Laser Vision-Based Plant Geometries Computation in Greenhouses

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Abstract—Plant growth statuses are important parameters in the greenhouse environment control system. It is time-consuming and less accuracy that measuring the plant geometries manually in greenhouses. To find a portable method to measure the growth parameters of plants portably and automatically, a laser vision-based measurement system was developed in this paper, consisting of a camera and a laser sheet that scanned the plant vertically. All equipments were mounted on a metal shelf in size of 30cm*40cm*100cm. The 3D point cloud was obtained with the laser sheet scanning the plant vertically, while the camera videoing the laser lines which projected on the plant. The calibration was conducted by a two solid boards standing together in an angle of 90. The camera’s internal and external parameters were calibrated by Image toolbox in MatLab®. It is useful to take a reference image without laser light and to use difference images to obtain the laser line. Laser line centers were extracted by improved centroid method. Thus, we obtained the 3D point cloud structure of the sample plant. For leaf length measurement, iteration method for point clouds was used to extract the axis of the leaf point cloud set. Start point was selected at the end of the leaf point cloud set as the first point of the leaf axis. The points in a radius of certain distance around the start point were chosen as the subset. The centroid of the subset of points was calculated and taken as the next axis point. Iteration was continued until all points in the leaf point cloud set were selected. Leaf length was calculated by curve fitting on these axis points. In order to increase the accuracy of millimeter level, while laser measurement is non-contact sensing, non-destructive and time-saving. David Story [4] used machine vision-guided plant sensing and monitoring system to detect calcium deficiency in lettuce crops grown in greenhouse conditions using temporal, color and morphological changes of the plant. The machine vision system extracted plant features to determine overall plant growth and health status, including top projected canopy area(TPCA)as a morphological feature; red–green–blue(RGB) and hue–saturation–luminance(HSL) values as color features; and entropy, energy, contrast, and

I. INTRODUCTION

A facility farming is growing fast in recent years. Many scientists and experts are working hard on the artificial control of greenhouse environment [11, 14, 25, 27, 30, 31]. But the target of greenhouse environment control is providing appropriate environment for the crops in the greenhouse. Results of the control system were displayed on the status of crop growth. So it is of more importance to detect the crop response at different growth status [25], Remote sensing [17] is widely used in field farm crops, while in greenhouses it is not adaptive due to the block of glass. So many experts made endeavor on the geometric crop properties detection in greenhouses to obtain the crop growth response for the plant speaking-based greenhouse environmental control system.

In conventional greenhouse, crop growing conditions are obtained via human observations or presetting environmental parameters, instead of the plants’ specific needs at a different status. Contact sensing is typically used to determine a plant’s physical characteristics, a process that is cumbersome, labor-intensive, and often destructive. Computer vision is a good choice for geometric crop properties detection in greenhouses, because of non-contact sensing, non-destructive and time-saving.

Index Terms—Laser Vision; 3D Point Cloud; Plant Geometry; Leaf Length; Leaf Area; Plant Height; Canopy Width
homogeneity as textural features. The methodology developed was capable of identifying calcium-deficient lettuce plants 1 day prior to visual stress detection by human vision. Ling et al [12] used spectral and morphological characteristics of lettuce leaves to detect nutrient deficiency. This study showed that the reflectance of wave bands between 415nm and 720 nm could be used as a signal wave band for machine vision implementation. A wave band closer to the visible was recommended because it gives a better signal strength. The study also suggested the possibility of using multiple signals based on water and nutrient stress detection in plants, using machine vision systems that could determine deviations from “well-grown” as an indicator of deficiencies and plant status. Meyer et al [16] used a machine vision system to detect single leaves and poinsettia foliage, and reported that a normalized difference index provided the best method of discriminating nitrogen-deficient from healthy plants. Low-nitrogen plants grown in greenhouses and growth chambers showed similar increases in red reflectance, but had different levels of near-infrared reflectance due to differing amounts of plant canopy cover. E.V.Henten [18] used an indirect non-destructive measurement by means of image processing to detect crop growth of lettuce and build 3D models of the relationship between relative soil coverage by the crop canopy and by dry weight.

Geometric crop properties measurements are a broad research topic in agriculture. With the development of computer vision, 3D measurement shows a great potential in vegetation growth parameters measurement [1-3, 10]. Hans J. Andersen [7] investigated the potential of using area-based binocular stereo vision for three-dimensional analysis of single plants and estimation of geometric attributes such as height and total leaf area. Dominik Seidel [5] measured total above-ground biomass (stems, twigs, leaves), the biomass of axes (stems and twigs), of leaves biomass and the leaf area of 63 experimental trees by means of terrestrial 3D laser scanner. Hosoi and Omasa [8] used a portable 3D laser scanner to calculate canopy leaf area density profiles for deciduous trees. His studies focused on measurements of the biomass, and mostly concentrated on forest trees resting upon relationships among parameters which were measured with terrestrial laser scanners, e.g. diameter at breast height or total tree height, and the trees biomass [28]. The application of terrestrial laser scanning (TLS) and mobile or vehicle based laser scanning (MLS) enables fast 3D data acquisition. They provide a direct capture of tree geometry generating high resolution point measurements representing the geometrical characteristics of target objects in 3D space [13]. Generally, Terrestrial LiDAR (Light Detection and Ranging) Scanners (TLSs) have recently turned into potential tools for 3D vegetation structure measurement. It provides accurate measures of distances to objects using a large number of sampling laser beams within the instrument field of view, thus creating a cloud of points positioned in 3D space. It is widely used in field farms and forests. But in greenhouses, TLSs do not show the superiorities because of the space limitation.

In our studies, we are aiming to find a portable and low cost vegetation geometric properties measurement system basing on laser vision. The main parameters of plant geometric properties include the leaf length, leaf area, plant height and canopy width of a single crop in greenhouses. This laser vision-based measurement system will have great prospects on both improving the visualization and digitization for plants growth monitoring and analysis and providing multi-aspect data for the greenhouse environmental control system.

II. MATERIALS AND METHODS

A. Crops and Acquisition

A growth experiment with water spinaches in greenhouses which was built on the roof of laboratory building at College of Engineering, Nanjing Agricultural University served as the study object to test the applicability of 3D-laser scanning as a non-destructive method for growth parameters detection in greenhouses, which is a three ridge-Venlo greenhouse size 8m* 16m.

The measurement principles, as shown in Fig. 1, is comprised of a CCD web-camera (HikVision® DS-2CD332D-I) that recorded the video of laser scanning line, projected onto the crop stems by a laser sheet with a downward slope angle of 45 degree. The laser sheet was created by mounting a horizontal raster on a 80 mW, 520 nm (green) laser diode. And it had an approximate thickness of 2 mm and an aperture angle of 60 degree. The laser sheet was mounted on a Pan-Tilt (PTZ®W3300) with horizontal rotation angle of 355 degree and vertical lift angle of 60 degree. All the components were mounted on a mental shelf with 30cm by 40cm by 100cm. The laser sheet scanned the crop up and down with a horizontal laser line. A PC machine was used to control the Pan-Tilt through 485-cable and the camera through a network, respectively. The video resolution was 1080*1270 pixels with the frame of 30 fps, and the frame image resolution was 640*480 pixels by programming in

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MatLab®. The camera was calibrated using a standard procedure contained in a MatLab® Toolbox based on Tsai’s method, which enabled distortion correction of the imagery.

**B. Calibration of 3D Measurement System**

3D measurement system consists of camera perspective transformation model and light plain equation model [32, 34] which is used for building the relation between 2D coordinates and 3D coordinates of target points, shown in Fig. 2. O, is the center point of camera pinhole model. OZc is the camera optic axis, which is perpendicular to CCD plane, with point O as the intersection. The distance of O-Oc is the focal length, f. X-axis and Y-axis in retinal coordinates is parallel to u-axis and v-axis in image coordinates, respectively.

![Image](image_url)

**Figure 2. Sketch of 3d measurement principle of line plane equation**

In the process of measurement, laser line sheet (L) projects a curve on the surface of the object that contains 3D spatial information of the object. In the world coordinates, laser light plain equation in the camera coordinates can be described as:

\[
a_X + b_Y + c_Z + d_c = 0 \quad (1)
\]

On the laser light plain, planar coordinates \(O_{c} - X_{c}Y_{c}Z_{c}\) was built. The relation between the laser light plane and the retinal plain is

\[
\begin{bmatrix}
X \\
y \\
z
\end{bmatrix} =
\begin{bmatrix}
1 & r_2 & r_3 & l_x & \rho \\
r_2 & 1 & r_4 & l_y & \rho \\
r_3 & r_4 & 1 & l_z & \rho
\end{bmatrix}
\begin{bmatrix}
X_L \\
y_L \\
z_L
\end{bmatrix}
\]

where \(z_{c} = 0\) . \( X = f \cdot \frac{X}{z_{c}} , Y = f \cdot \frac{Y}{z_{c}} \) were substituted into Eq. (2).

Penalty function was used to solve the optimal equation, as followed,

\[
\rho \begin{bmatrix}
X \\
y \\
z
\end{bmatrix} = \begin{bmatrix}
fr_1 & fr_2 & fT_x & X_L \\
r_1 & r_2 & r_3 & r_4 & \rho \\
1 & 1 & 1 & 1
\end{bmatrix}
\]

\[
= T_{z}^{*} \cdot \rho
\]

\[
= T_{z}^{*} \cdot \rho
\]

**Figure 1. 3D laser sheet measurement system**

\[
\begin{bmatrix}
X \\
y \\
z
\end{bmatrix} =
\begin{bmatrix}
a_1 & a_2 & a_3 & 0 \\
a_4 & a_5 & a_6 & 0 \\
a_7 & a_8 & 1 & 0
\end{bmatrix}
\begin{bmatrix}
X_L \\
y_L \\
z_L \\
1
\end{bmatrix}
\]

where \(i=1,2,3,\ldots,N\), and the constrains of the penalty function is \(f_{p1} = M_1(a_i^2 + a_j^2 + a_k^2 - 1)\), corresponding optimal target function

\[
I(a_i, a_j, a_k) = \sum_{i=1}^{N} \left( f_{p1} + f_{p2} + f_{p3} \right)
\]

. Gaussian-Newton method was used to solve the parameters.

Integrating traditional camera calibration plane targets and light plain calibration [27, 35] 3D targets, a vertical target was used in this paper, consisted of two rectangular boards standing at an angle of 90 degree. A certain number of solid dots 10mm in diameter and donut dots with OD 10mm and ID 6mm were spread on each of the board target evenly. The distance between centers is 50mm. Two targets, in the size of 210mm width and 297mm height, were mounted at a corner at an angle of 90 degree. The intersection of the two boards was defined as Y-axis, defined the mid-point as the original point of the world coordinates. OX and OY were defined on the target board in the right-hand rule, respectively. An image without laser line was taken. The image coordinates of all the solid dots and donut dots and that in the world coordinates were known. And considering the radial constrains in the camera, we can obtain

\[
x_{u}Y_{u}r_{u} + y_{u}Y_{u}r_{u} + z_{u}Y_{u}r_{u} = X_{L}X_{d}r_{u}
\]

Substitute the known point coordinates \(\{(x_{ui}, y_{ui}, z_{ui}), (u_{i}, v_{i})\}\) into equation (5), we can obtain

\[
A \cdot B = X_{d}
\]

where the row vector

\[
A = [x_{y}, y_{u}, y_{d}, z_{y}, y_{d}, -x_{u}, x_{d}, -x_{d}, -z_{y}, -z_{d}]
\]
is known, and the column vector
\[ B = \left[ r_s/s, r_s/s, r_s/s, t_s/s, t_s/s, t_s/s, r_s/s, r_s/s, r_s/s \right]^T \]
is unknown. All the parameters can be solved when the known point coordinates were substituted into Eq. (6). An image with laser line on it was taken. The points were both on the laser line and the plain of XY and YZ. Similarly, the known point coordinates were substituted into Eq. (1), and the equation of laser light plane in the world coordinates was

\[
\begin{align*}
    a_{u}x_{u1} + b_{u}y_{u1} + c_{u}z_{u1} + d_{u} &= 0 \\
    a_{u}x_{u2} + b_{u}y_{u2} + c_{u}z_{u2} + d_{u} &= 0 \\
    \cdots & \\
    a_{u}x_{un} + b_{u}y_{un} + c_{u}z_{un} + d_{u} &= 0
\end{align*}
\]

(7)

Least-square method was used to solve the equation set, and the parameters of laser light plane equation in the world coordinates were obtained. Since the vector \[ \begin{bmatrix} t_x, t_y, t_z \end{bmatrix}, \begin{bmatrix} r_1, r_4, r_5 \end{bmatrix} \text{and} \begin{bmatrix} r_2, r_5, r_6 \end{bmatrix} \] are transformation vector and the unit direction vectors of \( X_e \)-axis and \( Y_e \)-axis in camera coordinates respectively, we can obtain

\[
\begin{align*}
    a_x &= r_2r_6 - r_3r_5 \\
    b_x &= r_2r_6 - r_5r_6 \\
    c_x &= r_3r_5 - r_4r_6 \\
    d_x &= a_xt_x + b_xt_y + c_xt_z
\end{align*}
\]

(8)

Parameters \( r_1, r_4, r_5 \) can be calculated by the transformation of camera coordinates and world coordinates.

C. Images Processing and Laser Line Centroid Method

1) Images Processing

The first step was background removing to reduce the noise disturbances after extracting the frame images. Difference imaging was used to remove the background. No laser line projected video was recorded at the beginning. Afterwards, laser sheet was opened to scan on the crop. So images with laser line projected and without laser line projected were extracted. The laser line stripe was shown in Fig. 4.

Figure 4. Background removing result

2) Laser Line Centroid Extraction and Point Clouds Reconstruction

The second step was extracting the laser line centers. The noise of the sunlight, reflection of the surface of the target crop and other disturbances would make an influence on the laser line centers extraction. So the noise filtering was a necessary process before proceeding to the extraction. Ideal distribution of laser light is Gauss Distribution, so Gauss filter was chosen to remove the noises.

Conventional center extraction methods were extremum method and threshold method, while the two methods were affected by the noises severely. In this paper, centroid method [19, 20] based on the center of gravity computation of rigid-body, was chosen to obtain the centroid of the pixels gray distribution on every cross-section of the laser line stripe. Fig. 5 showed result of laser line centers on one image. The pixel coordinate of the center points were easily obtained by programming in MatLab®. Thus, 3D point clouds construction [9, 17, 18, 21, 22, 26] of target plant was plotted in Fig. 6.

Figure 5. Laser line centers

D. Leaf Length Calculation

In this paper, we proposed an iteration which fit with the features of plant point clouds. Axis points of a leaf were extracted and fitted by curve fitness. The length of axis curve was the leaf length. Details were as followed: Firstly, rotate the main plot of the plant, select the target leaf, and save the target leaf points as leaf subset, named \( \text{Leaf-i} \). A basal point \( P_0 \) was chosen by mouse click,
which is usually at the end of the leaf point subset in 3D plot in the first iteration step ($i=1$). This basal point $P_0$ became the first point in the axis point set. Secondly, a known distance $d_{crit}$ was predefined. All points in Leaf-$i$ with a distance to $P_0$ less than $d_{crit}$ are selected by going through all over the points in Leaf-$i$, namely subset $i$. Calculation of the centroid of subset $i$ is conducted, marked as $P_1$, which is the basal point in the next iteration step. And all the points selected in the first iteration step are deleted. The next iteration step stats from the reduced leaf subset. Iteration continues until all the points in the subset of Leaf-$i$ are deleted. At last, all centroid points are saved in point set named $Ta$. The length of the curve made of these centroid points is the length of the leaf. Fig. 7 shows the result of the leaf axis extraction. Sometimes, bi-directional iteration is necessary to avoid the missing point at the end of the point set. The red points and the blue points are two axis extraction results basing on two start points at two ends of the point set. All the two axis points are used to fit the curve. This method shows robust in case that there are some missing points in the leaf point set because of laser sheet scanning angle.

### E. Leaf Area Estimation

Leaf area takes on a high correlation to leaf length, which can be described by mathematical model. Different plants show different correlation models on leaf length and leaf area. In this paper, Pearson Correlation Analysis was conducted at a sample of 200 water spinach leaves obtaining regression model [33].

\[
\ln(LA) = \alpha \times l + \beta 
\]

### III. RESULTS

#### A. Leaf Length Calculation

In the process of leaf length calculation, the number of leaf axis points affected the result of leaf axis curve fitting. Technically, the value of $d_{crit}$ should be larger than half of the width of leaf point set. The value of $d_{crit}$ is in the inverse proportional relationship to the number of axis points. If $d_{crit}$ was assigned a large value, the number of axis points was too rare to finish the curve fitting. Otherwise, if $d_{crit}$ was assigned a small value, the number of axis points was too redundant to ensure the accuracy of curve length calculation. In this paper, the value of $d_{crit}$ ranged from 1 to 20, producing a set of axis point number and fitted leaf length couples. In Fif.8,a singular point valued 50 of the axis point number fit with $d_{crit}$ valued 1. In this figure, the value of $d_{crit}$ can be inversely computed from the average number of axis point 7. Finally, the length of leaf can be obtained.

![Image](image_url)
To evaluate the performance of the laser scanning measurement system, a sample of 180 water spinach leaves were measured using manual measurements and laser scanning measurement system. Fig. 7 shows the result of leaf axis extraction. Fig. 9 shows the calculated leaf length from laser scanning measurement system, versus the manually measured leaf length. A straight line was fitted, yielding a slope of 0.998, an intercept of 0, and a standard error of 0.909 and a coefficient determination of 0.915. For the leaf length measurement, the average error is less than 5mm with accuracy of leaf lengths is 95.39%, which is in the boundary of error. A few laser measurement results take on larger errors, because that some leaves were shaded from the others which make an effect on the curve fitting.

B. Leaf Area Estimation

To establish the regression model of leaf length and leaf area, a destructive experiment of leaf sampling was conducted. All the sampled leaves were listed on a piece of A4 paper, which is marked with a calibration square with area of 1*1cm². Real areas of leaves were computed by pixel counting, comparing with the calibrated square. The regression model was established with 200 training leaves and 50 testing leaves. Fig. 10 shows the original image and segmented image of sampled leaves.

Exponential regression model was used to evaluate the leaf area, and the result was derived, with $R^2_{adj}$ of 0.9864 and confidence interval of 95%. The result of the leaf area model is shown in Fig. 11.

$$\ln(LA) = 0.164l + 1.923 \quad (10)$$

Results of ANOVA analysis of leaf area estimation model are shown in Table 2 and Table 3 with the model significance of 0 and $F$ statistical testing of 267.97. The coefficients of the leaf area model are shown in Table 3 with standard error of 0.763 and 5.315. The accuracy of the model is 81.9%.

To test the leaf area model, the area of 50 sampled leaves were measured by pixels calibration and estimated by the model. Relationship of leaf area estimation and pixels calibration measured was shown in Fig. 12. A straight line was fitted, yielding a slope of 0.947, an intercept of 0.434.

![RGB image and segmentation image of leaves](image1)

![Regression model of leaf length and leaf area](image2)

![Relationship of leaf area estimation and observed measurement](image3)

C. Growth Trend

Laser scanning the whole plant profile can be used to record and monitor plant growth with leaf area, plant height and canopy width. A sampled water spinach growth conditions (plant height, canopy width) was monitored within 10 days after field planting. The height...
growth of sampled plant was shown in Fig. 13(a), and the canopy width growth of sampled plant was shown in Fig. 13(b). Fig. 14 shows the leaf area growth of six sampled plants during the period of June twenty-seventh and July twentieth in 2013.

![Figure 13. Growth of heights and canopy area](image)

![Figure 14. Total leaf area growth trend](image)

IV. DISCUSSIONS

Plant geometries measurement system based on laser vision performed well in measuring leaf length, plant height and canopy width. Our leaf axis point extraction has been based mainly on iteration fitting to the properties of plant 3D point clouds. This method addressed the situation of missing points in the leaf point set. And bi-directional iteration increased the accuracy of axis point extraction (shown in Fig. 7). Exponential modeling was applied to estimate the leaf area using leaf length avoiding destructive sampling in leaf area measurement. To record and monitor the whole process of plant growth, leaf areas models of different growth periods are necessary. In this paper, we modeled the leaf area with leaf length to estimate the leaf area, but in additional, comparison a mound the leaf area estimation using TLS [15] and the traditional LAI estimation is of value.

For the leaf length measurement, the average error is less than 5mm with accuracy of leaf lengths is 95.39%, which is in the boundary of error. A few laser measurement results take on larger errors, because that some leaves were shaded from the others which make an effect on the curve fitting. In additional, the results are affected by the over-wide laser line. Manual measurement gave result information an accuracy of millimeter level, while laser vision-based measurement system improved the measurement precision. For the leaf area estimation, the accuracy of modeling trained by 200 sampled leaves is 81.9% with 50 testing sampled leaves. For the plant growth properties, plant height and canopy width are obtained by point clouds reconstruction of plant. The test experiment proved that laser vision-based method could be used on plants geometry measurement and growth monitoring in greenhouses. This method will improve visualization and digitalization of plants in greenhouses, and make a progress on greenhouse environment control system.

Although we have concentrated on laser vision-based plant geometries measuring, we would also expect, more generally, that 3D point clouds information would be capable of measuring more phenotypes [3] of plants in greenhouses. The laser vision sensors could also be easily combined with additional sensors to monitor automatically for stress, deficiency [4], spectral information et al at the same time. An overall phenotypes database of plant would be established to provide information for greenhouse environment control system.

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