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A method for estimating plant height of facility tomato based on 3D point cloud

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Abstract: **Plant height can be used to estimate biomass, indicate water stress, and can be also an effective indicator for nutrition content and yield. It is also an important parameter to assess crop growth in the field and to evaluate crop model performance. To achieve plant height for facility tomato quickly, accurately and non-destructively, a method was proposed to estimate tomato plant height based on image sequences. In this study, a truss equipped with visible light (RGB) camera system was used to obtain tomato canopy image sequences in the facility. Three-dimensional (3D) point cloud was reconstructed based on the structure from motion (SFM) algorithm. To estimate tomato plant height, the conditional Euclidean clustering algorithm was used to segment and extract tomato plants automatically from the 3D point cloud. The results showed that the root mean square error (RMSE) between estimation value and true value for tomato plant height was 4.62 cm and the coefficient of determination was 0.971. The method in this study can extract plant height for tomato effectively in a non-destructive way, which also provides a methodological guidance and platform for the other phenotypic parameters extraction for more facility crops.**

Keywords: Plant height; Facility tomato; Visible light images; 3D point cloud; image processing

I. Introduction

Plant phenotype refers to all physical, physiological and biochemical characteristics and shapes that reflect the structural composition, growth and development process, and outcome of plants, which is influenced by genes or the environment[1]. Traditional methods of obtaining phenotypic information mainly use manual measurement, but the measurement process often requires destroying the plant's own structure, and is time-consuming, inefficient, subjective, difficult to measure on a large scale, and at the same time can not guarantee the accuracy, which greatly limits people's research on the plant genome. With the development of artificial intelligence, computer vision and remote sensing technology, more and more methods for extracting plant phenotypic information have been proposed to support plant breeding and phenotyping research. Therefore, the development of automated, efficient, and non-invasive methods for measuring phenotypic traits to improve the efficiency of tomato phenotyping is essential to promote the development of tomato breeding science[2-3].

Crop phenotypic parameters can be divided into intrinsic physiological parameters and extrinsic morphological parameters, of which the acquisition of morphological

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parameters is generally realized by 3D reconstruction. In recent years, 3D reconstruction of plants based on 3D point clouds and measurement of phenotypic parameters have been widely used in crop phenotyping research[4-5]. Hosoi [6] and others used portable high-resolution LiDAR to collect point cloud data from three locations around the tomato canopy and aligned the data in parallel to accurately measure the leaf area of tomato with an average error of 4.6%. In order to improve the efficiency and automation of crop phenological measurements, research on mounting phenological acquisition sensors on robots to realize efficient automated phenological measurements has been born in recent years.

The acquisition of three-dimensional structural phenotype information has been highly emphasized in recent years. Lidar can efficiently acquire target 3D point cloud data by scanning with high accuracy, speed and no contact. Jin [7] et al. proposed a median normalized vector growth algorithm (MNVG) using ground-based Lidar data, which segmented the corn 3D point cloud data into stems and leaves and extracted the phenotypic information such as plant height, 3D volume, leaf area, and leaf inclination angle. Webster [8] et al. used SFM-MVS motion recovery structure algorithm combined with multi-view stereo vision method based on RGB images and thermal infrared images to generate 3D RGB point clouds and 3D hotspot clouds of individual trees and the whole forest, and distance filtering based on RGB point clouds improved the quality of hotspot clouds. It was found that the forest structural features were accurately resolved in both the RGB and hotspot clouds compared to the radar point cloud, and the thermal features of individual trees and the forest differed somewhat at the canopy structure scale. Xu [9] et al. used the depth camera Kinect-2.0 to reconstruct oilseed rape leaves in three dimensions, and the leaf area was calculated and obtained. With the development of computer vision, the method of acquiring target 3D information based on images is more and more applied to agriculture, the method of fast measurement speed, high accuracy, strong portability, and RGB color information, which fully solves the shortcomings of LiDAR, which is expensive and can not be applied widely.

This study proposes a rapid and non-destructive method for estimating tomato plant height in facility. Image sequences for tomato canopy was acquired by using a truss equipped with a visible light camera. 3D point cloud model was constructed using structure from motion (SFM) and multi view stereo imaging (MVS) algorisms. The point cloud model was then segmented using conditional Euclidean clustering algorithm, and finally tomato plant height was estimated. This study provided a scientific method to monitor tomato growth status dynamically in facility.

II. Materials and Methods

A. Experiment overview

The tomato experiment was conducted in Mulberry Garden Research and Innovation Experimental, Zhejiang Academy of Agricultural Sciences (120°20´E, 30°31´N). Two tomato cultivars ‘Aomeila 1618’ and ‘Zhefen 202’ were transplanted on 16 March and harvested on 20 July in 2023. There were five plots for each cultivar and two rows of tomato in each plot. The plot size was 1 m×2 m. Tomato plants were transplanted at 25 cm distance within the row and 50 cm between rows. Therefore, the plant density was 8 plants/m2.

III. Research Methods

A. Facility tomato image acquisition

Canopy RGB images for facility tomato were achieved every 14 days, starting from the 10 days after transplanting. The RGB images were acquired by a Canon EOS R5 camera mounted on a truss platform (truss-RGB system) (Figure. 1). The camera lens was vertically downward during the shooting, and flat shot was taken for the whole experimental area. The image data were all obtained at noon under sunny days. In the same time, three plants were taken in each plot to measure plant height (i.e. the distance from the soil surface to the top of the plant).

Figure.1 The integrated platform for truss equipped with RGB camera

B. 3D reconstruction

In order to obtain the 3D point cloud model for tomato canopy in the facility, Agisoft Metashape Professional (Agisoft, LLC, St. Petersburg, Russia, version 1.8.3) software was used to process the RGB image sequence. The main principle of this software is the SFM/MVS algorithm, which extracts the key points from the images by the scale invariant feature transform (SIFT) algorithm. Overlapping images were matched according to the key points, and then the sparse point cloud was established, the camera positions and parameters were solved at the same time. The MVS algorithm was used to construct a dense point cloud from the sparse point cloud (Figure. 2).

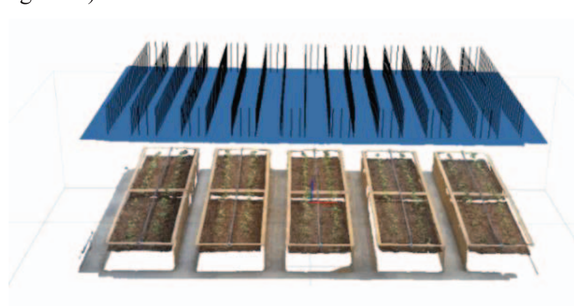

Figure.2 3D point cloud reconstruction for experimental area

C. Point cloud preprocessing

Due to the high density and the noise points for the original point cloud, it is not favorable for subsequent processing. To improve the processing efficiency and guarantee the accuracy, voxel filtering algorithm was used to down sampling, which reduces the number of point clouds without destroying the overall geometric structure of the point clouds, and has no influence on the phenotypic information parameters extraction in the subsequent process. At the same time, in order to avoid the influence of outlying noise points, statistical filter algorithm was used to eliminate them. After filtering, to guarantees the continuity and the normal smoothness of the point clouds, Moving lest squares (MLS) algorism was used to smooth the point cloud [10].

D. Point cloud segmentation

According to the spatial distribution characteristics of the tomato population, the dense point cloud was segmented by the conditional Euclidean clustering algorithm. The background such as soil, ground and planting basket, was eliminated, which means that only the plant part was remained (Figure. 3).

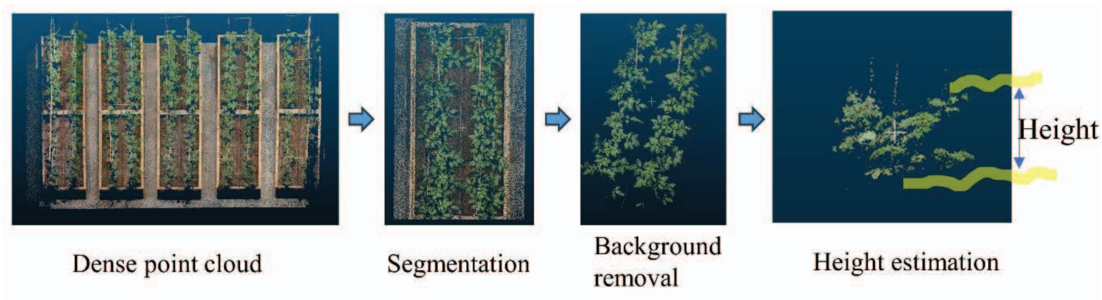

Figure.3 The process of plant height estimation from 3D point cloud

E. Tomato plant height estimation

Plant height is an important parameter to reflect the growth of plants in different environments. Plant height was obtained by subtracting the lowest point ($Y_{\min}$) from the highest point ($Y_{\max}$) in the vertical direction of the 3D point cloud, and then multiply by the scale factor k, which is according to the scale between point cloud size and the actual size:

$$H = (Y_{\max} - Y_{\min}) * k \tag{1}$$

IV. Results and analysis

Data from 10 plots and 6 growing stages were used to estimate the accuracy of plant height. The goodness between the estimated plant height and the true value was assessed by the Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2), which is calculated according to the formulas below:

$$R^2 = \frac{\sum_{i=1}^{N}(x_i-\bar{x})^2(y_i-\bar{y})^2}{N\sum_{i=1}^{N}(x_i-\bar{x})^2\sum_{i=1}^{N}(y_i-\bar{y})^2} \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(y_i-x_i)^2}{N}} \tag{3}$$

Where xi, $\bar{x}$ are the true values and the mean value of the true. yi, $\bar{y}$ are the estimated value and the mean value of the estimated. N is the total number of samples, which is 60. The larger the value of R2 and the smaller the value of RMSE indicates that the deviation between the estimated value from the method and the actual manual measurements is small, and the accuracy is high.

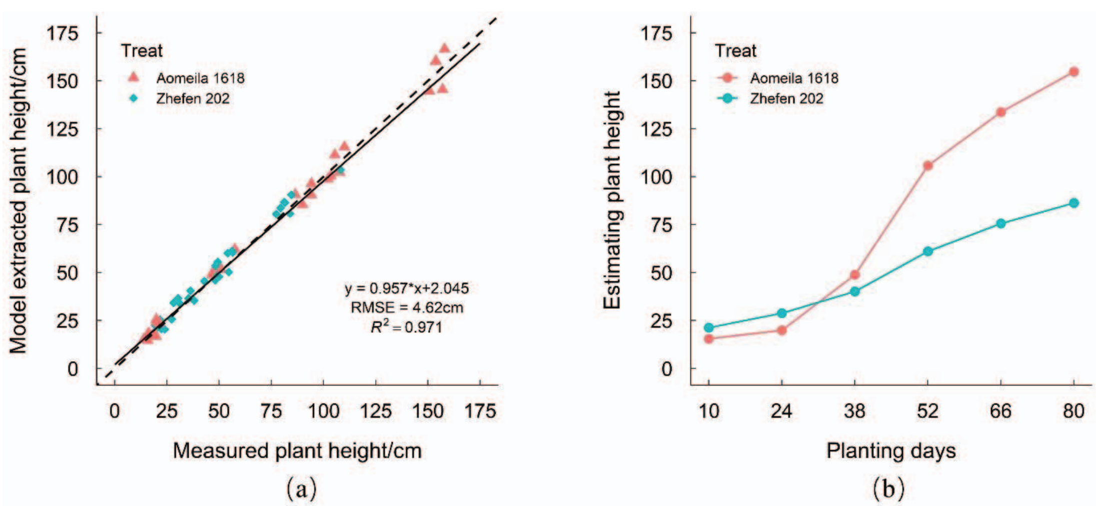

Figure.4 (a) The comparison between estimated and true value for plant height (b) The dynamic of plant height during the growing season.

The comparison between the true value and the estimated value for tomato plant height was shown in Figure 4a. As can be seen from the figure, the RMSE for plant height was 4.62 cm. The coefficient of determination R2 reached 0.971, which indicates that the estimated value has a good consistent with the true value. Based on the image sequences obtained from truss–RGB system, the accuracy of the 3D point cloud, which is generated by SFM/MVS algorithm, was good enough to help estimate tomato plant height. The dynamic of plant height for the two tomato cultivars over the six growing stages was shown in Figure 4b. In the first two stages, the growth rate of tomato for the two cultivars was relatively slow, with a rate of 0.6 cm/day. After the third stage, Aomeila 1618 grew rapidly, with a growth rate of 2-4 cm/day. However, the growth rate of Zhefen 202 was relatively slow, with a rate of 0.8-1.5 cm/day.

V. Conclusions

The truss-RGB system can be used to estimate the plant height of tomato in facility through SFM/MVS algorithm and the conditional Euclidean clustering algorithm. Avoided the limitation of two-dimensional digital images and the shortage of LiDAR, the method in this study guarantees the estimation accuracy of plant height, which is also automatically and more conducive to implement. The system can acquire digital images and extract phenotypes automatically. With the method, manual labour would be reduced, and can be applied to other facility crops. The dynamic of plant height is an important performance for crop growth. This study provides a means for crop breeding and growth dynamic monitoring.

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