Leaf Extraction from Complicated Background

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***Abstract*—Leaf extraction is an important step for automatic feature extraction, leaf classification and plant species identification, etc.. But it is still a challenging problem especially from the images with complicated background such as with some interferents and overlaps between two adjacent leaves. In this paper, we have developed a leaf extraction algorithm to extract the target leaf from the images with complicated background. In this algorithm, the marker-controlled watershed segmentation method is applied on the gradient images of Hue, Intensity and Saturation of the HSI color space, separately. The solidity (integrity) measure is then used to evaluate how well the segmented image is for extraction of the target leaf and determine the final leaf extraction result. Experimental results on some practical soybean leaf images demonstrate the effectiveness of the proposed algorithm.**

Keywords-Leaf; extraction; HSI; watershed; solidity

I. INTRODUCTION

Plant species classification and identification is one of the difficult and important tasks in agriculture due to its variety and different field conditions. The traditional method based on expert's manual labeling is very time consuming. With the development of computer science and information technology, machine vision is a promising technology to solve some tasks in the agriculture such as species identification, plant modeling and herbicide application for weed control [1, 2]. The framework based on this technology uses the vision sensors such as CCD to capture the plant images firstly. The digital image processing and pattern recognition techniques are then applied for feature extraction and image analysis. Finally, the plant can be identified or some other tasks can be finished. The plant leaf is one of the important parts and is also a common source of information used to identify plants. Thus, leaf extraction is an important step for automatic feature extraction, leaf classification and plant species identification, etc.. But it is still a difficult problem to extract the leaves from images with complicated background such as with some interferents and overlaps between two adjacent leaves (see Fig. 1, the leaves are soybean leaves). The purpose of this paper is to develop an algorithm for the automatic extraction of plant leaf from the images with complicated background.

There are several approaches proposed for the automatic leaf extraction from images by using the image processing and machine learning techniques in the literature [1-4]. Franz et al. (1991) proposed an approach to identify completely visible and partially occluded sets of leaves by using the curvature functions and the Fourier-Mellin correlation [1]. In this approach, curvature was used to describe boundries of both completely visible and partially occluded leaves. Completely visible leaves were identified by aligning the curvature function of each leaf with that of each of the models. Functions were aligned to minimize local differences in curvature. A Fourier-Mellin correlation was used to calculate scale factors for resampling curvature functions of partially occluded leaves. Partially occluded leaves were identified by aligning the resampled curvatures with each of the models. However, this technique can not work well to identify the aggregate boundaries of multiple leaves. Franz et al. further developed an algorithm to extract boundaries of occluded leaves by using an edge detection technique to link endpoints of leaf edge segments [3]. But user intervention was required at various steps during the process of this approach. Joao Camargo Neto et al. proposed an approach for automatical extraction of individual leaf from young canopy images using Gustafson-Kessel clustering and a genetic algorithm [2]. In this approach, Gustafson-Kessel clustering technique is applied to divide the images into a number of small regions firstly, and the genetic algorithm was then employed to combine the image regions into an integrated leaf. This approach can work well for the young canopy images in which the contrast between leaves and the background is clear and leaf overlap is small. Deformable templates using active contours were proposed by Manh et al. to locate boundaries of green foxtail leaves [4]. This approach attempted to combine color separation and shape feature analysis into a single operation. But it needed to manually select energy level or color. Xiao-Feng Wang et al. recently proposed approach for segmentation of leaf images using the automatic marker-controlled watershed segmentation method [5]. This approach can work well for segmentation of leaf images with some interferents and leaf overlapping, but it requires the prior shape information.

(a) (b) (c)

Figure 1. Three sample leaf images with complicated background.

Most of existing approaches for leaf extraction requires manual operation or prior information, and the leaf extraction results are not satisfactory for the images with complicated background. However, in addition to the target leaf, the leaf images captured in field often have complicated background

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consisting of some interferents such as branches, soil and non-target leaves, etc.. Moreover, the target leaf usually overlaps other leaves which may create the confusion between the boundaries of adjacent leaves. These challenges bring great difficulties to the automatic leaf segmentation and extraction. In this paper, we propose an algorithm to extract the target leaf from the images with complicated background. In this algorithm, the marker-controlled watershed segmentation method is applied on the gradient images of Hue, Intensity and Saturation of the HSI color model, separately. The integrity (solidity) measure is then used to evaluate how well the segmented image for extraction of the target leaf and determine the final segmentation result.

This paper is organized as follows. In Section 2, we present the proposed leaf extraction algorithm in detail. The experimental results on the practical soybean leaf images are presented in Section 3. Finally, the conclusion is given in Section 4.

II. THE PROPOSED LEAF EXTRACTION ALGORITHM

For the leaf images with complicated background, the traditional methods such as thresholding, edge detector and morphological processing cannot perform well to segment the target leaf from the complicated background due to their limitations. We propose an automatic leaf extraction algorithm by using the marker-controlled watershed segmentation three times and the solidity measure. Instead of using the RGB color image, our algorithm is performed on the HSI color space which consists of Hue, Saturation and Intensity values. The flow chart of our proposed algorithm is shown in Fig. 2.

A. Non-green background elimination

Since the color of leaf image is often blue by visualization, the non-green background of image such as soil and residues can be eliminated by using thresholding method firstly. The G component of RGB color image represents the green intensity and thus usually has higher values in leaf region than in other background region. We compose an excess green index, i.e., ExG=2G-R-B and an excess red index, i.e., ExR=1.4R-G-B based on the RGB color space [6]. The non-green background is then removed by using OSTU thresholding method on ExG-ExR [7]. Morphological image processing approach is further used to deal with details and the small holes. The result of non-green background elimination is shown in Fig. 3.

B. Marker-controlled watershed segmentation

The watershed method [8] is an image segmentation method that divides an image into some regions based on the topology of image. A grey-scale image can be considered as a topographic surface. If the surface is flooded from its minima while avoiding the merging of the waters coming from different sources, the image is partitioned into two different sets: the catchment basins and the watershed lines. If this technique is applied to the gradient images, the image segmentation is produced with the catchment basins and watershed lines corresponding to the homogeneous grey level regions and the region boundaries of image, respectively. However, in practice, the watershed method produces an over-segmentation due to noise or local irregularities in the gradient image. To improve this method, the topographic surface can be flooded from a previously defined set of markers. One mark is a connected unit corresponding to a special watershed region. Using markers can limit the number of allowed segmentation regions. Marker-controlled watershed segmentation thus includes a two-step process: finding the markers and segmentation criterion and performing a marker-controlled watershed. The marker-controlled watershed method is widely used in image segmentation because of its time efficiency and good segmentation performance [5].

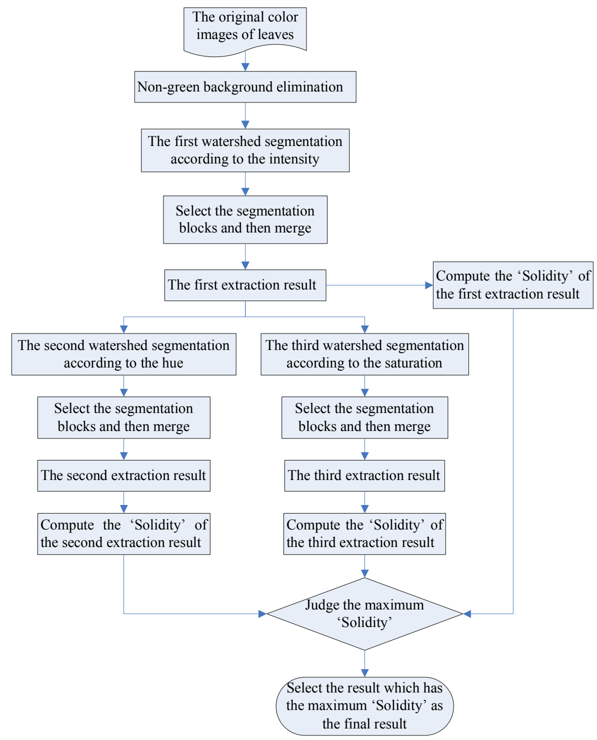
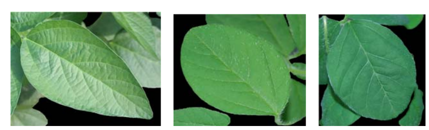


Figure 2. The flow chart of our algorithm.


(a) (b) (c)
Figure 3. The result of non-green background elimination.

The marker-controlled watershed method is applied on the HSI color images instead of the grey-scale image. The original color leaf image is transformed into HSI space which consists of H (Hue), S (Saturation) and I (Intensity) values [8]. The HSI model can decouple the intensity component from the color-carrying information (hue and saturation) in a color image.

The processing steps of our marker-controlled watershed segmentation are as follows:

1) Compute the gradient map of the I (Intensity) image and do histogram equalization shown as Fig. 4 (b).

2) Apply the opening-by-reconstruction operation [9] to the gradient map and the result is denoted as *Iobr*.

3) Apply the closing-by-reconstruction operation [9] to the above produced image and get the result denoted as *Icbr*.

4) Compute the local maxima of *Icbr* as the markers shown as Fig. 4 (c).

5) Adopt the 'minima imposition' technology [10] to eliminate all other minima except the makers. This technology imposes the markers positions as the global minimum.

6) Employ the watershed method to the result image with the generated markers and produce image segmentation shown as Fig. 4 (d).

For the sample leaf images of Fig. 1, Fig. 4 (a), (b), (c) and (d) show the Intensity image, the gradient map, the generated markers and the image segmentation produced by the marker-controlled watershed segmentation, respectively. For better visualization, each segmented region is indicated with a different color value in Fig. 4 (d).

Since the segmented region with the target leaf is often larger than other regions, the largest region is selected for target leaf extraction. Furthermore, the closing and opening morphological operations are used for the selected image region to remove the contour protrusions and leaves stalk. Fig. 5 shows the extracted leaf images from the first image segmentation results.

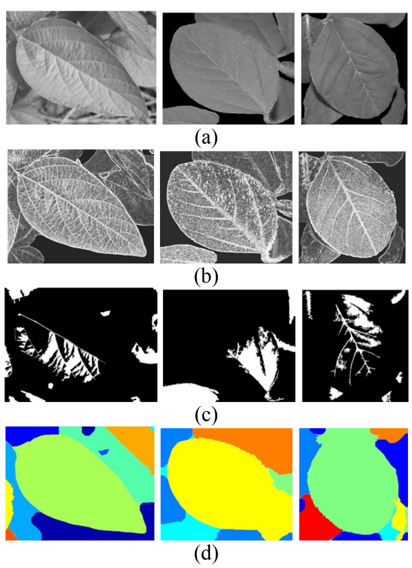


Figure 4. (a) Intensity image, (b) gradient map, (c) generated markers, (d) the image segmentation.

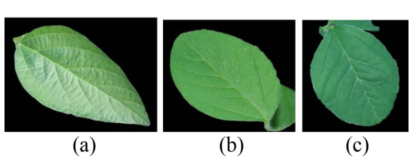


Figure 5. The extracted leaf images from the first segmentation results.

From Fig. 5, we can see that the target leaf extraction for the first image is successful but the results are not satisfactory for the second and third images. Intensity of HSI image describes the intensity of color light and is the character of the quantity of color light. For the leaf images with more complicated background especially with much leaf overlapping on target leaf, the marker-controlled watershed segmentation on intensity image is not enough to extract the target leaf. The hue and saturation of HSI contain the color-carrying information of a color image. The hue of HSI image describes the property of pure color whereas saturation gives a measure of the degree to which a pure color is diluted by white light [8]. To overcome the above problem, we propose to further apply the marker-controlled watershed segmentation to the H (Hue) and S (Saturation) components of HSI color space of the selected image region by the first segmentation. It should be noted that the segmentation on Hue (the second segmentation) and Saturation (the third segmentation) are both based on the first extraction result. These two segmentation processes are same as the first one but different method is used to select the regions for target leaf. On the image, we draw a rectangle centered on the image center with its length and width being a quarter (1/4) of the image length and width. If the pixels of a region are included in the rectangle, this region is selected to merge for target leaf extraction. The results of the second and third marker-controlled watershed segmentations are shown in Fig. 6 and Fig. 7, respectively.

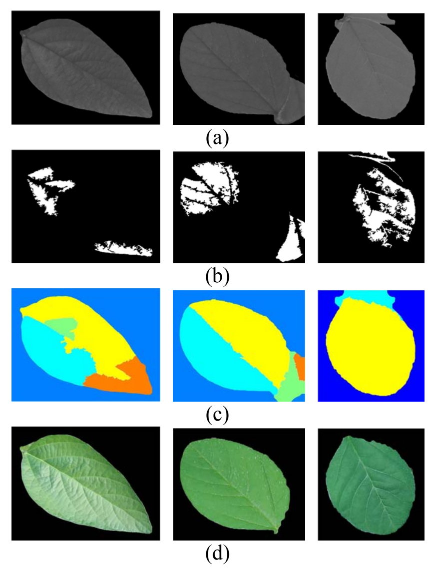


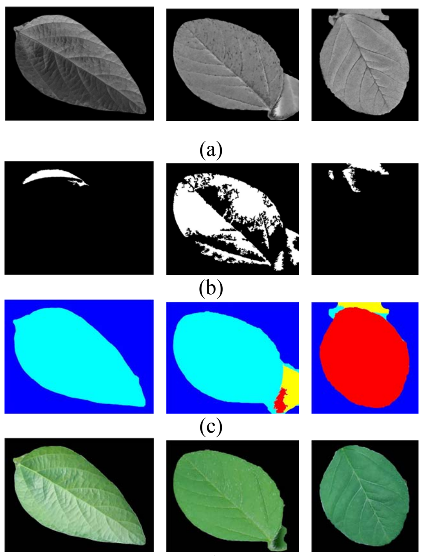
Figure 6. (a) Hue image, (b) Generated markers, (c) the image segmentation, (d) the extracted leaf images from the second segmentation results.

C. *The solidity of extracted leaf image*

From the above results, we can see that the three segmentations have different effects on extraction of target leaf. For image of Fig. 1 (a), the target leaf is better extracted from the first segmentation (see Fig. 5 (a)) than from other two segmentations. For image of Fig. 1 (b), the target leaf extraction from the second watershed segmentation is better than those from other segmentations (see the second image of Fig. 6 (d)). For image of Fig. 1 (c), the target leaf extraction from the third watershed segmentation is better than those from other segmentations (see the third image of Fig. 7 (d)). Therefore we propose to select a best extraction result based on a 'Solidity' measure which also evaluates the integrity of extracted leaf image. The 'Solidity' measure is computed as the proportion of the pixels in a convex hull [2]:

Table I. The solidities of the leaf extraction results by the three segmentations for three sample images

Image	By the first segmentation	By the second segmentation	By the third segmentation	The maximum one
Fig. 1(a)	0.9854	0.9854	0.9854	1
Fig. 1(b)	0.9591	0.9825	0.9597	2
Fig. 1(c)	0.9598	0.984	0.9881	3



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

Figure 7. (a) Saturation image, (b) Generated markers, (c) The image segmentation, (d) The extracted leaf images from the third segmentation results.

$$\text{Solidity} = \frac{\text{Extracted Area} \times 100\%}{\text{Convex Area}} \tag{1}$$

where 'Extracted Area' is the number of pixels in the extracted leaf region. 'Convex Area' is the number of pixels in the convex hull covering the extracted area. The difference between the area of extracted leaf region and the area of the corresponding convex hull isminimized when the extracted region had a close representation of a possible leaf [2]. In other words, the higher "Solidity", the more integrity the extracted leaf has. Since the extracted area is often less than the area of convex hull, the 'Solidity' is a positive value larger than zero, but no more than 100%. The result with maximum 'Solidity' is selected as the final extraction result. Table I shows the solidities of the leaf extraction results by the three segmentations for three sample images. We can see that the best leaf extraction is the extraction with the maximum 'Solidity'.

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. *Test data set*

In order to test the proposed algorithm, we capture 152 soybean leaf images in field using a camera. For evaluation of the leaf extraction results, we manually classify the extraction results into three levels: perfect extraction, good extraction and bad extraction. In perfect extraction, the boundary extracted target leaf is almost same as the ground truth (see Fig. 8. (a)). In good extraction, the extracted target leaf may include a small part (less than 2%) of non-target leaf or background or a small part (less than 2%) of the target leaf is not extracted (see Fig. 8. (b)). In bad extraction, more than 2% of the target leaf are not extracted or the extracted target leaf include more than 2% of non-target leaf or background (see Fig. 8. (c)). Table II shows the leaf extraction results by the proposed algorithm on 152 test images. If we consider the perfect extraction and good extraction as the successful extraction, the success rate is 84.87%.

(a) (b) (c)

Figure 8. (a) Perfect extraction, (b) good extraction and (c) bad extraction.

Table II. The leaf extraction results by the proposed algorithm

Leaf extraction	Perfect extraction	Basic extraction	Failed extraction
Number	95	34	23
Percentage	62.50%	22.37%	15.13%
Success rate	84.87%		

Table III. Results comparison for different methods

Extraction Method	Successful number	Success rate	Failed number	Failure rate
Based on watershed segmentation on Intensity	28	18.42%	124	81.58%
Based on two watershed segmentations on Intensity & Hue	46	30.26%	106	69.74%
Based on two watershed segmentations on Intensity & Saturation	111	73.03%	41	26.97%
Proposed algorithm	129	84.87%	23	15.13%

In addition, we also compare the proposed algorithm for leaf extraction based on three watershed segmentations on HSI color space to other approaches. One approach for the leaf extraction is based on watershed segmentation on intensity, and the other two approaches are based on two watershed segmentations on intensity and hue/saturation. The watershed segmentation is same for these approaches. Table III shows the results comparison. From the results, we can see the proposed algorithm performs better than others. To show which segmentation the final successful extraction is based on, we compute the number of successful leaf extractions from each watershed segmentation among the 129 successful leaf extractions shown as Table IV.

Table IV. The number of successful extraction from each watershed among the 129 successful leaf extractions

Sequence when success	Number	Percentage
The first	28	21.71%
The second	18	13.95%
The third	83	64.34%
Total successful number	129	

We further analyze the solidities of the extracted target leaf on the test images. The mean of the solidities is 0.97506 for the successful leaf extraction while the mean of the solidities is 0.94748 for the failed leaf extraction. Fig. 9 shows the probability distribution map of solidities obtained in the successful extractions. We can see that most of solidities are in the range of [0.955 0.995] for the successful extraction.

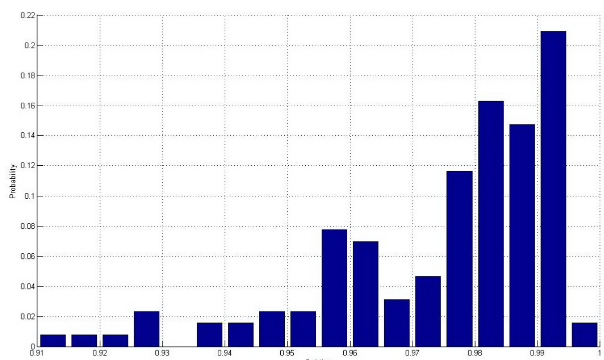


Figure 9. The probability distribution map of the solidities obtained in the successful extractions.

B. Discussion

The main reason of failed leaf extraction is that the edge of some overlapping leaves is not clear. The hue, saturation and intensity of each leaf are very close to other non-target leaves. It is difficult to distinguish these leaves even manually. Therefore, it is difficult for watershed algorithm to set up a dam at the edge, which results in failed leaf extraction.

IV. CONCLUSION

This paper has proposed a new algorithm which can automatically extract the target leaf from the color images with complicated background. We apply the marker-controlled watershed segmentation to the Hue, Intensity and Saturation of HSI color images separately which contain both the intensity and color information. The target leaf is then extracted from each image segmentation. Finally, the solidity measure is used to select the best leaf extraction. Experimental results and comparison on 152 practical soybean leaf images demonstrate the effectiveness of the proposed algorithm for target leaf extraction from the images with complicated background such as with soil and residue interferents and overlaps on non-target leaves.

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