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Image segmentation of overlapping leaves based on Chan–Vese model and Sobel operator

Zhibin Wang [a,b,c], Kaiyi Wang [a,b,c,*], Feng Yang [a,d], Shouhui Pan [a,b,c], Yanyun Han [a,b,c]

[a] Beijing Research Center for Information Technology in Agriculture, Beijing 100097, China
[b] National Engineering Research Center for Information Technology in Agriculture, Beijing 100097, China
[c] Key Laboratory of Agri-informatics, Ministry of Agriculture of China, Beijing 100097, China
[d] School of Economics & Management, China Agricultural University, Beijing 100083, China

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A B S T R A C T

To improve the segmentation precision of overlapping crop leaves, this paper presents an effective image segmentation method based on the Chan–Vese model and Sobel operator. The approach consists of three stages. First, a feature that identifies hues with relatively high levels of green is used to extract the region of leaves and remove the background. Second, the Chan–Vese model and improved Sobel operator are implemented to extract the leaf contours and detect the edges, respectively. Third, a target leaf with a complex background and overlapping is extracted by combining the results obtained by the Chan–Vese model and Sobel operator. To verify the effectiveness of the proposed algorithm, a segmentation experiment was performed on 30 images of cucumber leaf. The mean error rate of the proposed method is 0.0428, which is a decrease of 6.54% compared with the mean error rate of the level set method. Experimental results show that the proposed method can accurately extract the target leaf from cucumber leaf images with complex backgrounds and overlapping regions.

1. Introduction

The segmentation of plant leaves from complicated background is an important step for obtaining biomass characteristics [1]. It is important to accurately and non-destructively segment the target leaf from collected images because the classification of crop species [2], monitoring of crop growth status [3], recognition of crop diseases and insect pests [4] can be accurately implemented using the entire leaf image.

Since the 1980s, numerous effective methods for leaf segmentation have been proposed [5]. Frequently used image segmentation methods include threshold-based methods, edge-based methods, region-based methods, clustered-based methods, and model-based growing methods. Neto et al. [6] developed a new system for individual leaf extraction, based on connected components, fuzzy clustering, and a genetic optimization algorithm. Zheng et al. [7] proposed a mean-shift-based color segmentation method for green leaves. Dornbusch and Andrieu [8] adopted a thresholding algorithm to estimate the lamina boundaries of winter wheat. Niu et al. [9] reported an improved watershed algorithm to segment the cotton leaf area. Peng et al. [10] presented an improved Chan–Vese (C-V) model for detecting the boundary in given leaf images by combining local statistical

* Corresponding author at: Beijing Research Center for Information Technology in Agriculture, Beijing 100097, China.
E-mail address: wangky@nercita.org.cn (K. Wang).
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information with global information. However, segmentation is a very difficult task because of the uncertainties of background and overlapping leaves, i.e., leaves overlap with each other because of how they grow. Most of the proposed methods can achieve good results when segmenting a single crop leaf, but, for overlapping leaves, their results are not satisfactory. Thus, a variety of segmentation techniques need to be combined. Wang et al. [11] proposed an adaptive thresholding algorithm to segment a single leaf from a leaf image randomly extracted from the video stream of an online system using the Otsu and Canny operators. To identify individual leaves automatically, Zhang et al. [12] proposed a segmentation algorithm based on similar tangential direction. Cerutti et al. [13] described a two-step active contour segmentation algorithm based on a polygonal leaf model, processing the image to retrieve the contour of the leaf from a complex natural background. Chopin et al. [14] proposed a novel tool that takes an initial segmented image and returns a more accurate segmentation by utilizing basic a *priori* information about the shape of the plant leaves and local image orientations. A comparative study of various segmentation methods applied to the extraction of tree leaves from natural images is presented in the work of Manuel et al. [15].

To improve the segmentation precision of overlapping crop leaves, we proposed a new image segmentation method based on the C–V model and Sobel operator. First, we use a threshold with respect to the relative levels of green in the image to remove those pixels that are not considered part of the leaf regions, i.e., soil, stems, and membranes. Second, the extracted region is processed by the C–V model and improved Sobel operator, respectively. The contour of the uncovered complete leaf in the upper layer is determined using the C–V model. Because of the overlapping, the segmentation result will not be satisfactory because a partially occluded leaf in the underlying layer will produce false contours. Hence, the exact leaf edge is detected by a 5×5 gradient operator with eight directions, which significantly reduces the amount of data to be processed and helps to identify the contours of the target leaf. Finally, the overlapping target leaf is extracted by combining the results obtained by the C–V model and Sobel operator. To verify the effectiveness of the proposed algorithm, a segmentation experiment was performed on 30 images of cucumber leaf.

The rest of this paper is organized as follows. Section 2 describes the materials and mechanism of the proposed method. Section 3 presents the experimental results. A discussion and future work is given in Section 4. Finally, the conclusion is provided in Section 5.

2. Materials and methods

2.1. *Materials and image acquisition*

The images of cucumber leaf used in this study were obtained in one of two ways. Some images were captured in the open field environment of the Xiaotangshan National Precision Agriculture Research Demonstration Base, Beijing, China. Digital cameras, for example, a SONY DSC-W35 with a wide-angle lens, were used to obtain the images. When collecting images, the camera was set to automatically adjust the focal length, aperture, and white balance, and the flash was turned off. The lighting conditions when taking the image were sunny, and direct sunlight, wind, and rain were avoided. Other images were collected from the Internet, for example, from http://www.agronet.com.cn/ [16]. All image resolutions were at least 2000×2000 pixels and the surface of the leaf had to be neat and clear.

Thirty images were used to test the effectiveness of our proposed algorithm. Of these, 10 images were collected from the Internet. Typical crop leaf images are shown in Fig. 1.

In this work, we collected image samples from different sources, different regions, and different seasons to represent a wide range of scenarios and provide more of a challenge for testing the performance of the proposed method. Moreover, with the development of the Internet, images of different kinds of crop leaf are easier to obtain, which is better for testing the performance of the algorithm.

2.2. *Segmentation algorithm*

We propose an effective image segmentation method for overlapping crop leaf that combines the C-V model and Sobel operator. The method includes four main modules, namely background removal, Sobel edge detection, C-V contour extraction, and segmentation result fusion. The background removal module is used to remove those pixels that are not considered part of the leaf regions. The contour of the target leaf is extracted using the C-V model. In the third module, eight directional Sobel operators are implemented to detect the edges of the leaf. Finally, in the results fusion module, the results obtained by the C–V model and Sobel operator are combined and the target leaf is extracted. A flowchart of the complete process is shown in Fig. 2.

2.2.1. *Background removal*

In a complex field environment, there are many factors that seriously affect the segmentation accuracy of target leaf, e.g., sand, soil, stems, membranes, petals, and water pipes. Although the background can vary in different environments, the pixels of crop images can usually be classified as background (non-leaf areas) and foreground (leaves) because their color is fundamentally different [17]. The regions of background are generally non-green (e.g., yellow), while leaf regions are usually green. Therefore, by adopting a color feature, the background can be removed accurately. Hence, we used the levels of the green channel in the RGB color space to remove those pixels that are not considered to be a part of the leaf regions.

In the RGB color space, the range of pixels for green objects is located in the green corner of the RGB color cube. According to the principle of color gradient, the relationship of pixel color channels for a green crop leaf is shown as

$$(G_{value} > B_{value}) \cap (G_{value} > R_{value}) \quad (1)$$

To enhance the effect of segmentation, Eq. (1) can be rearranged as

$$(G_{value} - B_{value} > \theta_1) \cap (G_{value} - R_{value} > \theta_2) \quad (2)$$

where θ_1 and θ_2 are the R_{value} and B_{value} control parameters, respectively. These values can be set according to the “green

Fig. 1 – Samples of cucumber leaf images.

quantity" theory [18]. For example, when the cucumber leaves were segmented, the values $\theta_1 = 10$ and $\theta_2 = 15$ were adopted.

2.2.2. *Chan-Vese model*

The C-V model, proposed by Chan and Vese, is one of the most popular region-based models for image segmentation [19,20]. It combines the reduced Mumford-Shah model and level set method to solve an energy minimization problem. The C-V model is widely applied to images that need to be segmented into two regions: target and background.

For a given image $I(x, y)$ on image domain Ω, the object of the C-V algorithm is to minimize the following energy function:

$$E(c_1, c_2, C) = u \cdot Length(C) + \lambda_1 \int_{\Omega_1} |I(x, y) - c_1|^2 dxdy + \lambda_2 \times \int_{\Omega_2} |I(x, y) - c_2|^2 dxdy + \upsilon \cdot Area(inside(C)) \quad (3)$$

where C represents the curve, constants c_1 and c_2 denote the average intensities inside and outside the curve, respectively, and coefficients υ, λ_1, and λ_2 are fixed parameters. The length of C and the area inside C are used to control the smoothness of the boundary.

Using the level set to represent C, that is, C is the zero-level set of a Lipschitz function $\phi(x, y)$, we can rewrite the energy function $E(c_1, c_2, C)$ as

$$\begin{aligned} E(c_1, c_2, \phi) = {} & \lambda_1 \int_{\Omega} |I(x, y) - c_1|^2 H(\phi(x, y)) dxdy + \lambda_2 \int_{\Omega} |I(x, y) \\ & - c_2|^2 (1 - H(\phi(x, y))) dxdy \\ & + \mu \int_{\Omega} \delta(\phi(x, y)) |\nabla \phi(x, y)| dxdy + \upsilon \\ & \times \int_{\Omega} H(\phi(x, y)) dxdy, \end{aligned} \quad (4)$$

where $H(\phi)$ and $\delta(\phi)$ are the Heaviside and Dirac functions, respectively. Generally, the regularized versions are selected as

$$H(\phi) = \frac{1}{2}\left[1 + \frac{2}{\pi} arctan\left(\frac{\phi}{\varepsilon}\right)\right], \ \delta(\phi) = \frac{1}{\pi} \cdot \frac{\varepsilon}{\varepsilon^2 + \phi^2} \quad (5)$$

Keeping c_1 and c_2 fixed, we minimize $E(c_1, c_2, C)$ with respect to $\phi(x, y)$, and deduce the Euler-Lagrange equation for $\phi(x, y)$. Parameterizing the descent direction by an arbitrary time t, we can obtain the corresponding variation level set formulation as follows:

$$\begin{cases} \frac{\partial \phi}{\partial t} = \delta(\phi)\left\{\mu \cdot \mathrm{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right) - \upsilon - \lambda_1 [I(x, y) - c_1]^2 + \lambda_2 [I(x, y) - c_2]^2\right\} \\ c_1 = \frac{\int_{\Omega} I(x,y) H(\phi) dxdy}{\int_{\Omega} H(\phi) dxdy} \\ c_2 = \frac{\int_{\Omega} I(x,y)[1 - H(\phi)] dxdy}{\int_{\Omega} [1 - H(\phi)] dxdy} \\ \phi(x, y, 0) = \phi_0(x, y) \end{cases} \quad (6)$$

In Eq. (6), the C-V method utilizes the local gradient information to control the curve deformation movement and the evolution of the contour curve.

When the C-V model is used to extract the target leaf from an image, two problems need to be solved. The first one is initialization, and the other one is when to stop evolving the curves. By analysis of the collected leaf images, we found that the target leaf is usually located in the middle of the image and has a relatively complete leaf edge. Therefore, when initializing the C-V model, we select the center of the image as the initial point and when the curvature of the evolving curve is stable for a certain period of time, the curve stops evolving.

2.2.3. *Sobel edge detection*

The leaves overlap with each other in an image so that the edges between different leaves are often unclear. In this paper, an improved Sobel operator is used to accurately detect the edge of a leaf. This operator significantly reduces the amount of data to be processed and helps to identify the contours of the target leaf.

The Sobel operator is a discrete differentiation operator. It computes an approximation of the gradient of an image intensity function. Typically, the operator uses two 3×3 kernels that are convolved with the original image to calculate the approximations of the derivatives—one for horizontal changes and one for vertical changes. For leaf image $I(x, y)$, the gradient function is defined as

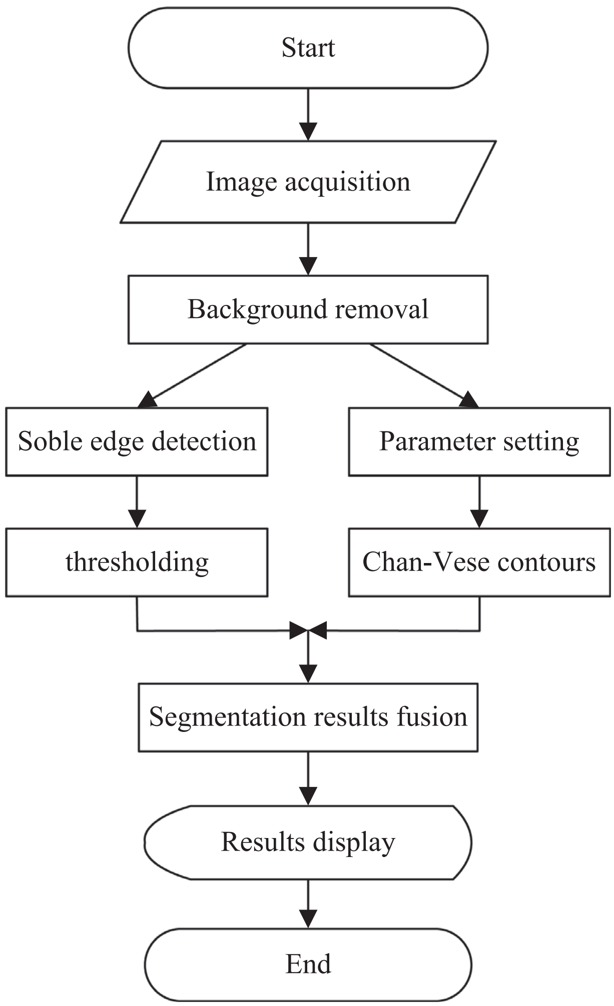

Fig. 2 – Flow chart of the proposed method.

$$gr(x,y) = \left[\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right]^T = [G_x, G_y] \tag{7}$$

where the gradient magnitude and direction can be written, respectively, as

$$|gr(x,y)| = \sqrt{G_x^2 + G_y^2} \tag{8}$$

$$\Theta = arctan\left(\frac{G_x}{G_y}\right) \tag{9}$$

Because of the direction and size limits of the Sobel operator template, the edge detection result derived by traditional algorithms show a high number of false points and discontinuities. To accurately detect the gradient in other directions, reduce the influence of noise on the detection results, and improve the robustness of the operators, 5×5 gradient operators with eight directions, 0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135° and 157.5° were used [21]. The weight matrix can be calculated using the Pascal triangle theory. The weight matrixes are shown in Fig. 3.

Using the templates in Fig. 3, eight directional gradients of a crop leaf can be calculated, respectively. Then, the accurate edge of the leaves can be detected using Eq. (7).

2.2.4. Segmentation results fusion

When the leaf image has been processed by the C–V model and improved Sobel operators, two binary images are obtained. The C-V segmentation results only consist of the general outline area of the target leaf, but there are some false contours produced by other leaves. The Sobel edge detection result contains the exact edge of the target leaf, but it is difficult to distinguish leaf edges and non-leaf edges, e.g., the edges of veins. Hence, we proposed a fusion method to achieve the accurate segmentation of the target leaf by combining the above two segmentation results. The steps of the fusion algorithm are as follows:

(1) For the result of C-V model, the minimum distance from the initial segmentation point to the edge of the contour is calculated. The formula is as follow:

$$\begin{cases} r = \min\left(\sqrt{(b_i(x) - x_0)^2 + (b_i(y) - y_0)^2}\right) \\ 1 \leqslant i \leqslant M \end{cases} \tag{10}$$

where, $b_i(x)$ and $b_i(y)$ are the X and Y coordinate values at point i on the edge of the contour of the C-V model, respectively, M is the total number of boundary points, and (x_0, y_0) is the initial segmentation point.

(2) For the Sobel operator detection results, discontinuous edges are eliminated. Then, the image is enhanced using a four-connected neighborhood. Finally, all pixels within a circle centered at (x_0, y_0) with radius r are set to 0.
(3) The pixels in the C-V segmentation result image are set to 0 if they correspond to the pixels in the Sobel detection result image (after step 2) that are 1. Next, we remove all connected components that have fewer than 100 pixels.
(4) The largest contour area in the remaining image is extracted, and regions that are closer to the boundary of the contour than some threshold are added to this area. The final result is the target leaf.

2.3. Measuring the accuracy of the algorithm

To test the accuracy of the proposed algorithm, manually segmented images were compared with automatically segmented images in which pixels classified as target leaf area were labeled 1 and non-target leaf area pixels were labeled 0. The receiver operating characteristic was utilized to evaluate performance of the proposed method [22]. We define "true positives" to be the correctly classified pixels of an actual target leaf image. If the pixels of a non-target leaf area are classified as 1, this is a "false positive." On the contrary, if a non-target leaf pixel is detected in a non-target leaf area, the result is called a "true negative," whereas a "false negative" indicates that a pixel of the target leaf was misclassified as belonging to the non-target area. The False Negative Rate (FNR), False Positive Rate (FPR), and Error Rate (ER) were calculated as

$$FNR = \frac{False\ Negative}{True\ Positive + False\ Negative} \tag{11}$$

$$FPR = \frac{False\ Positive}{False\ Positive + True\ Negative} \tag{12}$$

$$ER = \frac{False\ Positive + False\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \tag{13}$$

3. Results and analysis

All the experiments were conducted in the MATLAB 2011 programming environment on a computer with an Intel® Core™ i5-3210 (2.5 GHz) processor, 10 GB of memory (RAM), and Windows 7 operating system. In order to improve the efficiency of the algorithm, the bilinear interpolation method was used to adjust the leaf image to 10% of the original image. We used the center of the image as the initial segmentation point (x_0, y_0), and the initial split radius was one fifth of the maximum dimension of the image. The default parameter values were set as follows: length penalty $\mu = 0.001 \times 255^2$, area penalty $\upsilon = 1$, fit weights $\lambda_1 = \lambda_2 = 1$, time step $\Delta t = 0.1$, and Heaviside regularization $\varepsilon = 1$.

3.1. Segmentation results

Thirty images of cucumber leaf were used for segmentation. The mean error rate and standard deviation of the proposed method were 0.0428 ± 0.0230. Representative image segmentation results are shown in Fig. 4.

Fig. 4(b) shows that the effect of the background removal is obvious. The pixels that were not considered part of the leaves regions, such as water pipes, soil and buckets were removed. However, in the extracted regions, the leaves overlap with each other and the colors of different leaves are very similar. Hence, the C-V model and eight directional Sobel operators were used to process the image. The results are shown in Fig. 4(c) and (d), respectively. The results in Fig. 4 (c) show the target leaf extracted by the C-V algorithm. Due to the overlapping leaves, the segmentation result is not satisfactory since the occluded leaf in the underlying layer will produce a false contour. In Fig. 4(d), the edge of the target leaf detected by the improved Sobel operator is very clear and continuous, which can help to identify the contours of the target leaf. Therefore, by using the proposed fusion method, we can realize the accurate segmentation of the target leaf as shown in Fig. 4(e) and (f), respectively. In the process of image fusion, the image coordinates of the initial segmentation point were (156, 208), the value of radius r was 370 (computed using Eq. (10)), and we added regions that had an area greater than 210 pixels to the largest region.

Fig. 5 compares of the edge detection results of improved Sobel operators with those of the traditional approach.

Comparing Fig. 5(a) and (b), we can see that the edge detection results of the improved Sobel operator are better than those of the traditional method. The edges are clearer and continuous and the proposed method can detect gradient information in multiple directions, especially in the overlapping regions of the leaf.

In addition, as image acquisition technology develops, image resolution continues to increase. The original resolution of the text images was higher than 2000 × 2000 pixels. We reduced the image to 10% of the original image, not only to improve the efficiency of the algorithm, but also to extend the proposed framework to various agricultural applications, especially to those that use very limited devices for computation, for example, mobile smart devices.

3.2. Comparison and analysis of segmentation methods

At present, the level set method is a typical image segmentation algorithm based on partial differential equations and has become the focus of research in China and around the world [23,24]. In conventional level set formulations, the level set function typically develops irregularities during its evolution, which may cause numerical errors and eventually destabilize the evolution. Therefore, numerical approaches have been

$$\begin{pmatrix} 1 & 4 & 6 & 4 & 1 \\ 2 & 8 & 12 & 8 & 2 \\ 0 & 0 & 0 & 0 & 0 \\ -2 & -8 & -12 & -8 & -2 \\ -1 & -4 & -6 & -4 & -1 \end{pmatrix}$$

a. Operator of 0° direction

$$\begin{pmatrix} 4 & 6 & 4 & 1 & 2 \\ 1 & 12 & 12 & 8 & 0 \\ 2 & 8 & 0 & -8 & -2 \\ 0 & -8 & -12 & -12 & -1 \\ -2 & -1 & -4 & -6 & -4 \end{pmatrix}$$

b. Operator of 22.5° direction

$$\begin{pmatrix} 6 & 4 & 1 & 2 & 0 \\ 4 & 12 & 8 & 0 & -2 \\ 1 & 8 & 0 & -8 & -1 \\ 2 & 0 & -8 & -12 & -4 \\ 0 & -2 & -1 & -4 & -6 \end{pmatrix}$$

c. Operator of 45° direction

$$\begin{pmatrix} 4 & 1 & 2 & 0 & -2 \\ 6 & 12 & 8 & -8 & -1 \\ 4 & 12 & 0 & -12 & -4 \\ 1 & 8 & -8 & -12 & -6 \\ 2 & 0 & -2 & -1 & -4 \end{pmatrix}$$

d. Operator of 67.5° direction

$$\begin{pmatrix} 1 & 2 & 0 & -2 & -1 \\ 4 & 8 & 0 & -8 & -4 \\ 6 & 12 & 0 & -12 & -6 \\ 4 & 8 & 0 & -8 & -4 \\ 1 & 2 & 0 & -2 & -1 \end{pmatrix}$$

e. Operator of 90° direction

$$\begin{pmatrix} 2 & 0 & -2 & -1 & -4 \\ 1 & 8 & -8 & -12 & -6 \\ 4 & 12 & 0 & -12 & -4 \\ 6 & 12 & 8 & -8 & -1 \\ 4 & 1 & 2 & 0 & -2 \end{pmatrix}$$

f. Operator of 112.5° direction

$$\begin{pmatrix} 0 & -2 & -1 & -4 & -6 \\ 2 & 0 & -8 & -12 & -4 \\ 1 & 8 & 0 & -8 & -1 \\ 4 & 12 & 8 & 0 & -2 \\ 6 & 4 & 1 & 2 & 0 \end{pmatrix}$$

g. Operator of 135° direction

$$\begin{pmatrix} -2 & -1 & -4 & -6 & -4 \\ 0 & -8 & -12 & -12 & -1 \\ 2 & 8 & 0 & -8 & -2 \\ 1 & 12 & 12 & 8 & 0 \\ 4 & 6 & 4 & 1 & 2 \end{pmatrix}$$

h. Operator of 157.5° direction

Fig. 3 – Templates of the eight directional Sobel operators.

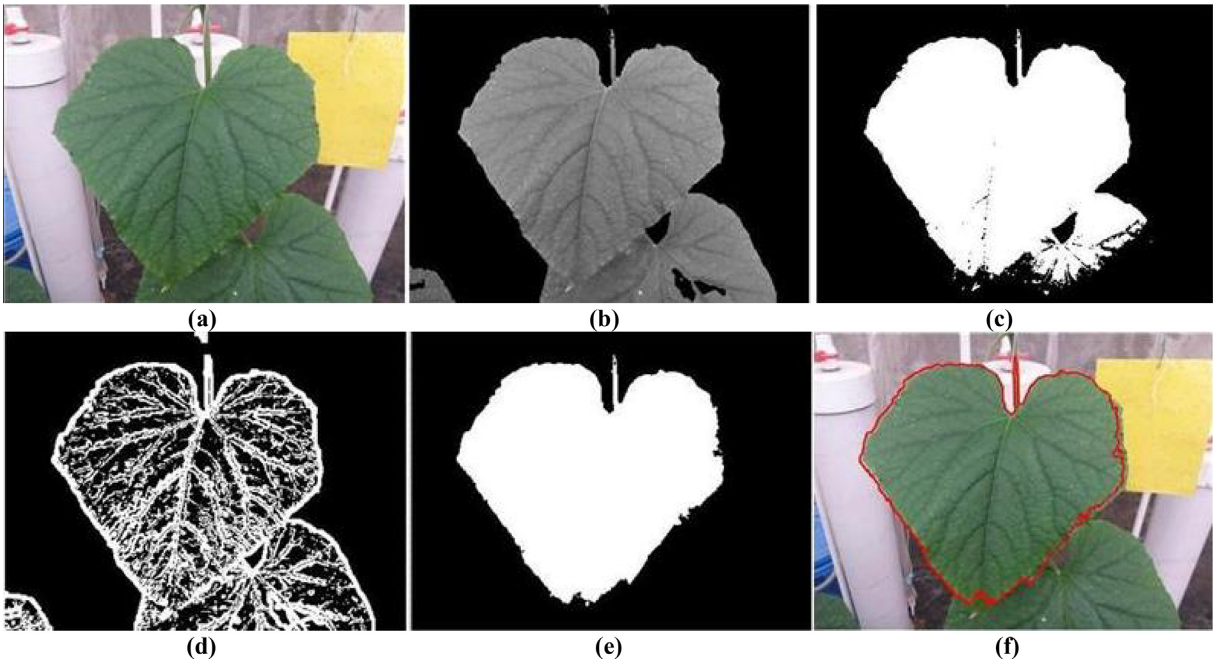

Fig. 4 – Segmentation results of leaves: (a) original image; (b) result of background removal; (c) segmentation result of the C-V model; (d) result of edge detection; (e) segmentation results fusion; and (f) segmentation result labeling.

adopted to overcome these problems. In particular, a level set method that requires no re-initialization and was proposed by Li et al. [25,26], has good performance when dealing with image segmentation problems. In this method, a more general variational level set formulation with a distance regularization term and an external energy term that drives the motion of the zero level contours toward the desired locations is used to ensure sufficient numerical accuracy. Moreover, it can be implemented with a simpler and more efficient numerical scheme for both full domain and narrowband implementations than conventional level set formulations.

To test the accuracy of the proposed method, we compared the proposed method with the level set method supposed by Li et al. [25,26]. In this experiment, the background of the cucumber leaf images was first removed, and then the proposed method and the level set method were applied to the results. Three comparison groups of segmentation results and error rate statistics are shown in Fig. 6 and Table 1, respectively.

The images used in Fig. 6(a) and (b) are very smooth, and there are overlaps between the different leaves. However, the image in Fig. 6(c) is not smooth, and there is overlap between the leaf and stalks. The above images are examples of overlapping under different conditions, and the experiments with these images were more conducive for testing the performance of the segmentation method. Fig. 6 shows that our proposed method achieves good segmentation results and can extract the target leaf accurately, but the level set algorithm finds it difficult to segment the overlapping regions of the leaf.

In Table 1, the image resolution constitutes 10% of the original image. The three comparison groups for the segmentation result statistics correspond to the segmentation results that are shown in Fig. 6(a), (b) and (c), respectively. The segmentation performance of the algorithm was analyzed from three aspects, namely FNR, FPR, and ER.

The results in Table 1 show that the proposed method had a lower ER than the level set method for all three groups in the

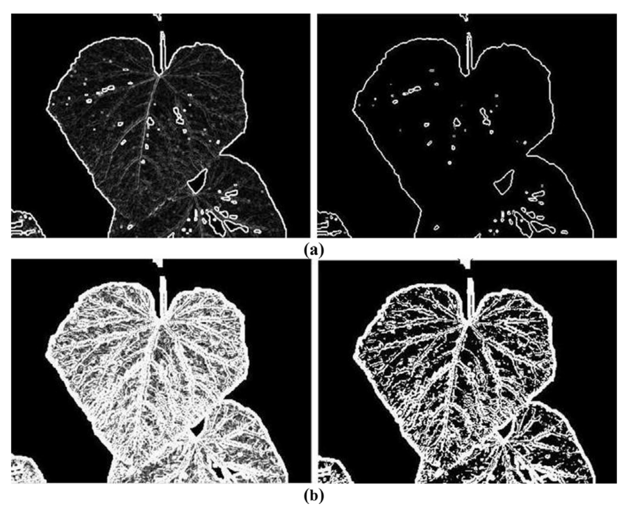

Fig. 5 – Comparison of edge detection results of eight directional Sobel operators with those of the traditional approach. (a) Detection results of the traditional Sobel operator, and (b) detection results of the eight directional Sobel operators. Left images are the results of edge detection. Right images are the results of the leaf images thresholded at 249.

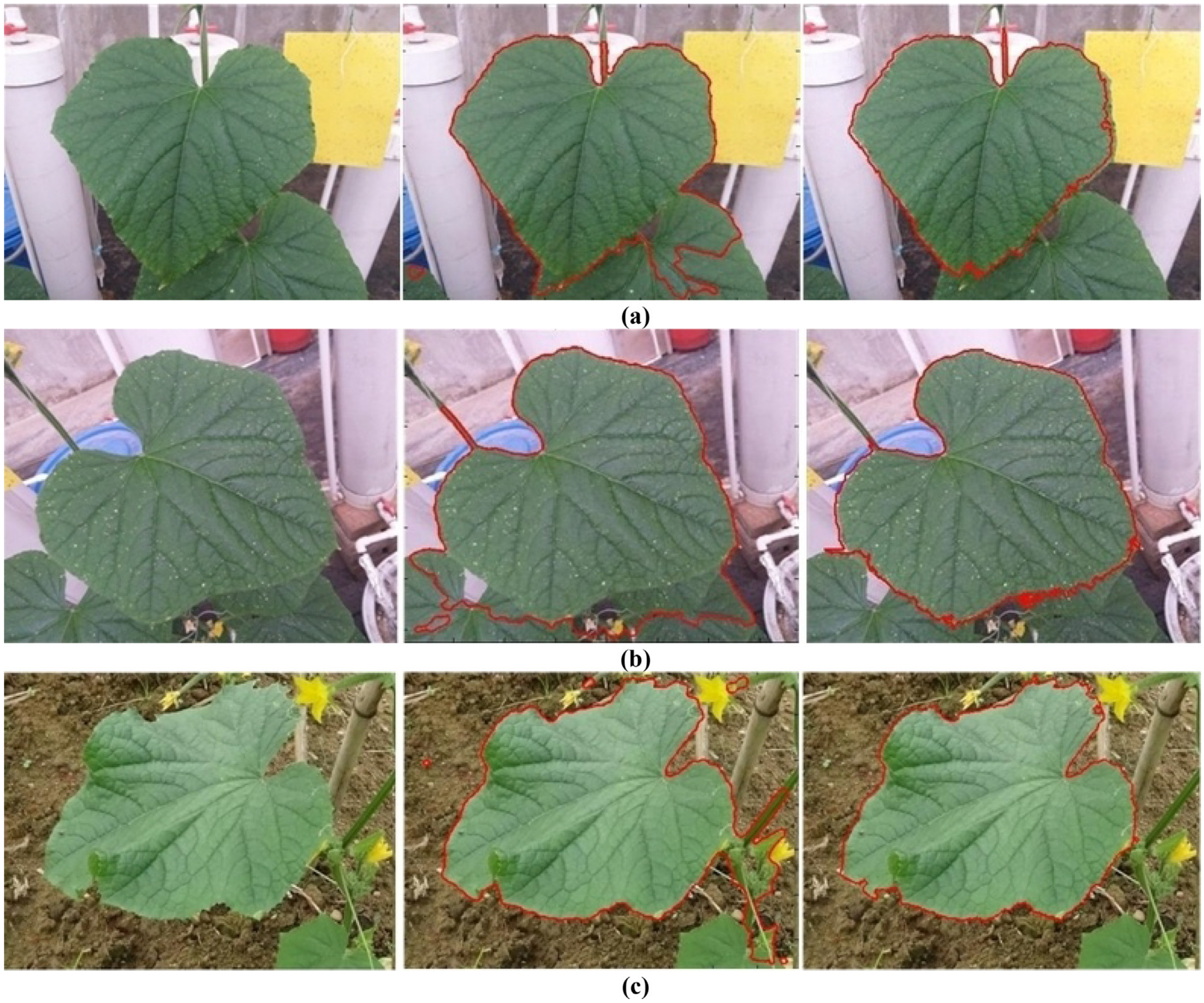

Fig. 6 – Three comparison groups of segmentation results for proposed and level set methods, which are shown in (a), (b), and (c), respectively. Original images of the leaves are on the left. Middle images are the segmentation results of the level set algorithm. Right images are the segmentation results of the proposed algorithm. Red contours indicate segmentation results.

experiments. The mean error rate was 1.61%. The misclassified pixels consisted of false positives and false negatives. For the false positives, the FPR of the proposed method is lower than that of the level set method, but for the false negatives, the FNR is higher. The main reason is that the proposed method can accurately segment target leaves, especially for overlapping regions. The level set method is able to use the evolution equation to achieve the global optimum segmentation results of the image; however, at the edge of the leaf, where there is little difference in brightness between the leaf area and surrounding area, there is the problem that the curve crosses the boundary. Hence, the level set method usually over-segments the image, as shown in Fig. 6.

More comparison details are shown in Fig. 7 and Table 2. Fig. 7 shows the relationships between the ER, FPR, and FNR of the automatic segmentation methods for each leaf image. Table 2 shows the statistics of the segmentation results. Together, these results demonstrate that the proposed method produces a better segmentation for images of crop leaf.

4. Discussion

The accurate segmentation of individual leaves is a key problem in several precision farming applications, for example, in the identification of weeds within crop fields. In this study, we focus on the main problem in this field of research: the identification of a single leaf from a picture of overlapping leaves, and proposed an effective segmentation method based on the C-V model and Sobel operator. Three steps, background removal, target leaf determination, and overlapping region segmentation, ensure the effectiveness of this algorithm. This method can make full use of the image color, shape, and gradient information. Locally, the C-V model is used to determine the approximate region of the target leaf. Globally, the eight-direction Sobel edge detection operator is used to detect the fine contour of the leaf. Finally, both local and global information are combined to achieve accurate segmentation of the target leaf. Therefore, the proposed algorithm is effective for segmenting overlapping leaves.

Table 1 – Comparison of segmentation error rates of the proposed method with those of the level set method.

Group of comparison experiment	Image resolution	Proportion of pixels of target leaf	Level set method			Proposed method		
			FNR	FPR	ER	FNR	FPR	ER
First group	129,792	0.3623	**0.0128**	0.0847	0.0587	0.0351	**0.0100**	**0.0191**
Second group	121,056	0.4402	**0.0145**	0.1383	0.0838	0.0188	**0.0177**	**0.0148**
Third group	148,518	0.4223	**0.0110**	0.0680	0.0439	0.0187	**0.0113**	**0.0144**

However, there are some improvements that can still be made to the proposed method in future work. First, in the field, there are several environmental factors such as illumination that may influence the characteristics of the images, making it more difficult for an automatic algorithm to perform an accurate segmentation [27]. Our proposed method is not robust against these conditions. To ensure good segmentation results, the images used in this study were collected in a partially controlled environment in which direct sunlight, wind, and rain were avoided when the images were captured. Hence, the robustness of the proposed method should be strengthened. A more realistic approach would be to study the impact of the main factors affecting segmentation and subsequently design methods to deal with them. Second, the pictures taken for the analysis were usually captured directly perpendicular to the leaves such that the target leaf is in the middle of the picture and the initialization point is located in the middle of the image. Although other initialization points can be selected, the segmentation result will not be the best. This is a suitable approach when the proposed method is used on mobile smart devices. However, this is not a configuration that can be generally assumed. In typical applications, several leaves need to be identified in a single photograph. Therefore, the need for a predefined initialization point in the proposed method should be addressed. In addition, there are some heuristic parameters for the results fusion that are mainly set using trial and error. An automatic parameter-setting method also should be studied. Third, the proposed method was only applied to cucumber leaves: the leaves of other crops were not tested. Hence, we plan to further test our proposed method by applying it to different crops. Finally, the inability of the proposed algorithm to effectively deal with leaf veins [28] should be addressed.

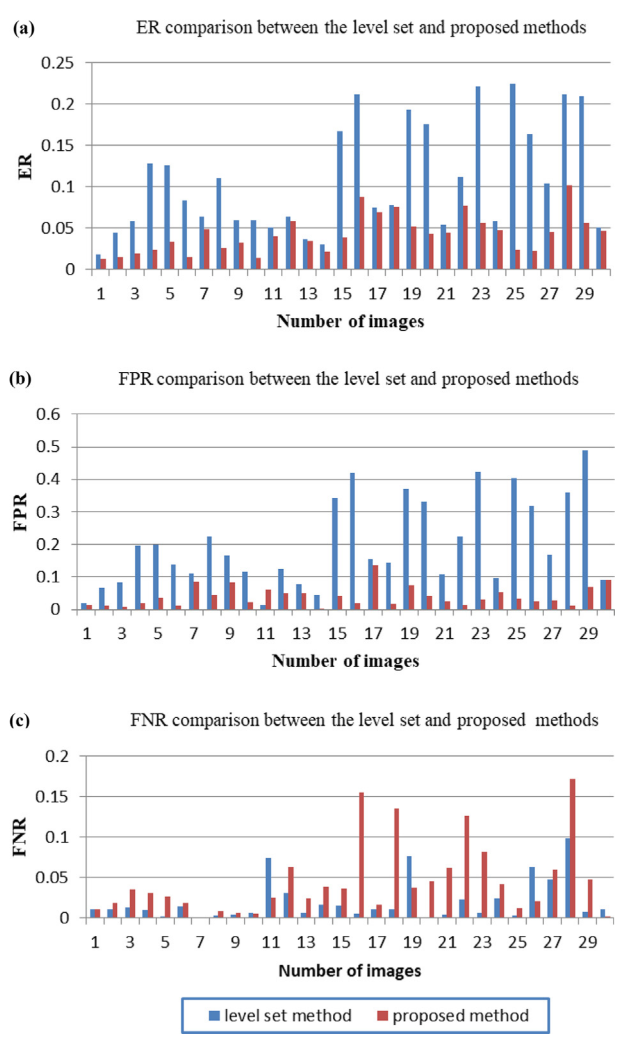

Fig. 7 – Comparison of the ER, FPR, and FNR of the proposed method with those of the level set method.

5. Conclusion

An effective segmentation method for images of overlapping leaf based on the C–V model and Sobel operator was presented in this paper. Four main modules consisting of background removal, Sobel edge detection, C-V contour extraction, and segmentation results fusion were used to enhance the effectiveness of the proposed method. Segmentation experiments were performed on 30 images of cucumber leaf. The experimental results show the following: (1) the method can accurately extract the target leaf from cucumber leaf images with a complex background and overlapping regions. The mean error rate and standard deviation of the proposed method was 0.0428 ± 0.0230. (2) The proposed method has better image segmentation results compared with the level set method. Moreover, the mean of the segmentation error rate decreases by 6.54%. (3) Compared with the traditional Sobel operator, the improved Sobel operator, which is based on template consisting of 5×5 pixels of eight directions, achieves better edge detection performance in different directions. Moreover, the image edge is relatively complete, with clear contours and better continuity, especially in the overlapping regions. Together, these results demonstrate the accuracy and robustness of the proposed method for target leaf segmentation.

In the future, three parts of the proposed method can be improved and strengthened. First, we plan to extend the proposed framework to various agricultural applications; for

Table 2 – Results of image segmentation using different segmentation methods.

Estimation	Image resolution	Proportion of pixels of target leaf	Level set method			Proposed method		
			FNR	FPR	ER	FNR	FPR	ER
Mean ± standard deviation	76,443 ± 30,261	0.5079 ± 0.0853	**0.0204 ± 0.0255**	0.2012 ± 0.1349	0.1082 ± 0.0661	0.0455 ± 0.0458	0.0406 ± 0.0307	**0.0428 ± 0.0230**

example, by developing a segmentation system for crop leaf based on mobile smart devices. Second, we will try to improve the algorithm's performance by designing an approach that is robust against various environmental conditions, developing better techniques for selecting the predefined initialization point, and implementing automatic parameter value selection. Third, we plan to further test our proposed method by applying it to different kinds of crops.

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