Measurement of Plant Leaf Area based on Computer Vision

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Abstract—It is laboring and tedious to measure plant's leaf area. For this problem, a novel approach based on computer vision was proposed for measuring leaf area. Firstly, plant leaves image were captured by image scanner and transformed to HSI color space. Secondly, combining with saturation, leaves were segmented from background with Otsu approach based on Hue information. Then, morphological filtering was performed to eliminate most noises. After that, blob analysis was used to fill the holes in the leaves and extract the leaves to measure area from original image. Experiments showed that the proposed approach had better segmentation result than the indices-based ones. Moreover, the proposed approach was proofed to be fast and efficient to measuring leaf area comparing with leaf area meter.

Keywords: Plant leaf; Image segmentation; Otsu approach ; Leaf area

I. INTRODUCTION

Leaf area is one of the most important crop parameters that determine radiation intercepted by the crop canopy, and has a strong impact on the calculation of crop canopy photosynthesis and transpiration [1].As one of a leaf's main biological characteristics, area, perimeter, circularity, and bending energy exercise a great influence on plant growth and development. Measurement of leaf area is of value in studies of plant nutrition, competition, soil-water relations, protection measures, crop ecosystems, respiration rate, light reflectance, and heat transfer in heating and cooling processes [2].In crops like tea, tobacco, and green leafy vegetables, where leaves are the major commercial product, leaf area is a good direct indicator of product yields.

The importance of leaf area determination in plant sciences has stimulated the use of a great variety of methods for leaf area measurement. Some basic methods are the graphical method, length and width correction, and leaf specific weight correlation. Other methods include visual or ocular evaluation of detached leaves, contact printing on a light sensitive paper and measuring the area by planimeter, blue printing and optical comparators, and the use of an airflow planimeter that measures the area as a function of the surface obstructing the flow of air. However, these direct leaf area measurement methods are usually tedious. Computer vision has made a great development in plant monitoring and provides a new solution for determining leaf area automatically and accurately [3].This is becoming a research hotspot and is less laborious than the traditionalmethod. Computer vision based leaf area measurement approaches are classified into semi-automatic and fully automatic classes. The semi-automatic class is less efficient and requires human intervention with Photoshop [4,5] or interactive computer software [2] for leaf area measurement. The fully automatic class accomplishes the same task with the use of complicated image processing software [6-8]. However, the problems associated with these existing methods are that they are destructive and laborious. Thus, this paper proposed a new approach for measuring leaf area. In our approach, color information, Otsu approach, morphological filtering and blob analysis were combined to extract the plant leafs.

II. IMAGE ACQUISITION

Experiments on plants subjected to water and nutrient stress were performed in the glass greenhouse of Tongji University in Jiading district. Initially, the ratio of turf, vermiculite, and perlite within the matrix was determined, and rectangular pots were selected for the tests. A total of 27 basins were divided into 9 groups with 3 repetitions. The weight method was adopted to decide the irrigation time every day. Plant leaves were picked after experiment.

As shown in Fig.1, the scanner (Type: Gemstar JT-DBG001) base and the white board were placed on a horizontal plane table. Plant leaves were put on the white board, images (resolution: 1544x1122, with 24-bit color) were captured by the scanner with the vertical scanning and stored on the computer connected by a USB cable. A total of 68 samples were collected for image analysis, illustrated as Fig.2.

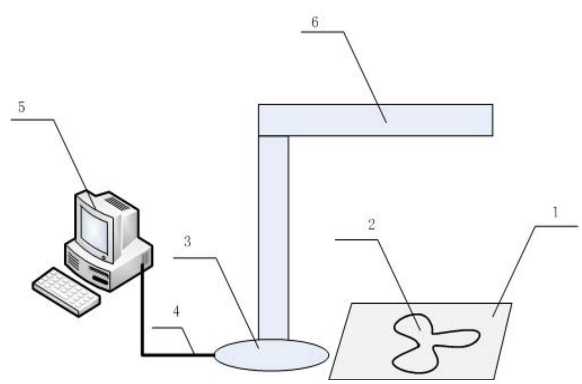

Fig.1 How the leaf images are taken
1 White board 2 Plant leaf 3 Base 4 USB cable
5 Computer 6 Scanner

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Fig2. Plant leaf image

III. Image processing

A. Plant leaves image segmentation

The first step in the analysis was segmentation of the leaf into multiple regions of interest (sets of pixels), corresponding to different objects or parts of objects [9].Several factors hamper the segmentation of plant leaves from the background: the soil and plant material, shadows of the plant canopy, angle of solar illumination, and angle of the camera relative to the canopy and the sun. To segment vegetation from soil, researchers have employed different kinds of indices. Woebbecke et al. (1995)[10] proposed the ExG index, which provides a near-binary intensity image outlining a region of interest, from which segmentation can be accomplished using a suitable threshold. Perez et al. (2000)[11] used only green and red channels to present the normalized difference vegetation index (NDI), and the color index of vegetation extraction (CIVE) was proposed by Kataoka et al. (2003)[12], which involves principal component analysis. The excess red vegetative index (ExR = 1.4r−b) and ExG-ExR index were proposed by George E. Meyer et al. in 2008[13]. Their research showed that the ExG-ExR index had superior vegetative separation accuracy over the ExG and NDI indices, and that ExG−ExR also worked exceptionally well with natural lit color digital images. The principle underlying these approaches based on color indices is identification of differences in the color components of prominent areas of interest. With the thresholding techniques, it is easy to segment the leaf part. The problem associated with these approaches based on color indices is the over-segmentation.

As shown in Fig. 2, our goal is segment the leaf part, where the color of stem is near the white board. As mention before, the approaches based on color indices could lead to over-segmentation. There are obvious differences between the leaves and the background on the color component of hue and saturation. Thus, our approach used the hue and saturation information for image segmentation. The first step for image segmentation is converting color space from RGB to HSI (hue, saturation, intensity) space, as following:

$$\begin{cases} \theta = \cos^{-1}\left[\dfrac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right] \\ H = \begin{cases} \theta & B \le G \\ 360-\theta & B > G \end{cases} \\ S = 1-\dfrac{3\min(R,G,B)}{R+G+B} \\ I = (R+G+B)/3 \end{cases} \tag{1}$$

where H, S, I denotes the hue, saturation and brightness respectively.

As shown in Fig.2, the aim of our approach is classify the pixels into two categories, corresponding to leaf part and background. There is obvious difference between object and background on the hue component, leading to the shape of the hue histogram is bimodal. The proposed method utilized Otsu approach[14] for hue thresholding. In traditional way, Otsu approach is used to calculate an optimized gray level in the range of [0,255] for image binarization. From equation (1), we can see that the hue is a 360-degree color wheel, shown in Fig.3, where the three primary colors (red, green and blue) are separated from each other at 120 degrees. Because the leaves are green, leaf hue is in the green zone $H_O = [H_{O\min,} H_{O\max}]$, and others region responds to background. The different from the Otsu approach based on gray level is that it demands two thresholds $H_{O\min,}$ and $H_{O\max}$ to classify the pixels in to two categories. Thus, the traditional Otsu approach must be modified.

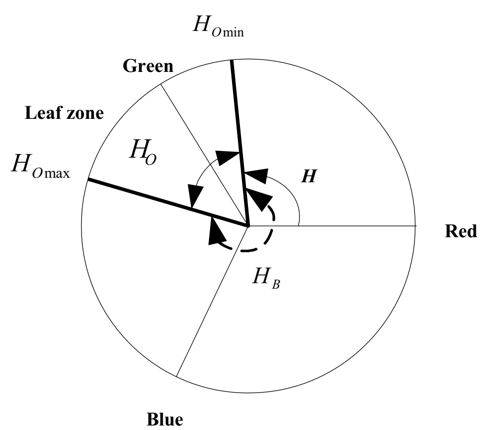

Fig.3 Hue range of pant leaf

To simplify the calculation, the H was quantized into 360 levels (If the number of levels is large, we can use fast algorithms to improve the calculation speed [15]). Thus, the image is presented in L hue levels (0,1，⋯，L-1，L=360). The number of pixels at level i is denoted by ni; then, the total number of pixels N equals N=n0+n1+⋯

+nL-1 .For a given color image, the occurrence probability of hue level i is given by pi=ni/N, satisfying $\sum_{i=0}^{L-1} p_i = 1$. The mean hue of the whole original image is $\mu_T = \sum_{i=0}^{L-1} ip_i$. Assume that an image is divided into two classes HO and HB, corresponding to object and background, by two hue value HOmin and HOmax. That is HO=[HOmin , … , HOmax] , HB=[0 , … , HOmin,HOmax, …, L-1]. The occurrence probability of the two classes are $\omega_O(H_O) = \sum_{i \in H_O} p_i$ and $\omega_B(H_O) = 1 - \omega_O(H_O)$ respectively. The mean hues of the two classes are given by μ_O and μ_B ,

$$\mu_O(H_O) = \sum_{i \in H_O} ip_i / \omega_O(H_O) = \mu(H_O) / \omega_O(H_O) \tag{2}$$

$$\mu_B(H_O) = \sum_{i \in H_B} ip_i / \omega_B(H_O) = \frac{\mu_T - \mu(H_O)}{1 - \omega_O(H_O)} \tag{3}$$

The between-class variance of the 2 classes can be calculated by

$$\sigma_B^2(H_0) = \omega_0(H_0)[\mu_0(H_0) - \mu_T]^2 + \omega_B(H_0)[\mu_B(H_o) - \mu_T]^2 \tag{4}$$

That is

$$\sigma_B^2(H_O) = \frac{[\mu_T \omega_O(H_O) - \mu(H_O)]^2}{\omega_O(H_O)[1 - \omega_O(H_O)]} \tag{5}$$

where $H_O=[H_{Omin},\ldots H_{Omax}]$.In Formula (5), with exhaustive search we select two optimal parameter H_{Omin} and H_{Omax} that maximizes the between-class variance $\sigma_B^2(H_O)$ in Eq. (6) .

$$(H^*_{O\min,}, H^*_{O\max}) = \underset{0 \le H_{o\max} < L, 0 \le H_{o\min} < H_{o\max}}{\arg\max} \sigma_B^2(H_O) \tag{6}$$

Meanwhile, in addition to hue difference, the leaf's saturation is also different from the background. Thus, leaf's saturation information is used in the segmentation, given as follow:

$$S > S_0 \tag{7}$$

where S_0 is a fixed value and is set to 0.3.From the analysis as above, the pixels which hue value are between $H^*_{O\min,}$ and $H^*_{O\max}$,and saturation satisfying Eq. (8) are classified as leaf. Others are background.

B. Morphological operation

Due to some colors in background were close to the color of crop leaf, noises were appeared in the resulted image. To improve processing efficiency, image noises are reduced by morphological operation.

Opening operations can be viewed as a morphological filter that smoothes object contours, breaks isthmuses, and eliminates small objects. The expression of opening X by B is

$$X \circ B = (X \Theta B) \oplus B \tag{8}$$

where X represents the opening set (the image), B represents the opening element structure. The opening operation is actually an erosion operation of X by B followed by a dilation of the result by B. The erosion and dilation operations are also morphological filters. Erosion operation can be expressed as

$$X \Theta B = \{x \mid (B_x) \subseteq X\} \tag{9}$$

The dilation operation is defined as

$$X \oplus B = \{x \mid \dot{B}_x \cap X \neq \phi\}, \tag{10}$$

where $\dot{B}$ is the reflection of set B as

$$\dot{B} = \{x = -b, b \in B\} \tag{11}$$

C. Blob analysis

In the image processing field, a blob refers to a region with certain characteristics of intensity, color, tone, texture, etc. The most fundamental operation in blob analysis is labeling of connected components in a binary image. Many algorithms have been proposed to address this issue, such as multi-scan algorithms, two-scan algorithms, a hybrid between multi-scan algorithms and two-scan algorithms, and tracing-type algorithms [16].Multi-scan algorithms are time consuming, while two-scan algorithms complete labeling in two scans. During the first scan, provisional labels are assigned to object pixels and label equivalences are recorded. During the second scan, all equivalent labels are replaced by their representative label. In the present study, a two-scan algorithm was carried out to label the blobs.

Geometric characteristics including the area, center of form, location, and size are calculated to describe the form. Binary images do have some residual noise. With the results of blob analysis, these residual noises, whose sizes are smaller than the predefined threshold, will first be filtered out. Second, the small holes in the object will be filled with object color. Finally, the leaves are extracted.

IV. Experiment

For the image in Fig.2, the Otsu method based on hue combining the saturation was performed to segment leaf image, where there were noise residues, shown in Fig.4(a). The leaf's hue range was (35,163).Morphological filtering was used to remove most noises, and blob analysis was implemented to eliminate the noises whose sizes were less than 50 pixels and to fill the holes in the object, as shown in Fig.4(b) and Fig4.(c) respectively. Finally, the leaves images were extracted as illustrated in Fig.4(d).

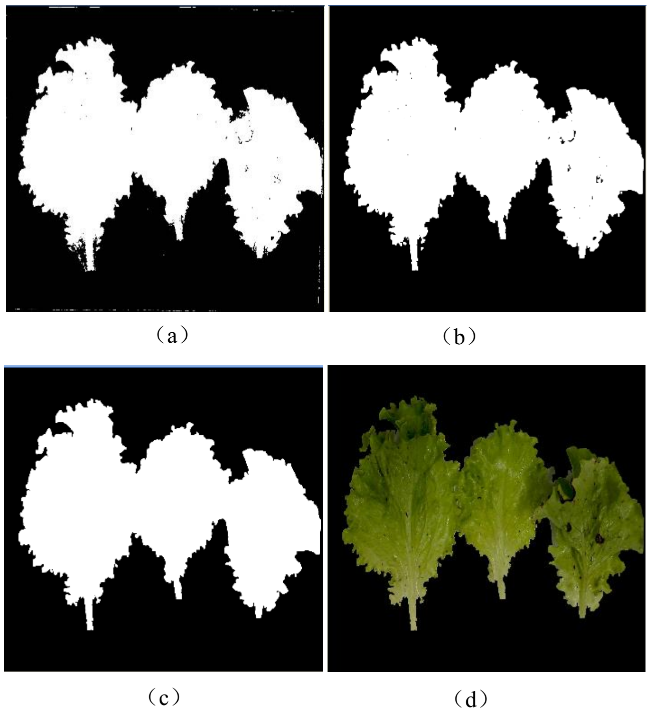

Fig.4 Image processing procedure
(a) image segmentation (b) morphological filtering
(c) filling holes (D) extracting leaf image

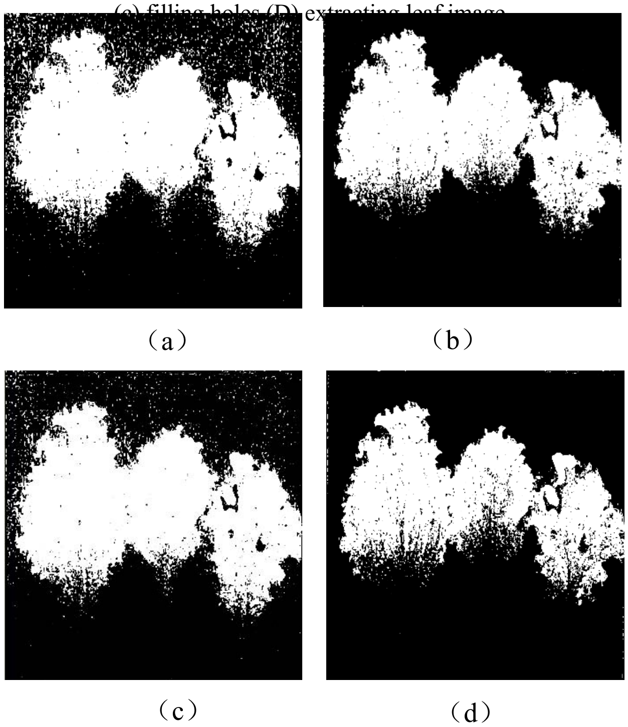

Fig.5 Segmentation results based on color index
(a) ExG (b) NDI (c) CIVE (d) ExG-ExR

In order to compare the segmentation results, the Otsu method based on color indices was used. Four color indices including ExG, NDI, CIVE, ExG-ExR were selected to segment the leaf image as shown in Fig.5. Comparing with Fig.4(a), the experiment showed that the proposed method can get a better segmentation result.

In this paper, a rectangular card was used as a reference object to calibrate the system. Its actual area is A_r corresponding N_r pixels. For image in Fig.4 (c) or Fig.4(d), all pixels which were not black were classified as leaves pixels, denoted as N. Thus, the real leaf area is calculated as follow:

$$A = \frac{A_r}{N_r} \cdot N \tag{12}$$

The proposed approach was used to calculate the leaf area of 10 images as illustrated in Table 1, where A is the area measured by this method, and A_1 is the area measured by a leaf area meter (Brand: CN-RY, Type: YMJ-A). The errors between the measuring results with these two methods were small. Furthermore, the proposed method can adaptively select the threshold value and all images were scanned in the same environment. Thus this algorithm can be applied directly to a number of images, without additional parameter adjustment. The proposed algorithm was developed using C # language. On a PC (memory:4GB, CPU: P8600), the leaves area of 68 images were calculated in 2 minutes and 28 seconds automatically. Therefore, the proposed measurement method is fast, efficient and accurate.

Table 1 Comparison with leaf area meter

No.	Leaf (pixels)	A(cm^2)	A_1(cm^2)	Error(cm^2)
1	659434	227.00	227.3	-0.30
2	749662	258.75	259.03	-0.28
3	667298	229.70	229.2	0.50
4	560698	193.01	192.9	0.11
5	462252	159.12	158.99	0.13
6	762511	262.48	262.08	0.40
7	727328	250.37	251.02	-0.65
8	521687	179.58	178.9	0.68
9	623660	214.68	213.93	0.75
10	654176	225.18	225.48	-0.30

V. CONCLUSIONS

Leaves are the main organs of plant photosynthesis and transpiration. Fast and accurate leaf area measurements assume great significance. Due to the color information (hue and saturation) of leaf and background are obviously different, Otsu method based on hue combining the saturation was performed to segment leaf image. Because both the hue and saturation information were used in the leaf segmentation approach, the proposed method could get a better result than the Otsu approach based on color indices. Blob analysis was used to fill the holes in the leaf and extract the leaves to measure area from original image. Experiments showed that the proposed approach was fast and efficient for measuring leaf area. In addition, the image scanner is low-cost. Thus, the proposed approach is easy to implement.

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REFERENCES

[1] Xu R., Dai J., Luo W.,et al.(2010). A photothermal model of leaf area index for greenhouse crops. Agricultural and Forest Meteorology,150, 541~552.

[2] Igathinathane C, Prakash V S S, Padma U. Interactive computer software development for leaf area measurement . Computers and Electronics in Agriculture, 2006,51:1~16.

[3] Lin K Y, Chen J, Si H P, et al. A review on computer vision technologies applied in greenhouse plant stress detection. Communications in Computer and Information Science, 2013, 363(4):192~200.

[4] Yang J F, Chen Q, Han X R, et al. Measurement of vegetable leaf area using digital image processing techniques . Transact ions of the CSAE,2002,18(4)：155~158. (in Chinese)

[5] Zai S M,Wen J, Guo D D, et al. Determination of leaf area of sweet pepper based On support vector machine model and image processing [J]．Transactions of the CSAE,2011,27(3)：237~241．

[6] Ma Y P, Bai Y L, Gao X Z, et al. Investigation of the method for measurement of corn leaf area based on image. Chinese Agricultural Science Bulletin,2009,25(22):329~334.(in Chinese)

[7] Wang J W, Liu H. Computing method of plant leaf area based on snake model . Computer Engineering, 2013,39(1):234-238.

[8] Xia Y W, Xu D Y, Du J S, et al. On-line measurement of tobacco leaf area based on machine vision[J]. Transactions of the Chinese Society for Agricultural Machinery,2012,43(10):167~173.(in Chinese)

[9] Parsonsc N.R., Edmondson R.N., Song Y. (2009). Image analysis and statistical modeling for measurement and quality assessment of ornamental horticulture crops in glasshouses. Biosystems Engineering, 104,161~68.

[10] Woebbecke D M, Meyer G E,Bargen K V, et al. Color indices for weed identification under various soil residue and lighting conditions [J]. Transactions of the ASAE,1995,38(1)：259~269.

[11] Perez A J, Lopez F, Benlloch J V, Christensen S. Color and shape analysis techniques for weed detection in cereal fields . Computer and Electronics in Agriculture,2000,25:197~212.

[12] Kataoka T, Kaneko T, Okamoto H, et al. Crop growth estimation system using machine vision . In: Proceedings of the 2003 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, pp. 1079~1083.

[13] Meyer G E, Neto J C. Verification of color vegetation indices for automated crop imaging applications . Computer and Electronics in Agriculture , 2008,63 :282~293.

[14] Otsu N. (1979). A threshold selection method from gray-level histograms．IEEE Transaction on System Man and Cybernetic,9(1)：62~66.

[15] He Z Y, Sun L N, Chen L G. Fast computation of threshold based on Otsu criterion. Acta Electronica Sinica,2013,41(2):267~272. (in Chinese)

[16] He L F, Chao Y Y, Suzuki K J et al. Fast connected-component labeling. Pattern Recognition, 2009(42): 1977~1987.