowest pixel value (0 in this case) to the highest pixel value ($L - 1$).

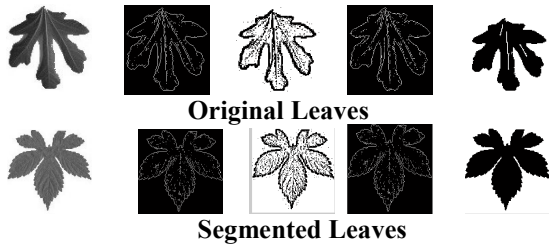


Figure 4 : Segmentation using Proposed hybrid

The above figure 4 shows the image segmentation using Hybrid method for different leaves. The original and segmented leaves are shown in Fig (a) to Fig (d).

5) H maxima Transformation

To remove the unwanted regions, the 3-D h-maxima transform is used for contrast simplification [13]. This morphological operation suppresses all points whose value with respect to their neighbors is smaller than a threshold level h . It is computed using:

$$HMAX_h(f) = R_f(f - h)$$

where $R_f(f - h)$ is the morphological reconstruction by dilation of image f with respect to $f - h$. The transform is then followed by an extended maxima operation to identify all regional maxima:

$$EMAX_h(f) = RMAX[HMAX_h(f)]$$

Morphological filters like the h-maxima transform belong to the class of connected operators. They preserve contour information and produce regions with approximately the same grey values (flat zones concept). The binary constraint is morphologically AND with each slice of the dataset obtained

from 3-D H-maxima transform to yield the final segmented results.

IV. EXPERIMENTATION AND EVALUATION

To test the accuracy of the preprocessing algorithms, three steps are followed.

- i) First, a leaf image is taken as input.
- ii) Second, different segmentation algorithms are applied for leaf images.
- iii) Third, the Energy, MSE and Evaluation time value is calculated for different algorithm.

The reconstruction of an image has the dimensions of 256 pixel intensity. The images in this contain a wide variety of subject matters and textures. Most of the images used are textile texture image with defect and without defect images. The Energy, Evaluation time and MSE must be less value for an better preprocessing algorithm. To estimate the quality of the reconstructed images, four performance metrics, namely, Energy, Mean Square Error (MSE), Peak signal to Noise ratio (PSNR) and Evaluation time are analyzed.

A. PSNR

The phrase Peak Signal to Noise Ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupted noise that affects the fidelity of its representation.

$$PSNR = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right) = 20 \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right)$$

Here, MAX_I is the maximum pixel value of the image.

B. Mean Square Error (MSE)

The metric MSE is defined as:

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N [g(i, j) - f(i, j)]^2$$

For two $m \times n$ monochrome images I and K , one of the images is considered a noisy approximation of the other. Other metrics like RMSE, MAE and PSNR are defined using MSE.

C. Evaluation Time

Evaluation Time (ET) of a filter is defined as the time taken by a digital computing platform to execute the filtering algorithms when no other software, except the operating system (OS), runs on it. Though ET depends essentially on the computing system's clock time-period, yet it is not necessarily dependant on the clock time alone. Rather, in addition to the clock-period, it depends on the memory-size, the input data size, and the memory access time. The execution time taken by a filter should be low for online and real-time image processing applications. Hence, a filter with lower ET is better

than a filter having higher ET value when all other performance-measures are identical. The experimental results are proved by subjective and objective method.

D. Energy

The gray level energy indicates how the gray levels are distributed. It is formulated as,

$$E(x) = \sum_{i=1}^x p(x)$$

where E(x) represents the gray level energy with 256 bins and p(i) refers to the probability distribution functions, which contains the histogram counts. The energy reaches its maximum value of 1 when an image has a constant gray level.

The larger energy value corresponds to the lower number of gray levels, which means simple. The smaller energy corresponds to the higher number of gray levels, which means complex.

The following tables 1, 2, 3 and 4 gives the result of PSNR, MSE, Elapsed Time and Energy value for different edge based segmentation algorithm.

Normally the PSNR value must be high for better quality of an image and MSE value must be low for an image. From the Visual Inspection in the following table, it can be seen that the Proposed method performs successfully by producing good results.

Table 1 Edge based image segmentation Method

| Images | PSNR | MSE | ET | Energy |
|----------|---------|----------|--------|--------|
| Image 1 | 1.0328 | 5.16E+04 | 0.435 | 0.889 |
| Image 2 | 1.3308 | 4.08E+04 | 0.476 | 0.901 |
| Image 3 | 1.5143 | 4.62E+04 | 0.527 | 0.896 |
| Image 4 | 2.14 | 4.03E+04 | 0.479 | 0.826 |
| Image 5 | 2.3533 | 3.81E+04 | 0.46 | 0.836 |
| Image 6 | 2.022 | 4.11E+04 | 0.5 | 0.852 |
| Image 7 | 2.056 | 4.00E+04 | 0.52 | 0.852 |
| Image 8 | 1.7063 | 4.24E+04 | 0.49 | 0.862 |
| Image 9 | 1.25 | 4.91E+04 | 0.561 | 0.89 |
| Image 10 | 1.28 | 4.87E+04 | 0.56 | 0.874 |
| Average | 1.66855 | 4.38E+04 | 0.5008 | 0.8678 |

Table 2 Adaptive thresholding method

| Images | PSNR | MSE | ET | Energy |
|----------|--------|----------|-------|---------|
| Image 1 | 1.31 | 4.64E+04 | 0.197 | 0.7816 |
| Image 2 | 1.365 | 4.78E+04 | 0.201 | 0.8111 |
| Image 3 | 1.549 | 4.58E+04 | 0.205 | 0.7859 |
| Image 4 | 2.385 | 3.97E+04 | 0.159 | 0.6971 |
| Image 5 | 2.05 | 3.75E+04 | 0.29 | 0.7474 |
| Image 6 | 2.08 | 4.00E+04 | 0.177 | 0.7439 |
| Image 7 | 1.745 | 4.00E+04 | 0.199 | 0.6658 |
| Image 8 | 1.25 | 4.38E+04 | 0.208 | 0.8618 |
| Image 9 | 1.341 | 4.87E+04 | 0.18 | 0.8092 |
| Image 10 | 2.14 | 4.80E+04 | 0.244 | 0.8068 |
| Average | 1.7215 | 4.38E+04 | 0.206 | 0.77106 |

Table 3 : Intensity distribution

| Images | PSNR | MSE | ET | Energy |
|----------|---------|----------|--------|--------|
| Image 1 | 8.188 | 9.99E+03 | 0.635 | 0.35 |
| Image 2 | 11.454 | 4.69E+03 | 0.39 | 0.366 |
| Image 3 | 11.99 | 4.13E+03 | 0.43 | 0.33 |
| Image 4 | 11.84 | 3.64E+03 | 0.47 | 0.21 |
| Image 5 | 13.4 | 3.67E+03 | 0.46 | 0.2 |
| Image 6 | 11.1 | 4.00E+03 | 0.49 | 0.21 |
| Image 7 | 11.91 | 4.11E+03 | 0.5 | 0.2 |
| Image 8 | 11.91 | 4.18E+03 | 0.46 | 0.29 |
| Image 9 | 11.05 | 5.18E+03 | 0.48 | 0.36 |
| Image 10 | 10.58 | 5.76E+03 | 0.514 | 0.33 |
| Average | 11.3422 | 4.94E+03 | 0.4829 | 0.2846 |

Table 4 Hybrid image segmentation

| Images | PSNR | MSE | ET | Energy |
|----------|------|---------|-------|--------|
| Image 1 | 53 | 0.26 | 0.88 | 0.69 |
| Image 2 | 56 | 0.1388 | 0.9 | 0.78 |
| Image 3 | 56 | 0.1634 | 0.9 | 0.6 |
| Image 4 | 52 | 0.344 | 0.91 | 0.5 |
| Image 5 | 53 | 0.29 | 0.92 | 0.5 |
| Image 6 | 53 | 0.29 | 0.92 | 0.5 |
| Image 7 | 53 | 0.3 | 0.95 | 0.52 |
| Image 8 | 55 | 0.18 | 0.91 | 0.58 |
| Image 9 | 54 | 0.21 | 0.94 | 0.56 |
| Image 10 | 55 | 0.19 | 0.96 | 0.54 |
| Average | 54 | 0.23662 | 0.919 | 0.577 |

The proposed method proves good in the observation of Subjective method. Figure 5 shows that by subjective method, hybrid method gives better results.

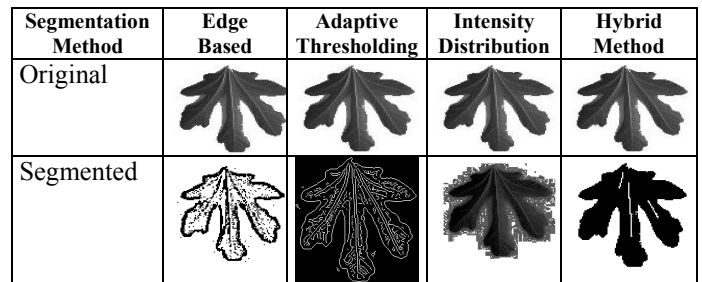


Figure 5 Original and Segmated Imagre could be observed using Subjective methods

V. CONCLUSION

Automatic Plant Identification is very important task for Agriculture, Forestry, Pharmacological science etc. Due to deterioration of environments, more and more plant species are at the margin of extinction. Hence there is a need for recognizing a plant by its category. Leaf Classification and Recognition for plant Identification plays a vital role in all these endeavors. Several researchers have dedicated their work to leaf characterization.

As an inherent trait, leaf edges and vein definitely contains the important information for plant species recognition despite its complex modality. A new approach that combines a thresholding method and a H-maxima transformation based method is proposed to extract the leaf edges. A preliminary segmentation based on the intensity histogram of leaf images is first carried out to coarsely determine edge regions using thresholding. This is followed by a fine segmentation using a H maxima transformation based method for object pixel as its inputs. Compared with other methods, experimental results shows that this combined approach is capable of extracting more accurate values of the leaf for the subsequent pattern classification. The approach can also reduce the computing time compared with other approach.

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