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A TWO-STAGE APPROACH FOR LEAF VEIN EXTRACTION

*Hong Fu and Zheru Chi**

Center for Multimedia Signal Processing, Department of Electronic and Information Engineering
The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong
*Corresponding author: enzheru@polyu.edu.hk

ABSTRACT

Living plant recognition is a promising but challenging task in the fields of pattern recognition and computer vision. As an inherent trait, the leaf vein definitely contains the important information for plant species recognition despite of its complex modality. In this paper, an efficient two-stage approach is presented for leaf vein extraction. At the first stage, a preliminary segmentation based on the intensity histogram of the leaf image is carried out to estimate the rough regions of vein pixels. This is followed at the second stage by a fine checking using a trained artificial neural network (ANN) classifier. Ten features distilled from a window centered at the pixel are used as the input to train the ANN classifier. Compared with conventional edge detection methods, experimental results show that the proposed method is capable of extracting more precise venation modality of the leaf for the subsequent leaf recognition.

1. INTRODUCTION

Leaf recognition is an important part of computerized living plant recognition. In recent years, various approaches have been proposed for characterizing plant leaves. These methods mostly concentrated on the peripheral contour representation and the recognition of the leaf, and some encouraging results have been obtained [1-2]. Only a few of primary investigations on the extraction of venation and vein-like objects have been done in recent years. Gouveia et al [3] proposed a two-step solution to segment the veins of a chestnut-tree leaf whose secondary venations are approximately straight and have the same inclination. Soille [4] applied morphological filters to extract leaf veins.

The veins of a leaf seem able to be extracted by edge operators, whereas vein extraction is of some difference from the edge detection. Most edge operators such as Sobel, Prewitt and Laplacian [5], focus on inspecting the locations in an image where a sudden variation in the grey level or color of pixel appears. For vein detection, some vein pixels belong to edge pixels, while others are at the locations where the grey level varies very smoothly, because the width of a vein often contains several pixels. Furthermore the width of the vein is very essential to distinct the primary vein from the accessory veins. Hence, only the information of edge is not enough to extract the real modality of veins.

This paper presents an efficient two-stage approach for leaf vein extraction. At the first stage, a preliminary segmentation based on the intensity histogram of the leaf image is carried out to estimate rough regions of vein pixels. This is followed at the second stage by a fine checking using a trained artificial neural network (ANN) classifier. At the fine checking stage, the vein detection is treated as a classification problem. All leaf pixels will be classified into two classes: vein and background. Ten features distilled from a window centered at the pixel are used as the input to a neural network classifier. A number of representative samples were manually collected to train the neural network. After a sufficient training, the network becomes a sound classifier for the classification of leaf pixels achieving the extraction of the veins.

2. PRELIMINARY SEGMENTATION

A simple preliminary segmentation is carried out to estimate the rough regions of veins by eliminating those pixels that most likely belong to the background.

The detailed steps of this algorithm are described below:

Step 1: Compute the edge of the whole leaf image $I(i,j)$ using the Sobel operator.

Step 2: Compute the second-order derivative $d2(i,j)$ of the pixels on both sides of the edge using Laplacian operator [5].

Step 3: Let

$$I1(i,j)=\begin{cases} I(i,j) & ,d2(i,j)>0 \\ 0 & ,d2(i,j)=0 \end{cases}$$

$$\text{and}\quad I2(i,j)=\begin{cases} I(i,j) & ,d2(i,j)<0 \\ 0 & ,d2(i,j)=0 \end{cases} \tag{1}$$

Step 4: Compute the histogram $h1$ of $I1(i,j)$, $h2$ of $I2(i,j)$ and h of $I(i,j)$. Let

$$RWH=\frac{<h1,h>}{<h2,h>} \tag{2}$$

where $<,>$ means the correlation operation.

RWH is called the "ratio of weighted histogram (*RWH*)". Because we only select the pixels on both sides of the edges, the numbers of pixels in $I1(i,j)$ and $I2(i,j)$ are approximately equal. Moreover, the background pixels are usually much more than vein pixels, so the correlation of $h1$ and h will be different from that of $h2$ and h. If $RWH > 1$, the veins consist of darker pixels, and vice versa.

Step 5: Select pixels within the region of veins from the whole leaf by setting a threshold T. For $RWH > 1$, select pixels from the whole image which have an intensity of smaller than T, where T has to ensure that $B\%$ (close to 100%) of $h2$ are selected. And for $RWH < 1$, select pixels from the whole image which have an intensity of larger than T, where T has to ensure that $B\%$ of $h1$ are selected. If $B\%$. 100%, almost all the vein pixels would be kept while many background pixels may also be included. That is to say, a large $B\%$ leads more precise result (without missing vein pixels) but more computational time required at the second stage of the fine classification with a neural network. On the other hand, a small $B\%$ helps save the processing time at the second stage but loses some vein pixels. There is a tradeoff between precision and efficiency.

3. AN ANN FOR FINE CLASSIFICATION

3.1. Feature Extraction

All the pixels in the rough vein regions from the first stage of preliminary segmentation are to be finely classified into two classes: the vein and the background. The criterions used to decide which class a pixel belongs to are the characteristics of its neighborhood. Ten features are distilled from a $7 \cdot 7$ window centered at the pixel $I(i, j)$:

1) Gradient values in four directions

Although not all the vein pixels are edge pixels as mentioned above, edge features are still helpful for identifying a vein pixel. Therefore, we use four gradient values calculated by the Sobel operator in the four directions that are horizontal, vertical, right oblique and left oblique.

2) Local Contrast

This feature is a measure of the local contrast of a darker pixel against its background, which has been successfully used in the segmentation of map images [6]. Since the map image is vein-like, we introduce local contrast as one of the ten features. The local contrast is defined as

$$J(i,j) = \frac{\max[0, B(i,j) - I(i,j)]\,\mathrm{sgn}[C(i,j)]}{LA(i,j)} \qquad (3)$$

where $\mathrm{sgn}[\ ]$ is the sign function. $I(i,j)$ and $LA(i,j)$ are the grey level of the object pixel and the average intensity of $7 \cdot 7$ neighboring pixels respectively. $C(i,j)$ measures the difference of a pixel intensity and the average intensity of its eight neighboring pixels. $B(i,j)$ is a measure of the average intensity of the relative brighter pixels in the local window.

3) Five statistical features of the pixel and its neighborhood

We assume that the vein pixels are somewhat brighter than the background pixels in one leaf image, therefore these two classes may have different statistical features. The grey level of the pixel as well as the mean, the standard deviation, the maximum, and the minimum of $7 \cdot 7$ neighborhood are used as the remaining five features.

(a)

(b)

Figure 1: Examples of leaf sub-images (a) and the extracted veins (b) by using the trained ANN classifier.

3.2. Neural Network Training and Testing

Some representative pixels (both vein and background pixels) are collected manually, and their pixel features are calculated as the training samples to train a feed-forward back-propagation (BP) neural network [7]. We used a neural network with 10 input nodes, one hidden layer of 20 nodes and one output. The training set consists of 2490 samples in which 50% are vein samples and 50% are background samples. The training data was collected from 42 sub-images extracted from 21 different leaf images. After 1500 epochs, the MSE (mean squared error) can be reduced to below 0.05. We use the training sub-images to test the classification validity of the trained ANN classifier. Examples are illustrated in Fig. 1. Fig. 1(a) shows leaf sub-images and Fig. 1(b) shows the extracted veins by using the trained ANN. The results show that the trained ANN classifier performs quite well.

4. THE LEAF VEIN EXTRACTION ALGORITHIM

The steps for leaf vein extraction are summarized below:

Step 1: Compute the *RWH*. If $RWH > 1$, reverse the image intensity. Conduct a preliminary segmentation by thresholding in order to eliminate those pixels that most likely belong to the background.

Step 2: Fine extraction with the trained ANN classifier.

5. EXPERIMENTAL RESULTS AND DISCUSSION

A leaf image (Fig. 2(a)) is processed by our method and the detailed results after each step are illustrated in Fig. 2. Fig. 2(b) shows the edge map obtained by the Sobel operator. Fig. 2(c) and (d) are the pixels with positive and negative second-order derivatives respectively. Their histograms are shown in Fig. 2(e). $RWH = 0.09$, which indicates that vein pixels are brighter than background pixels. Let $B\% = 99\%$ and select pixels that are larger than $T = 79$. The histogram of the whole leaf image and the threshold are shown in Fig. 2(f). The selected pixels (bright pixels) that occupy 46.85% of the whole leaf image are shown in Fig. 2(g), where most are the vein pixels while some of the background pixels are included. Employ the trained ANN classifier to classify the pixels remained after the preliminary segmentation and obtain the result shown in Fig. 2(h).

Perceptually, our method produces better results than using the Sobel operator. The main difference between the proposed method and the conventional edge detectors is that the former can produce a solid strip to represent a vein, while the latter can only produce two edge lines which are approximately parallel. Using our approach, the vein pixels both at the edge and within the veins are detected, which could lead to an easy and robust vein representation even if a certain amount of vein points are missing. On the contrary, the results of edge detectors contain only the edge pixels of veins, which is not adequate for computerized vein representation because it is very sensitive to the false detection, such as the missing vein edge points, due to the difficulty in connecting discontinuous lines. A connectivity analysis is conducted on the results of our method and the Sobel operator. We labeled all the connected components in the extracted veins and accounted the pixel number of each component. Fig. 3 shows the results of connectivity analysis, where Fig. 3(a) shows the result of our method and Fig. 3(b) is that of the Sobel operator. For our method, most pixels are connected with a few of large components while for the Sobel operator the pixels spread around. In other words, our method provides more reliable connectivity for the subsequent vein recognition.

Four other images whose pixels are not as training samples are also processed by our method and the results are shown in Fig. 4, where Fig. 4(a)~(c) are the original images, the preliminary segmentation results and the final extraction results respectively. It can be seen that the results are all satisfactory.

Our method needs a longer time for processing than conventional methods due to the time-consuming feature extraction and classification by ANN. It takes about 20 seconds (on a PC computer with PIII 600MHz and 192MB RAM working on WinXP platform) for the ANN classifier to process a $640 \cdot 480$ leaf image shown in Fig. 2(a). Our two-stage approach that combines the preliminary segmentation and the fine classification using the ANN classifier can save 53.15% of the computational time. Experimental results show that more than 50% of the computational time can be saved for most leaf images if we set $B\% = 99\%$. More save in the computational time can be secured because we only need to examine a small sub-image of leaf to find out the venation pattern of the leaf. The processing of (1/10) of the leaf image would be sufficient for the subsequent leaf classification. Therefore, about a second would be required to extract the veins of the leaf image.

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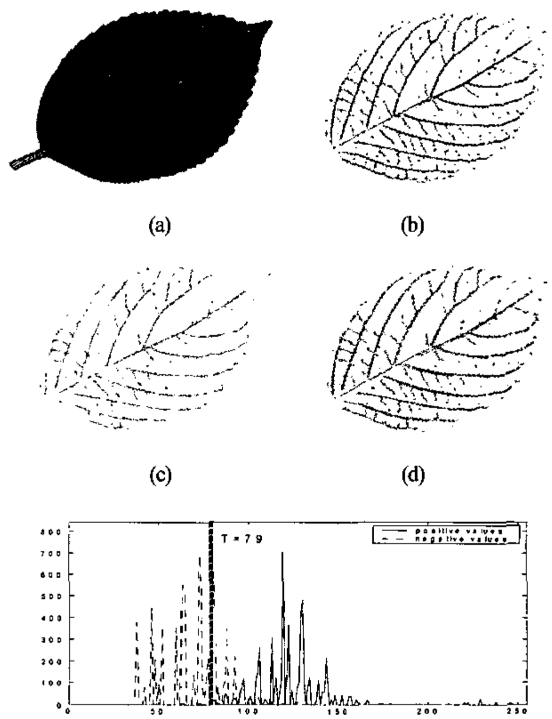
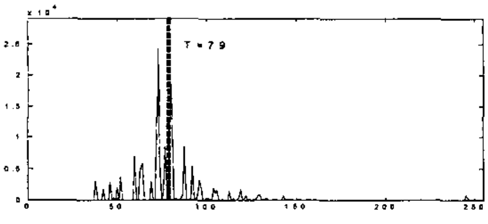


(a) (b) (c) (d)

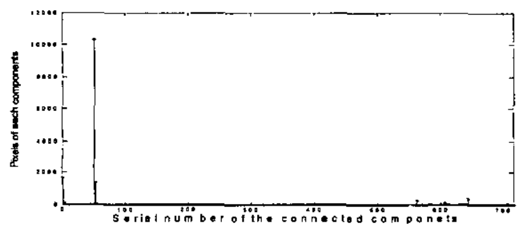
(e)



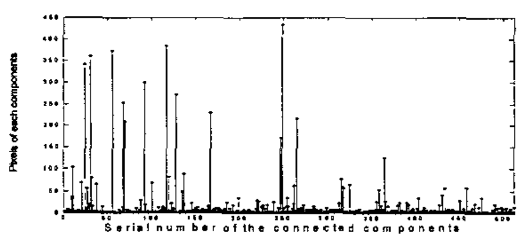
(f)

(g) (h)

Figure 2: The vein extraction of a leaf image. (a) A $640 \cdot 480$ leaf image; (b) Edges extracted by the Sobel operator; (c) Pixels with a positive second-derivative $I1(i, j)$; (d) Pixels with a negative second-derivative $I2(i, j)$; (e) The histograms $h1$ and $h2$, $T = 79$ and $RWH = 0.09$; (f) The histogram of the whole image and $T = 79$. (g) Preliminary segmentation by thresholding with $T = 79$ and 53.15% of computation saving; (h) The final result of the vein extraction.

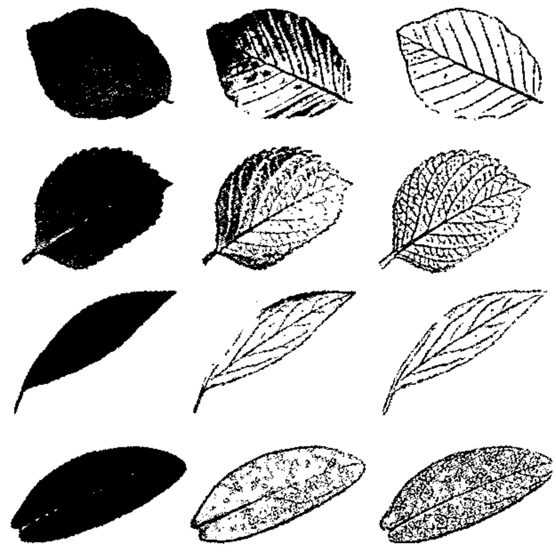


(a)



(b)

Figure 3: Connectivity analysis of our method and the Sobel edge operator. (a) Connectivity of Fig. 2(h); (b) Connectivity of Fig.2 (b).



(a) (b) (c)

Figure 4: Vein extraction results by using our proposed method. (a) Original leaf images; (b) Preliminary segmentation results; (c) Vein extraction results.