Combined thresholding and neural network approach for vein pattern extraction from leaf images

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Abstract: Living plant recognition based on images of leaf, flower and fruit is a very challenging task in the field of pattern recognition and computer vision. There has been little work reported on 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 an artificial neural network (ANN) classifier is proposed to extract leaf veins. A preliminary segmentation based on the intensity histogram of leaf images is first carried out to coarsely determine vein regions. This is followed by a fine segmentation using a trained ANN classifier with ten features extracted from a window centred on the 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 a direct neural network approach.

1 Introduction

1.1 Potential applications of living plant recognition

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 recognise plant species by using textual inputs, but neither of them support image processing as well as intelligent content-based image search techniques. A computer-aided living plant recognition system shown in Fig. 1 would release the user from boring tasks including labelling, measuring, classification and data entry by making full use of sophisticated image processing, computer vision and intelligent information processing techniques. Both image and textual inputs are acceptable in this system. For a text input, traditional text-based information processing and search techniques can be used. For an image input, dedicated image processing algorithms have to be applied to the processing of flower, leaf and stem images as well as the whole plant images.

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1.2 Approaches to leaf classification

Leaf classification is an important component of computerised living plant recognition. In the past decade, various approaches have been proposed for characterising plant leaves. These methods mostly concentrated on the peripheral contour representation for the recognition of the leaf, and some encouraging results have been obtained [4–7]. However, in some situations, it is difficult to distinguish two leaves of different species by their leaf shapes only. An example is shown in Fig. 2, where the two leaves' shapes are similar whereas the types of the veins are quite different. Actually, the vein pattern of a plant species is somewhat related to the pattern of plant. In general, the primary vein or veins are analogous to the main trunk or trunks of a tree and the secondary veins are analogous to the major limbs of a tree [8]. Though the vein extraction is very helpful for the leaf or even plant classification, only a few primary investigations on the extraction of vein or vein-like objects have been made in recent years. Gouveia *et al.* [9] have proposed a two-step solution to segment the veins of the chestnut-tree leaf whose secondary venations are approximately straight and have the same inclination. Soille [10] has applied morphological filters to extract leaf veins only for marking and segmenting the plants in the crop field.

Vein extraction is different from the edge detection. Most edge operators such as Sobel, Prewitt and Laplacian [11] focus on inspecting the locations in an image where a sudden variation in the grey level or the colour 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 little, because the width of vein is often several pixels. Normally, edge detection would produce broken edges and it is difficult to fill in missing vein pixels on the basis of edge detection results. The width of vein is very essential to distinct the primary vein from the accessory veins. Hence, only the information of edge is not adequate to extract the real modality of veins.

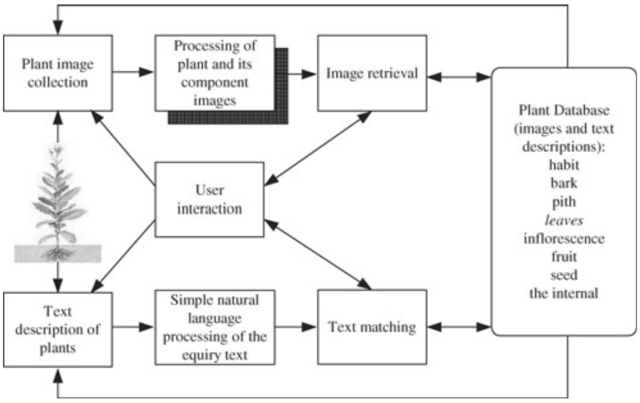

Fig. 1 *Block diagram of a computer-aided living plant species recognition system*

In addition, although the thresholding based on the histogram of the image may help extract some pixels within the vein edges, it cannot perform well because of different illumination conditions, the poor uniformity of the veins and the background, and so on. Therefore a more sophisticated approach is desirable.

1.3 Combined thresholding and neural network approach

This paper presents a new approach combining thresholding and artificial neural network (ANN) learning for leaf vein extraction in order to extract accurate veins but keep controllable computational complexity. After segmenting the leaf image, a preliminary segmentation on the basis of the intensity histogram of the leaf image is first carried out to determine the coarse regions of vein pixels. This is followed by a fine refining using a trained ANN classifier. All leaf pixels will be classified by the trained vein pixel classifier into two classes: vein and background. Ten features distilled from a window centred at the object pixel are used as the inputs of a neural network classifier. A number of representative samples were manually picked up to train the neural network. Post-processing is also carried out to improve the performance. The block diagram of our approach is shown in Fig. 3. Although this approach is developed for leaf vein extraction, it can also be extended to the extraction of other vein-like objects, such as the retinal vascular tree, the texture of granitoid rocks, and so on.

2 Leaf image capture and pre-processing

2.1 Leaf image capture apparatus

There has not been a standard procedure for taking leaf images. As per the experiences introduced by Gouveia *et al.* [9], we established a leaf image capture apparatus that includes a fluorescent light bank, a digital camera and its support, as shown in Fig. 4. A leaf sample is put on the fluorescent light bank so that its veins can be enhanced by the light from the backside.

2.2 Pre-processing of leaf images

The pictures are saved in JPG format. They are converted into greyscale 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 based on thresholding

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 ANN classifier. 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:

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

$$d1(i,j) = \begin{cases} 1, & \text{if } I(i,j) \text{ is an edge pixel,} \\ 0, & \text{otherwise} \end{cases}$$
$$i,j \in leaf\ \ region \tag{1}$$

Step 2: Compute the second-order derivative $d2$ of the pixels on both sides of the edge using the Laplacian operator defined in (2). 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. How to locate the pixels ‘on both sides of the edge’? Firstly, for each edge pixel, compute its edges in four directions using the Sobel kernels shown in Fig. 5 to estimate its direction. The max direction is regarded as the direction of the edge. Secondly, compute the second-order derivatives of the pixels in the 3×3 neighbourhood only in the direction perpendicular to the edge including the edge pixel. In other words, we only need to compute the second-order derivatives of three pixels for each edge pixel. As illustrated in Fig. 6*a*, the edge direction of edge pixel B is left oblique, so the pixels ‘on both sides of the edge’ are two of A, B and C, which are in the right oblique. Finally, delete the pixel whose second derivative is the median of the three in order to ensure that the two selected pixels are on both sides of the real edge, as

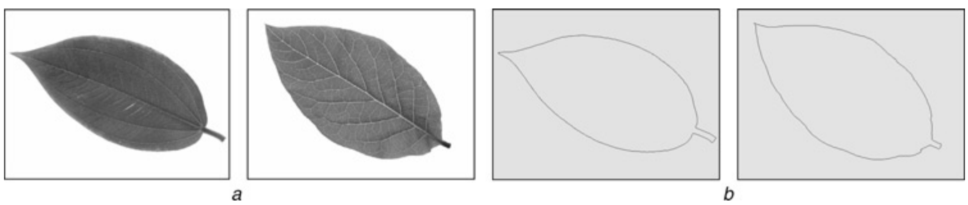

Fig. 2 *Two leaf images with similar shapes and different veins*

a Leaf images
b Leaf contours

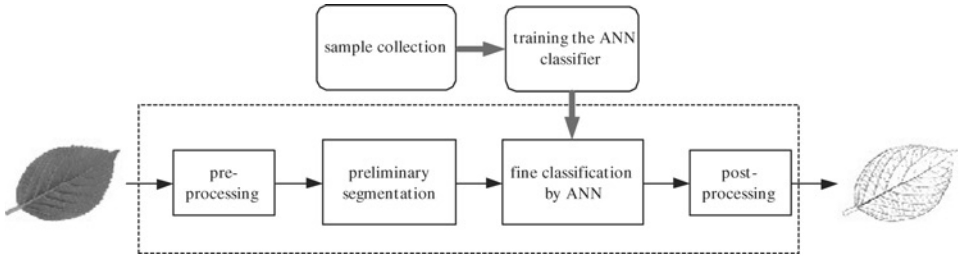

Fig. 3 *Block diagram of our vein extraction method*

illustrated in Figs. 6*b*–*d*

$$d2(i,j) = 8I(i,j) - \sum_{l=-1}^{1}\sum_{m=-1}^{1} I(i+l, j+m) \tag{2}$$

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

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

$$I2(i,j) = \begin{cases} I(i,j), & d2(i,j) < 0 \\ 0, & d2(i,j) \ge 0 \end{cases} \tag{3}$$

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.

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

$$\mathrm{RWH} = \frac{\langle h1, h\rangle}{\langle h2, h\rangle} \tag{4}$$

where $\langle,\rangle$ denotes the inner product.

$\langle h1, h\rangle$ is the weighted sum of the histogram h with $h1$ as the weights and $\langle h2, h\rangle$ is the weighted sum of the histogram h with $h2$ as the weights. RWH is the ratio of the two weighted histograms. Because we select only the pixels on both sides of the edges, the numbers of pixels in $I1(i, j)$ and $I2(i, j)$ are approximately equal. Moreover, there are more background pixels than vein pixels, so the correlation of $h1$ and h will be different from that of $h2$ and h. If RWH > 1, the majority of these pixels are brighter, in other words, vein pixels are most likely darker. RWH < 1 means that vein pixels are brighter than background pixels. If RWH > 1, the pixels that locate in the region of $h2$ are most probably veins. If RWH < 1, the pixels that locate in the region of $h1$ are most probably veins.

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 larger than T, where T has to ensure that B% (close to 100%) of $h1$ are selected.

An example is shown in Fig. 7. Fig. 7*a* is a sub-image extracted from a leaf image. At first, we obtained the edges shown in Fig. 7*b* by using the Sobel operator. Then we found the pixels with higher positive and negative second-order derivatives on both sides of the edges, as

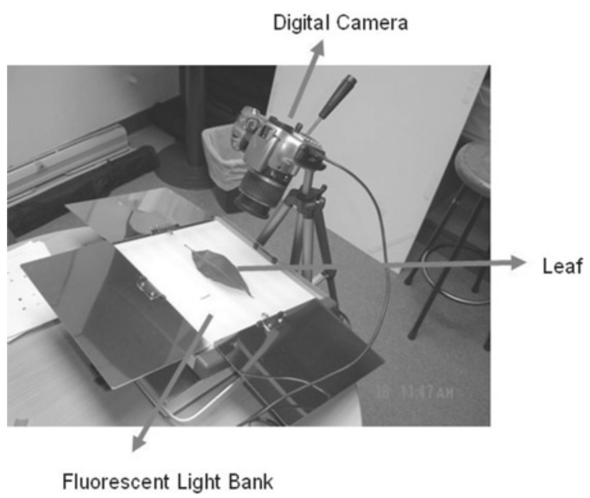

Fig. 4 *Leaf image capture apparatus*

−1	−2	−1
0	0	0
1	2	1

Horizontal

a

−1	0	1
−2	0	2
−1	0	1

Vertical

b

−2	−1	0
−1	0	1
0	1	2

Right oblique

c

0	−1	−2
1	0	−1
2	1	0

Left oblique

d

Fig. 5 *Sobel operators for four directions*

a Horizontal
b Vertical
c Right oblique
d Left oblique

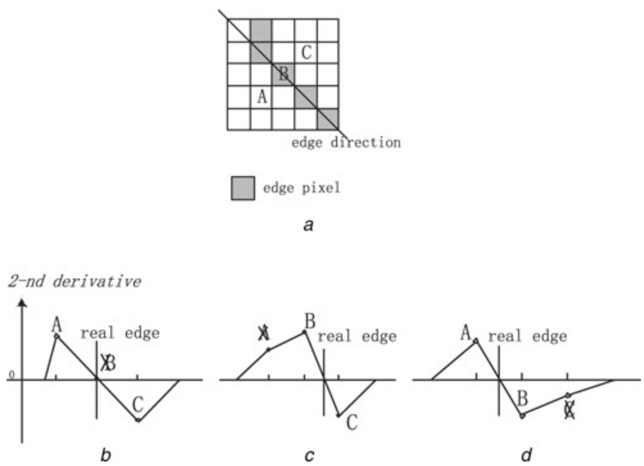

Fig. 6 *Location of the pixels on both sides of the edge*

a Three pixels A–C in the direction perpendicular to the edge
b, *c*, *d* Deleting the pixel whose second-order derivative is the median value

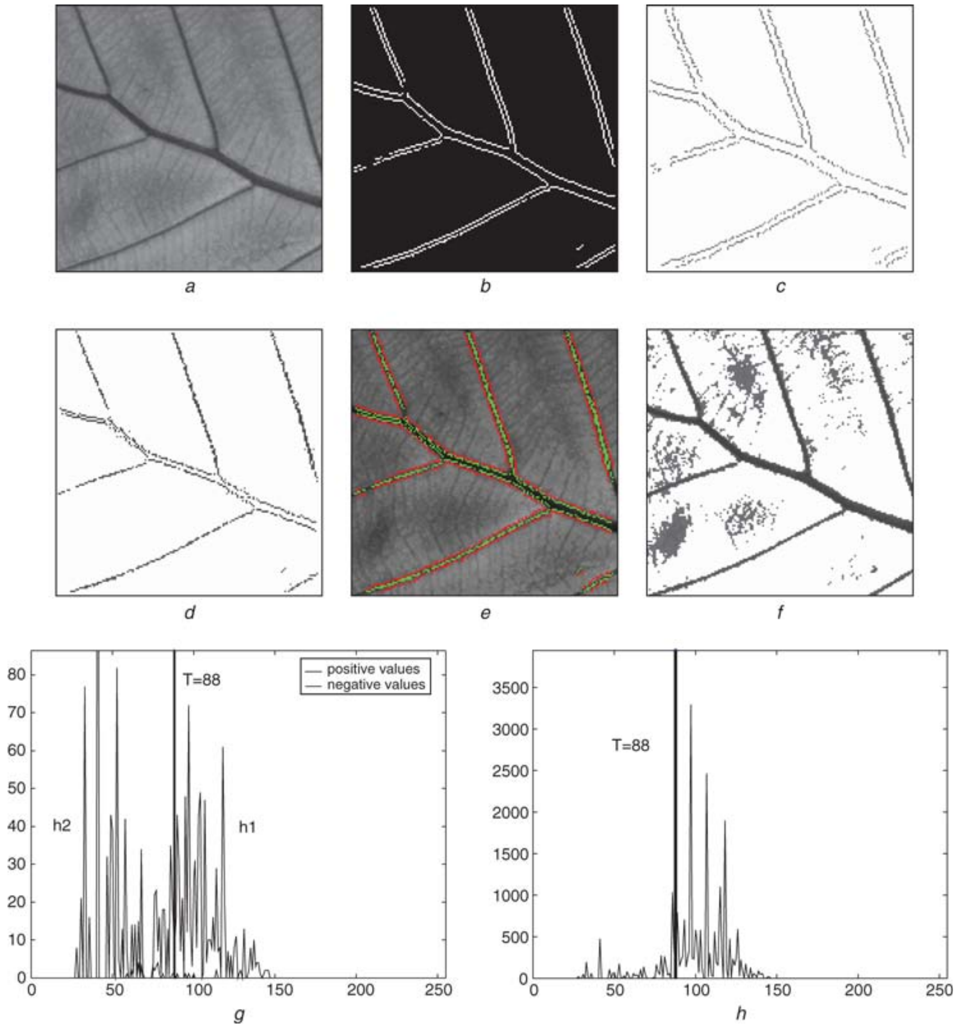

Fig. 7 *Example for selection of pixels*

a Leaf sub-image $I(i, j)$
b Edges extracted by the Sobel operator $d1(i, j)$
c Pixels with a positive second-derivative $I1(i, j)$
d Pixels with a negative second-derivative $I2(i, j)$
e Positive pixels $I1(i, j)$ (red pixels) and negative pixels $I2(i, j)$ (green pixels) labelled on the original image
f Preliminary segmentation result using the thresholding method with $T = 88$
g Histograms $h1$ and $h2$, $T = 88$
h Histogram for the whole image and $T = 88$ ($B = 99$)

shown in Figs. 7*c* and *d*, respectively. These pixels are also labelled on the original image for a clearer illustration as shown in Fig. 7*e*. The positive pixels are labelled as red and the negative ones as green. We can see that these pixels are on the both sides of the edges. The RWH is 3.6 according to (4), which indicates that vein pixels are darker than background pixels. A preliminary segmentation is carried out to select pixels whose grey level is smaller than a threshold $T = 88$ which ensures 99% of h_2 is selected as shown in Fig. 7*f*. The selected pixels contain almost all the vein pixels and only a small percentage of the background. For this image, 81.15% of computing time is saved for the subsequent ANN classification. It is difficult to determine the threshold T according to the intensity histogram of the image for our application. For example, as there is no obvious 'valley' on the histogram shown in Fig. 7*h*, those thresholding methods based on the shape properties of the histogram [12] may fail to find a correct threshold. Our proposed thresholding method transferred the histogram into two classes (Fig. 7*g*): positive values and negative values, no matter whether the histogram is bimodal. Therefore we can obtain a proper threshold to segment the vein pixels preliminarily.

4 ANN pixel classifier

4.1 Feature extraction

All the pixels in the coarse vein regions from the preliminary segmentation are to be finely classified into two classes: the vein and the background. The parameters used to decide which class the objective pixel belongs to are the character information of its neighbourhood. Ten features $f_1, f_2, \ldots, f_{10}$ are distilled from a 7×7 window centred at the object pixel $I(i, j)$:

1. Gradient values in four directions f_1, f_2, f_3, f_4
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 Sobel operators d_1, d_2, d_3, d_4 shown in Fig. 5 as four features for the vein extraction.
2. Local contrast f_5
This feature is a measure of the local contrast of a pixel against its background, and it has been successfully used in the segmentation of map images [13]. As the map image is vein-like, we used local contrast as one of the

ten features for vein extraction. The original local contrast definition has been slightly modified and is defined as

$$f_5 = \begin{cases} \dfrac{\max[0, B1(i,j) - I(i,j)]}{B1(i,j)}, & C(i,j) \geq 0 \\ \dfrac{\min[0, B2(i,j) - I(i,j)]}{I(i,j)}, & C(i,j) < 0 \end{cases} \tag{5}$$

where

$$C(i,j) = \frac{1}{8}[I(i-3,j) + I(i-2,j) + I(i+2,j) + I(i+3,j) + I(i,j-3) + I(i,j-2) + I(i,j+2) + I(i,j+3)] - I(i,j) \tag{6}$$

$$B1(i,j) = \frac{1}{N_{b1}} \sum_{\substack{i-4 \leq p \leq i+4 \\ j-4 \leq q \leq j+4 \\ C(p,q) \leq 0}} I(p,q) \tag{7}$$

where N_{b1} is the number of pixels whose $C(p, q)$ are not more than zero in the 9×9 neighbourhood of (i, j).

$$B2(i,j) = \frac{1}{N_{b2}} \sum_{\substack{i-4 \leq p \leq i+4 \\ j-4 \leq q \leq j+4 \\ C(p,q) > 0}} I(p,q) \tag{8}$$

where N_{b2} is the number of pixels whose $C(p, q)$ are more than zero in the 9×9 neighbourhood of (i, j).

For a pixel (i, j), $C(i, j)$ was used to determine whether a pixel is relatively brighter or darker than its neighbouring pixels. The first operand of $C(i, j)$ is the estimation of the background intensity of pixel (i, j). The second operand of $C(i, j)$ is the intensity $I(i, j)$ of pixel (i, j). When we compute $C(i, j)$, we use only eight out of 49 pixels in 7×7 region, as shown in Fig. 8. There are both vein pixels and background pixels in the 7×7 region. If we use all the pixels in the 7×7 region to calculate it, the first operand of $C(i, j)$ may not be a proper estimation of the background intensity. We use the selected neighbouring pixels rather than all the pixels in the 7×7 region to obtain an estimation of the background intensity.

For a relatively darker pixel ($C(i, j) \geq 0$), we compute the average intensity $B1(i, j)$ of brighter neighbouring pixels.

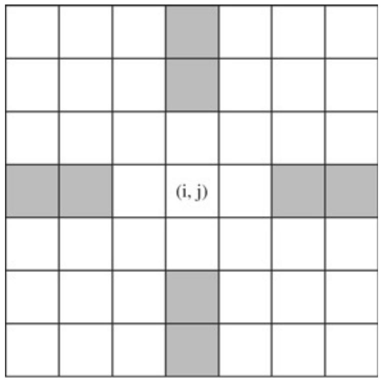

Fig. 8 *Eight neighbouring pixels for calculating C(i, j)*

The difference between the pixel intensity and its brighter neighbouring pixels reflects the contrast between this pixel and its background. Normally, we have $B1(i, j) - I(i, j) \geq 0$. This pixel is probably a noise pixel if $B1(i, j) - I(i, j) < 0$. So we use max $[0, B1(i, j) - I(i, j)]$ to force it to zero. Finally, we use $B1(i, j)$ to normalise the difference and we have $0 \leq f_5 \leq 1$.

Similarly, for a relatively brighter pixel ($C(i, j) < 0$), we compute the average intensity $B2(i, j)$ of brighter neighbouring pixels. The difference value of the noise pixel will also be forced to zero by $\min[0, B2(i, j) - I(i, j)]$. We use $I(i, j)$ to normalise the difference and we have $-1 \leq f_5 \leq 0$. Considering both these cases, the value range of the local contrast f_5 is $[-1, 1]$. Table 1 summarises the items and their meanings in the local contrast definition f_5.

3. Five statistical features of the pixel and its neighbourhood f_6–f_{10}

We assume that vein pixels are somewhat brighter than the background pixels in a leaf image. Therefore these two classes have different statistical features. The grey level of the pixel as well as the mean, the sample standard deviation, the maximum and the minimum of the 7×7 neighborhood pixels listed below are used as the remaining five features

$$f_6 = I(i,j) \tag{9}$$

$$f_7 = \frac{1}{49} \sum_{\substack{i-3<p<i+3 \\ j-3<q<j+3}} I(p,q) \tag{10}$$

Table 1: Explanation of local contrast f_5

Items	$C(i, j)$	$B1(i, j)$ or $B2(i, j)$	min $[0, B2(i, j) - I(i, j)]$ or max $[0, B1(i, j) - (i, j)]$	Local contrast f_5
Pixel (i, j)	$C(i, j) \geq 0$ relatively darker	$B1(i, j)$ average intensity of brighter neighbouring pixels	$\max[0, B1(i,j) - I(i,j)] = \begin{cases} 0, & \text{if } B1(i,j) - I(i,j) < 0 \\ B1(i,j) - I(i,j), & \text{if } B1(i,j) - I(i,j) \geq 0 \end{cases}$	$\dfrac{\max[0, B1(i,j) - I(i,j)]}{B1(i,j)}$ $0 \leq f_5 \leq 1$
	$C(i, j) < 0$ relatively brighter	$B2(i, j)$ average intensity of darker neighbouring pixels	$\min[0, B2(i,j) - I(i,j)] = \begin{cases} 0, & \text{if } B2(i,j) - I(i,j) > 0 \\ B2(i,j) - I(i,j), & \text{if } B2(i,j) - I(i,j) \leq 0 \end{cases}$	$\dfrac{\min[0, B2(i,j) - I(i,j)]}{I1(i,j)}$ $-1 \leq f_5 \leq 0$

$$f_8 = \sqrt{\frac{1}{48} \sum_{\substack{i-3<p<i+3 \\ j-3<q<j+3}} [I(p,q) - f_7]^2} \quad (11)$$

$$f_9 = \max[I(p,q), \quad i-3<p<i+3, \quad j-3<q<j+3] \quad (12)$$

$$f_{10} = \min[I(p,q), \quad i-3<p<i+3, \quad j-3<q<j+3] \quad (13)$$

4.2 ANN 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 ANN [14, 15]. We used an ANN with 10 inputs 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 real leaf images. Each sub-image has 85×85 pixels and contains the veins of various widths in which the thickest vein is about 8 pixels wide. After 1500 epochs, the mean squared error can be reduced to below 0.05. We use the training sub-images to test the classification validity. Examples are illustrated in Fig. 9. Figs. 9*a* and *d* show the sub-images. Figs. 9*b* and *e* show the extracted veins by using the trained ANN. To improve the results, a post-processing step (discussed in Section 5) is carried out to delete the isolated pixels, as shown in Figs. 9*c* and *f*. The results show that the trained ANN classifier performs well.

5 Experimental results and discussions

The steps for leaf vein extraction are summarised below:

Step 1: Pre-processing. It includes converting a colour image to a grey scale one and determining the leaf region.
Step 2: Preliminary segmentation. 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 3: Fine classification using the trained ANN classifier. Employ the trained ANN to classify the remaining pixels.
Step 4: Post-processing. As the vein image segmented by the trained network may contain some isolated small inlands (connect components of a small number of pixels) which are often noises, a step is carried out to detect and delete such pixels. The program labels eight connected pixel components by scanning the whole vein image and deletes the components that contain less than 6 pixels.

A leaf image (Fig. 10*a*) is processed by our method and the detailed results after each step are illustrated in Fig. 10. Fig. 10*b* shows the edge map obtained by the Sobel operator. Figs. 10*c* and *d* are the pixels with positive and negative second-order derivatives, respectively. Their histograms are shown in Fig. 10*e* with RWH = 0.09, which indicates that the vein pixels are brighter than the background pixels. Let $B = 99\%$ and select pixels that are larger than $T = 79$. The histogram of the whole leaf

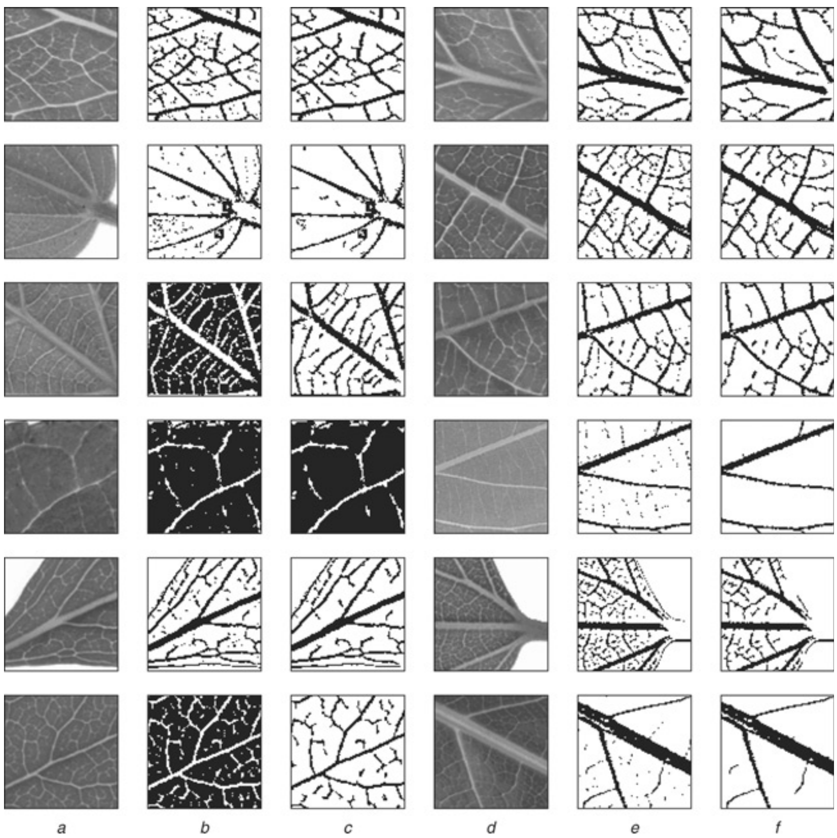

Fig. 9 *Examples*

a, *d* Leaf sub-images
b, *e* Extracted veins by using the trained ANN classifier
c, *f* Results after deleting isolated pixels

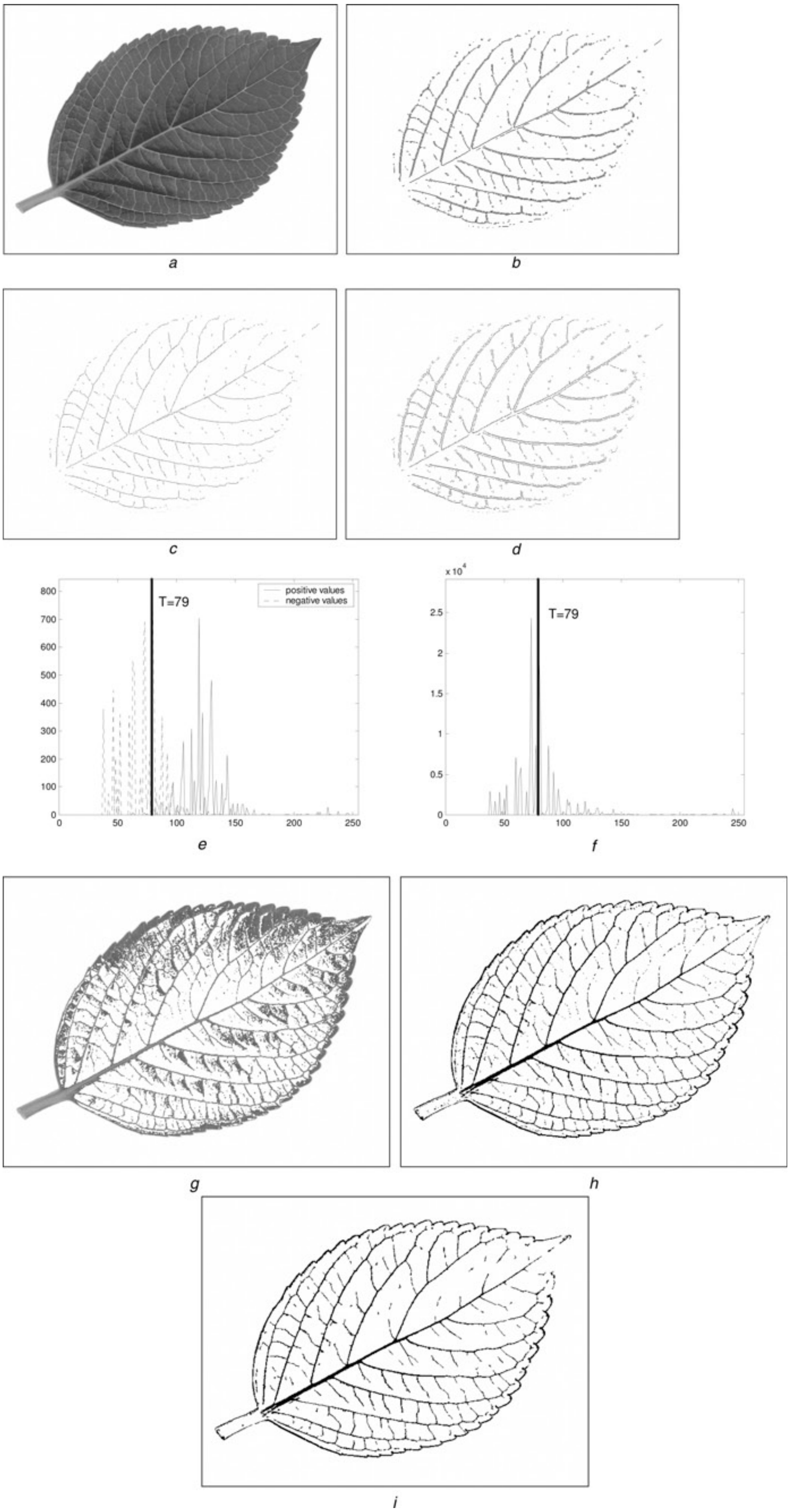

Fig. 10 *Vein extraction of a leaf image*

a 640 × 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 Histograms $h1$ and $h2$, $T = 79$ and RWH = 0.09
f Histogram of the whole leaf image and $T = 79$
g Preliminary segmentation by thresholding at $T = 79$ with 53.15% of computation saving
h Vein extraction result by using the ANN classifier
i Post-process result of (*h*) with $B = 99$

image and the threshold are shown in Fig. 10*f*. The selected pixels (bright pixels) that occupy 46.85% of the whole leaf are shown in Fig. 10*g*, where most are the vein pixels while some of the background pixels are also included. The trained ANN classifier was used to classify the remaining pixels after the preliminary segmentation and the result obtained is shown in Fig. 10*h*. Fig. 10*i* shows the final result after post-processing.

Six other images whose pixels are not used as training samples are also processed by our method and the results are shown in Fig. 11, where Figs. 11*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.

5.1 Testing data set and evaluation criterion

In order to evaluate our algorithm objectively and compare with other methods, 24 sub-images with size of 85×85 were cropped from the six images in Fig. 11 and then 1200 sample pixels (600 for veins and 600 for background) were picked up manually as the testing data set. The classification rate, that is (number of correctly classified pixels)/(number of testing pixels), was used as the criterion of the

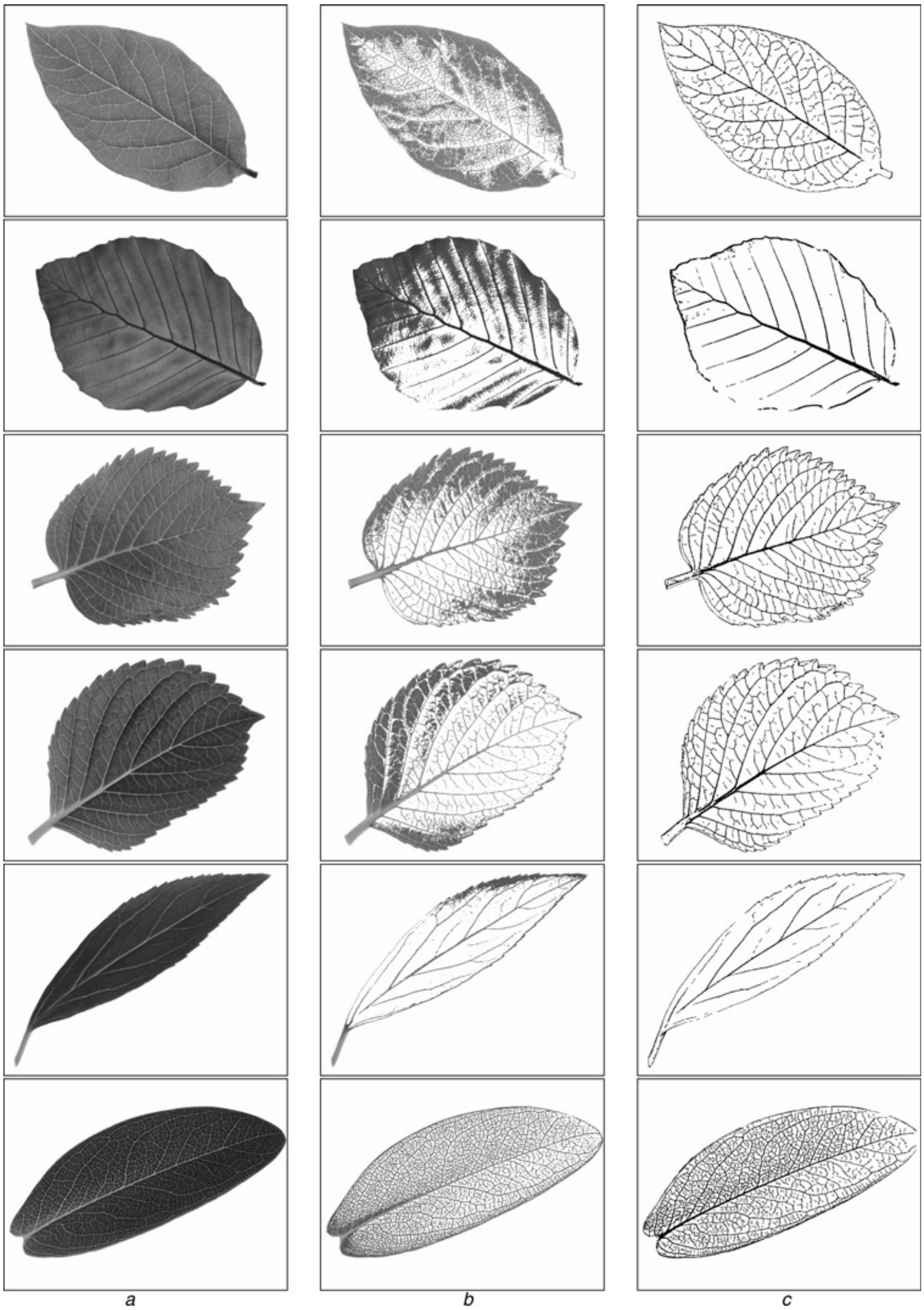

Fig. 11 *Vein extraction results by using our combined method with $B = 99$*

a Original leaf images
b Preliminary segmentation results
c Vein extraction results

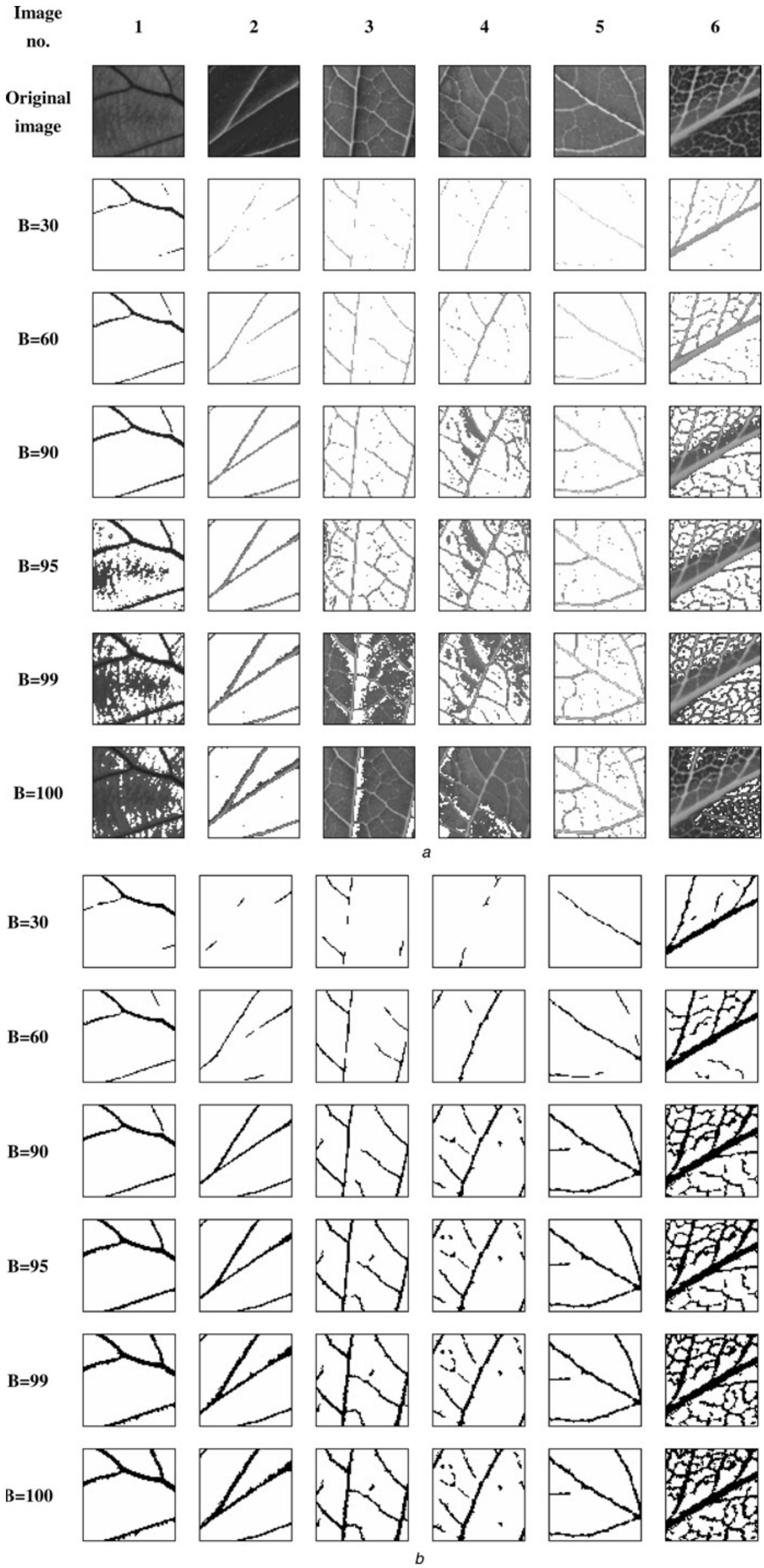

Fig. 12 *Preliminary segmentation*

a Preliminary segmentation results
b Final vein extraction results with different *B* values
A larger *B* leads to more accurate vein extraction but a longer computing time at the subsequent stage of the fine classification with a neural network. In contrast, a smaller *B* helps to save the processing time at the subsequent stage but loses some vein pixels

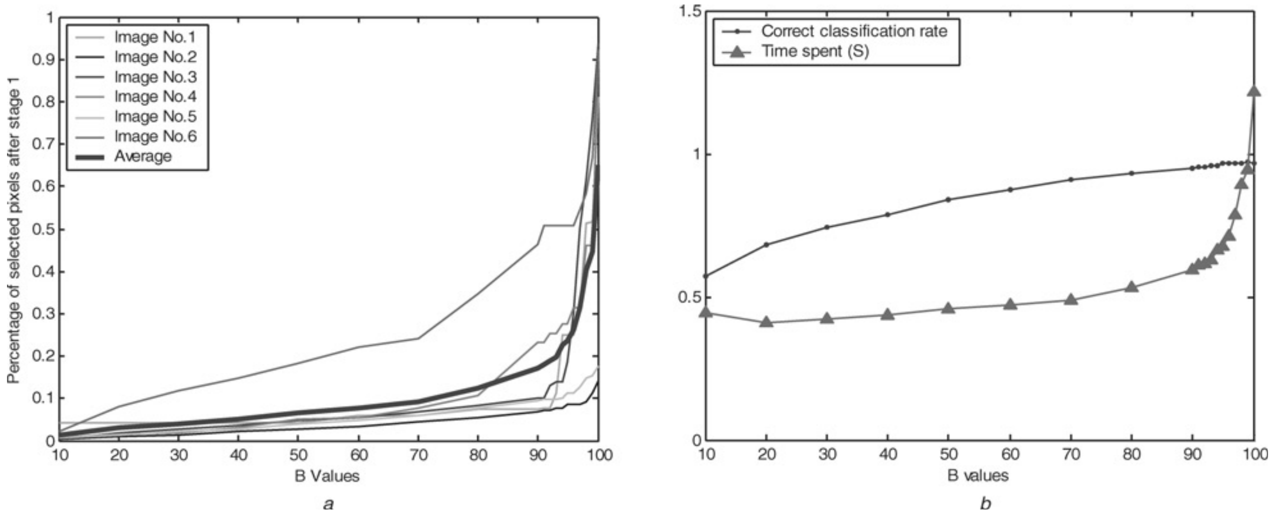

Fig. 13 *Percentages of selected pixels at stage 1*

a Images No. 1 to No. 6 shown in Fig. 12, and their average percentage
b Average correct classification rate and computing time with different *B* values

accuracy. The CPU time (seconds) was used to evaluate the speed. All the algorithms are implemented by MATLAB 6.0 on a Pentium IV 3 GHz PC.

5.2 Discussion on parameter B in the preliminary segmentation

Parameter B is a factor to balance the accuracy and speed. Fig. 12 shows some preliminary segmentation results and vein extraction results with different B values for some sub-images. Fig. 13 shows the percentages of selected pixel by the preliminary segmentation for the images shown in Fig. 12, as well as the accuracy and computing time with different B values. If B is approximated to 100, almost all the vein pixels would be kept while many background pixels may also be included. That is to say, a larger B leads to more accurate vein extraction (without missing any vein pixels) but a longer computing time is required at the subsequent stage of the fine classification with a neural network. In contrast, a smaller B helps to save the processing time at the subsequent stage but loses some vein pixels. The extracted results are becoming better whereas the computing time is becoming longer as B increases. When B is larger than 90, the computing time increases rapidly and the accuracy is approaching one. There is a tradeoff between accuracy and efficiency. We set B to 99 on the basis of an analysis on the performance curves depicted in Fig. 13, which means that 99% of the vein pixels are included and about 50% of the total pixels are processed at stage 2. By using $B = 99$, we can obtain satisfactory vein extraction results and an acceptable computing time as well.

5.3 Comparison with other methods

We compared our proposed method (noted as 'combined') with other methods including

- The top three thresholding methods (denoted as 'Cluster_Kitter', 'Entropy_Kapur' and 'Local_Sauvola') indicated by Sezgin and Sankur [12];
- Sobel operator;
- Direct neural network approach (denoted as 'ANN') with the same parameter used as the combined method.

The classification rate and the computing time for different methods are listed in Tables 2 and 3, respectively. Some vein extraction results using different methods are shown in Fig. 14. The thresholding methods perform well in some cases, but they are not stable. Sometimes they are misclassified veins and the background, for example, a result shown in column 4, row 4 in Fig. 14. The Sobel operator is not a good vein extractor because it loses the pixels between the vein edges. The accuracy of the direct neural network approach is better than those of the thresholding methods and Sobel operators, because of multiple visual

Table 2: Classification rate of different methods

Methods (1200 pixels)	Cluster_Kitter	Entropy_Kapur	Local_Sauvola	Sobel	ANN	Combined ($B = 99$)
No. of correct classified pixels	914	604	867	681	1013	1168
Correct classification rate (%)	76.17	50.33	72.25	56.75	84.42	97.33

Table 3: Computing time of different methods

Methods	Cluster_Kitter	Entropy_Kapur	Local_Sauvola	Sobel	ANN	Combined ($B = 99$)
Time, s	0.03	0.04	1.00	0.01	1.37	0.90

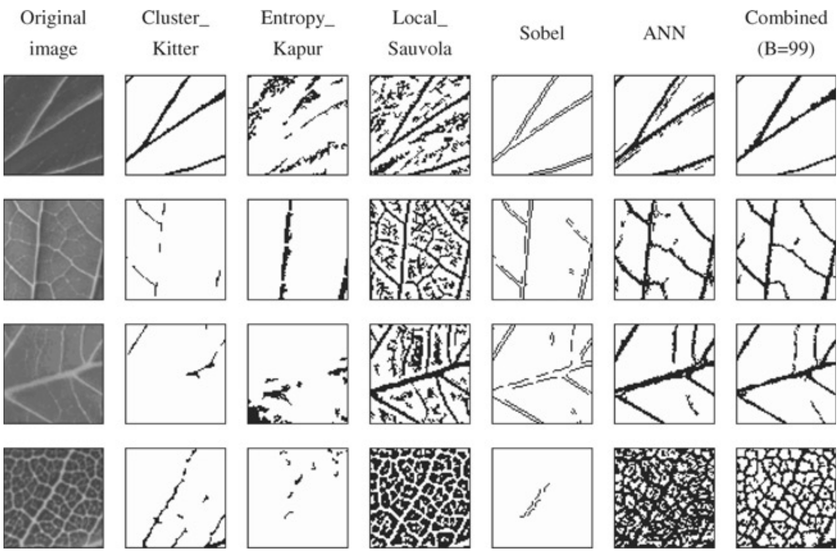

Fig. 14 *Vein extraction results using different methods*

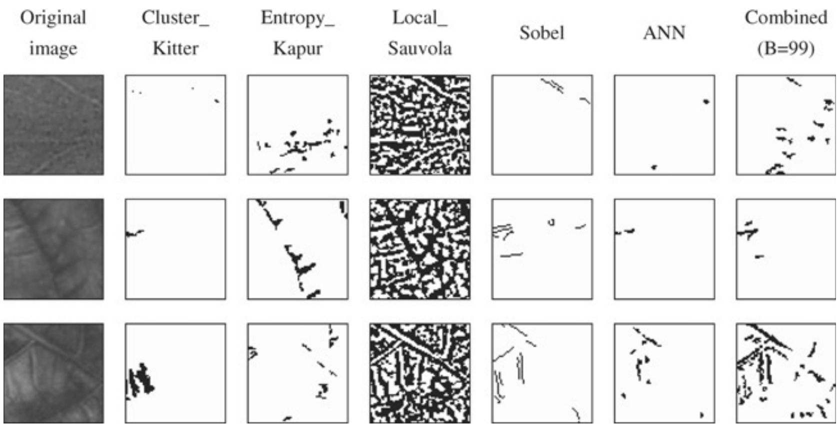

Fig. 15 *Examples of poor vein extraction results*

features used. The advantage of our combined method can be seen when it is compared with the direct neural network approach. In the first stage of the combined method, if the vein pixels are brighter than the background, the image is inverted. After this procedure, the vein pixels are darker than the background for all the leaf images. It can be regarded as a normalisation process to leaf images. By this normalisation, some features which are used as the input features of the neural network classifier, such as the intensity, the mean and sample standard deviation and so on will gather on the darker side of the histogram. Therefore it is easier to train the neural network. As shown in Table 2, the pure neural network approach can achieve an accuracy of 84.42% only, which is less favourable than the result of the combined method, 97.33%. As a whole, our proposed method has the most favourable result compared to others and is faster than the pure neural network approach.

Some poor results were found when quality of leaf photos is poor, as shown in Fig. 15. For these leaf images, all the methods tested failed to detect the veins. Some possible solutions are (1) adjusting the parameters of the image capturing apparatus to make the vein patterns enhanced and (2) investigating other visual featuresfor training a more sophisticated neural network classifier.

6 Conclusions

This paper addresses a combined approach for leaf vein extraction. A preliminary segmentation based on the intensity histogram of the leaf image is first carried out to determine the coarse regions of vein pixels. During the preliminary segmentation, a combined edge and second-order derivative analysis is conducted to determine the relative intensity of vein pixels compared with the background pixels. If vein pixels as a whole are brighter than the background pixels, the intensity of the leaf image is reverted in order to make all the leaf images have vein pixels that are darker than the background and therefore improve the performance of the ANN classifier. The preliminary segmentation step is followed by a fine classification using a trained ANN classifier, wherein ten features distilled from a window centred at the object pixel are used as the inputs. Compared with other methods, experimental results show that the proposed method is capable of extracting more accurate venation modality of the leaf image for the subsequent leaf recognition task. Our combined approach is also compared favourably with the direct neural network approach in terms of computing time required. Our future works will focus on the leaf vein pattern recognition based on the extracted veins.

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