A leaf vein detection scheme for locating individual plant leaves

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***Abstract*—Individual leaf detection from natural condition is a fundamental task for many agricultural automation systems. Individual leaf detection is challenging because of the complicity of shape variation and pose changing of living plant leaves. In this paper, we proposed a leaf detection scheme by examining leaf veins. Individual leaves could be located in the plant images and their direction could be estimated. Initially, background is removed by examining luminance and smoothness in G channel of RGB color space. Accordingly, a SKEDET method is proposed to extract candidate skeleton of leaves. The longest skeleton of a leaf is selected as the main leaf vein. Subsequently, the direction of leaf is estimated according to thickness of the vein. The experiments were carried out with sweet potato leaves. The experimental results demonstrated that the proposed method could stably detect individual leaves and their directions. The proposed method could be applied to many agricultural applications, such as plant inspection system, agricultural robotics.**

Keywords—leaf pose, leaf recognition, leaf skeleton, leaf segmentation

I. INTRODUCTION

Recently, computer vision is changing the conventional agricultural production. Computer vision has been considered as the "eyes" in advanced automation systems for precision agriculture. Over the last decade, many applications of leaf image analysis have been arisen due to the advantages of rapidly developed computer vision techniques. For example, fruit picking robots, de-leafing robots and pest management robots were presented using computer vision. Accuracy detection and segmentation of plant leaves is one the key issues for agricultural automation systems. The study of plant leaf image analysis has been widely conducted. Image-based plant modeling is reported to generate virual plants and trees from real plant leaf [1,2]. Automated plant classification provides a fast way for plant species identification. When a plant image is captured and transmitted to the computer which running the plant classification system, the precise species of the target plant could be predicted in few seconds. Since plant leaves contain rich information of plant status, plant leaf images are utilized to measure leaf area, plant diseases and insect pests, nitrogen nutrition, and etc., for implementing precision agriculture. Image-based plant phenotyping is a growing application area of computer vision in agriculture [3].

Plant leaf segmentation is a key issue to many agricultural automation systems. Plant leaves are hard to segment because of their blurry edge, disorder distribution and complex texture. Many studies reported to segment plant leaves and shown high accuracy under limited conditions. An effective approach is to utilize color distance and 3D distance to segment leaves [1]. Plant images were captured from different views (between 30 to 45 images) and used a standard structure from motion technique to compute the camera parameters and 3D points. And they built a weighed graph jointly using 3D and 2D information and applied normalized cut approach [4] to segment images into individual leaves. Teng et al. presented a segmentation scheme with multi-view images for each leaf [5]. Camera self-calibration was conducted and optical flow was applied to recover 3D scene points. Similar to [1], they used 2D/3D joint information to segment points of images into different groups. And the Lazy Snapping was adopted to extract the individual leaves. A RGB-D camera based leaf segmentation approach is reported in [6]. A Kinect V1.0 camera was utilized to capture color and depth images of plants. Mean shift clustering was performed on the depth image to segment objects from the natural background. The center of divergence was computed from the gradient field of the depth image. Finally, active contour models were implemented according to the center of divergence to segment individual leaves.

A priori knowledge of leaf shapes as the constraints for plant leaf segmentation was proposed in many agricultural practices [7-9]. Cerutti et al. used a parametric active polygon defining by 10 points and 4 numeric parameters to model the general shape of a leaf [9]. They initialized a region in the middle of the image and generate a color distance map based on 2-component GMM estimated in the initial region. Then the parameters of the leaf model were adjusted within an authorized range to produce the biggest region with little color-distant pixels. Xia et al. proposed modified Active Shape Models (ASMs) to detect more complex shapes of vegetable leaves [10]. In this scheme a Multi-Layer perceptron (MLP) was applied for differentiating leaf boundaries from veins and Bezier curve were utilized for finding the center position of each leaf. The authors chose 39 points on leaf boundaries for representation the leaf shapes. Then they produced Boundary-ASM and MLP-ASM to segment individual leaves.

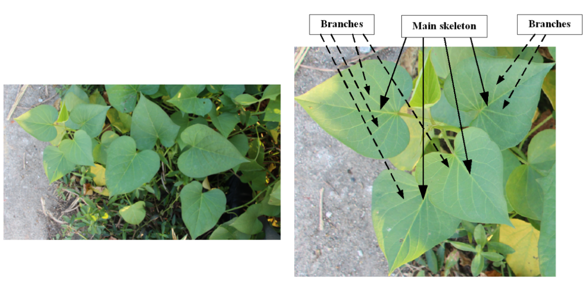
Although a number of studies have been carried out and achieved a great process accurate detection of individual leaves from natural condition is still a tough issue. In this work, we propose to detect individual leaves by analyzing skeleton and identify leaf veins. The experiments proved the accuracy and stability of our proposed approach.

II. Removal of Natural Background

In this study, skeleton is used to locate individual plant leaves. For leaf skeleton detection, image background is firstly removed. An original image is converted into the *RGB* color space. To reduce computational cost, the width and height of plant image was scaled to 30%. Zhang et al. proposed to used simple color segmentation and smooth threshold to extract leaf surface. In this work, non-green background is initially removed [11]. As shown in Fig. 1, the luminance of skeletons (including main skeleton and branches) is usually high. The leaf surface is usually smooth. For a given pixel *p*, the smooth degree of *p* is defined as

$$Smooth(p) = \frac{1}{N}\sum_{q \in D}(|\psi(p) - \psi(q)|) \qquad (1)$$

where $\psi(p)$ is the *G* component value (*RGB* color space) of a pixel and *D* is a square centered at *p*. This smoothness value measures the average luminance variation with the neighbors of *p*. The length of *D* was chosen as 9 pixels. *N* is the total number of pixels (e.g., 81) in the neighboring region. Smoothness threshold was given as 12. Plant images are usually very complicated, the leaf surface could show various features. Due to illumination conditions or disease, small parts of the leaf could be determined as background. As these parts are typically small and could be removed by morphological erosion operation (with 3-6 pixels kernel). On the other side, if a region containing less than 500 pixels should be removed due to its small size. A background removed plant image is presented in Fig. 2. Large leaves were remained, and background and small leaves were removed as we expected.



(a) (b)

Fig. 1 Plant images, (a) oringal images and (b) its details

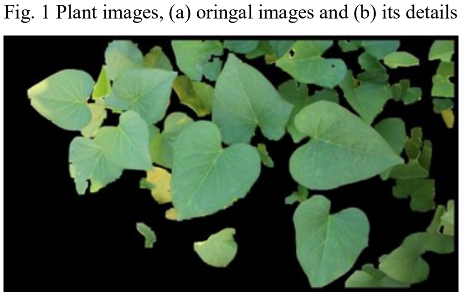


Fig. 2 Background removed plant image

III. Leaf Skeleton Detection

For leaf skeleton analysis color information is not necessary in this work. The original color image should be converted into grayscale image. We propose a SKEDET algorithm to detect candidate skeleton pixels according to luminance intensity of neighboring pixels. The detailed process is described as follows:

(1) For every pixel *p* in the gray image, a local image patch centered at *p* is obtained from the overall image.

(2) We define two status P_{n0} and P_{n1} for pixel *p* and they are initialized as 0. Examining every pixel *q* in the local image patch. If the gray value of q is fall in a certain range (e.g., [60, 230]), then

(a) If the difference of luminance intensity between q and p is > 1, $P_{n0} = P_{n0}+1$

(b) Otherwise, if the gray value of q is > p, $P_{n1} = P_{n1} +1$

(3) if $P_{n0} > 10$ and $P_{n1} > 0.65* P_{n0}$, pixel *p* is determined as a candidate pixel of skeleton.

In general, the intensity value of the pixels on skeleton show higher value than the surrounding pixels. Step (2) indicates that for a pixel *p*, if most of adjacent pixels have less luminance value than that of *p*, it will be determined as a candidate skeleton pixel. The result obtained from SKEDET is shown in Fig. 3.

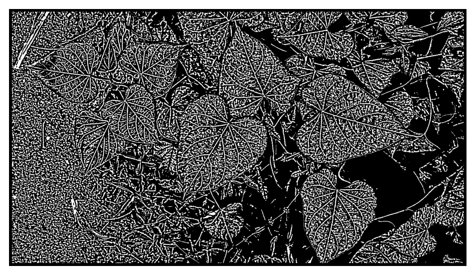


Fig. 3 Candidate skeleton pixels

Since leaf skeletons are approximately linear. The results of SKEDET algorithm keep this characteristic to extract skeletons from Fig. 3. A method presented in our previous work is applied to effective extraction of linear skeletons [12]. Brief descriptions are given below:

(1) For every candidate pixel , if it is a green pixel in Fig.3, draw straight lines for every angle (from 0 to 360 degrees).

(2) For each line, if there is a line (the length are set 48) which has more than a Line_threshold (between 7 and 35 pixels), keep as a candidate pixel; otherwise, it is regarded as a noisy pixels.

Fig. 4 Selected candidate skeletons

We apply the method and the result of Fig.3 are shown on Fig.4. For each leaf, only the longest skeleton is selected as the leaf vein. Every individual leaves could be located by examining their main skeleton. Unfortunately, identifying main skeleton is a challenging work. In this study, we use the length of connected component to obtain main skeletons or components containing main skeletons. The length of a connected component D is given by:

$$Len(D) = \sqrt{(x_{\max} - x_{\min})^2 + (y_{\max} - y_{\min})^2} \qquad (2)$$

Where x_{min}, x_{max} are the maximum and minimum X-coordinate values in D, and y_{min}, y_{max} are Maximum and minimum Y-coordinate values on D. The following process is proposed to obtain main skeleton components:

(1) For each connected component, we obtain its centroid Cp, and the farthest point *Tp* to *Cp* in the component. The inclination angle between *Cp* and *Tp* is considered the inclination angle of the component.

(2) For every connected component, its length is calculated according to equation (2). If the length of the component is less than 6 pixels, this component should be removed as noise.

(3) For two connected components, if their distance is closer than 6 pixels (the nearest two points between the two components) and their inclination angle differences is less than 5, these two components should be merged as one.

(4) For each component, we search its adjacent components and examine their length. The longer component will be remained and the short one should be removed.

Step (3) indicates that if there is a main skeleton which is separated different parts because of noises, those parts should be merged into one main skeleton. The purpose of step (4) is to removes branches which do not connect to main skeletons. The result of the skeleton identification is shown in Fig.5. Individual main skeleton components are extracted, and weak skeletons were removed.

Fig. 5 Determined leaf skeletons

After the main skeleton is extracted the longest skeleton is chosen to estimate the leaf angle. Since the skeleton near leaf tip is thinner than the other side. The leaf direction is estimated by examining the thickness of both side of the main skeleton, as shown in Fig. 6.

Fig. 6 Estimation of individual leaf direction

IV. EXPERIMENTAL RESULTS

Sweet potato was selected as test sets in this study. Plant images were captured in Guangzhou, Guangdong province, China. Cannon digital camera and smart phone (Samsung SCH-P729) were used for image capturing. the distance between the camera and plant leaves is set between from 0.1 to 1.8 meters. To avoid interferences from shadows, we acquired leaf images on cloudy days or in the morning or the dusk. A captured image can contain one leaf, several leaves and numerous leaves. In total, 90 plant images were collected to test the performance of our proposed scheme.

After background-removed, leaf skeleton candidates were extracted by the proposed SKEDET approach. Our experiences shown that candidate skeletons were accurately obtained from single leaf images and complicated multiple-leaf images. Every single leaf was accurately detection. For multiple-leaf image, 44 images containing 826 leaves were tested. The accuracy of leaf detection and direction estimation was up to 87.78%.

V. CONCLUSIONS

In this paper, we proposed a SKEDET scheme based on luminance to detect the leaf skeletons. According to the linear characteristics of main skeleton, skeleton length and luminance intensity along main skeleton were adopted to locate individua leaves. In addition, the direction of each leaf was estimated according to the thickness of both side of the leaf vein. The experiments proved the proposed leaf detection scheme is accurate and stable to locate the individual leaves and estimate their direction under natural conditions. Locating individual leaves and estimating leaf pose are crucial for agricultural automation systems. In the future work, individual leaf segmentation could be implemented based on the proposed method. And more detailed information of leaves could be measured.

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