Three-Dimensional Reconstruction of Maize Plants and Extraction of Phenotypic Parameters Based On Laser Point Cloud Data

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Three-dimensional reconstruction of maize plants and extraction of phenotypic parameters based on laser point cloud data

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Abstract

Background: Three-dimensional (3D) laser scanning technology could rapidly extract the surface geometric features of maize plants to achieve non-destructive monitoring of maize phenotypes. However, extracting the phenotypic parameters of maize plants based on laser point cloud data is challenging.

Methods: In this paper, a rotational scanning method was used to collect the data of potted maize point cloud from different perspectives by using a laser scanner. Maize point cloud data were grid-reconstructed and aligned based on greedy projection triangulation algorithm and iterative closest point (ICP) algorithm, and the random sampling consistency algorithm was used to segment the stem and leaf point clouds of single maize plant to obtain the plant height and leaf parameters.

Results: The results showed that the R^2 between the predicted plant height and the measured plant height was above 0.95, and the R^2 of the predicted leaf length, leaf width and leaf area were 0.938, 0878 and 0.956 respectively when compared with the measured values.

Conclusions: The 3D reconstruction of maize plants using the laser scanner showed a good performance, and the phenotypic parameters obtained based on the reconstructed 3D model had high accuracy. The results were helpful to the practical application of plant 3D reconstruction and provided guidance for plant parameter acquisition and theoretical methods for intelligent agricultural research.

Keywords: laser point cloud; phenotypic parameters acquisition; three-dimensional reconstruction; point cloud processing

Background

Accurate and rapid acquisition of 3D plant structure information is important for high-throughput phenotypic analysis, visualization and synergistic analysis of plant function and structure [1-3]. With the development of agricultural intelligence, laser scanning technology and its application in agriculture have become one of the hot spots for research [4-6]. Compared with traditional measurement methods, laser technology offers faster measurement, higher accuracy, and fuller digital features [7]. Su et al. proposed a method to extract phenotypic information of maize plants in a field using ground-based LiDAR [8]. Garrido et al. presented a new methodology for georeferenced 3D reconstruction of maize plant structure [9]. There were still problems such as low accuracy, expensive equipment and complicated operation in crop 3D reconstruction research, most field phenotyping platforms could not obtain fine phenotypic traits of single plant, and the recognition efficiency was determined to a large extent by the shading between crops [10]. To obtain a complete 3D reconstruction model of a single maize plant, a rotational scanning method was established in this study, using potted maize as material, to provide a reference for 3D reconstruction and phenotype acquisition of maize plants.

Phenotypic parameters such as plant height and leaf morphology are of great importance in crop morphology studies [11-12]. 3D plant modeling provides a non-

61 destructive means to measure geometric properties and phenotypic parameters of crops
62 and allows studies at the individual organ level [13]. However, aspects such as stitching
63 and segmentation of 3D point cloud data are challenging, especially for maize in the
64 young stage when the young leaves are not yet fully expanded. Based on the above, this
65 paper acquired complete maize point cloud data by a portable laser scanner,
66 reconstructed and stitched the point clouds of single maize plant to obtain phenotypic
67 parameters such as plant height and geometric properties of leaves, then analyzed and
68 compared them with the measured values. The results of the study were suitable for the
69 3D reconstruction of plants with different degrees of complexity and could provide
70 references for 3D virtual simulation of maize and plant phenotype research.
71
72 **Methods**
73 **Experimental design**
74 During the maize growing season in 2019 and 2020, field experiments were conducted
75 at a research site at Yangzhou City, in the lower reaches of the Yangtze River, China
76 (32°39′ N, 119°42′ E). This is an alluvial plain and is one of the primary maize
77 production areas in China. The soil was a sandy loam with pH 6.88 [Typic Fluvaquents,
78 Etisols (U.S. taxonomy)]. The average values of soil properties of the field across the
79 study years were as follows: total N of 1.12g kg^{-1}, available phosphorus of 31.74 mg
80 kg^{-1}, available potassium of 74.43 mg kg^{-1}, organic matter of 23.57 g kg^{-1}, 1.34 g cm^{-3}
81 of bulk density and 0.18 g g^{-1} of field capacity. Climate data across the study years were
82 measured at a local weather station in the field site. The average precipitation, sunshine

hours, and mean air temperature that concerned the entire vegetation period were 125 mm, 193 h, and 25.2 °C in 2019, and 144 mm, 182 h, and 24.6 °C in 2020, respectively. Three varieties Jingkenuo (VA), Huitian 8 (VB) and Zijiaoxi (VC) were used as the research material. The plant height and leaf phenotypic parameters of the three varieties differed significantly, with plant height gradually decreasing from VA to VC. Compared with VA, the leaves of VB were relatively wide and long, and those of VC were relatively narrow and short. Seeds of tested varieties were provided by Yangzhou Seed Company (Yangzhou, China).

Point cloud data acquisition

The point cloud data was acquired using a rotational scanning method with a device consisting of a computer system, scanner equipment and a rotating platform. The scanner (Space Spider, Artec Corporation, Luxembourg) was fixed on a tripod, and the maize plants were fixed on a rotating platform with a speed of 1-2 r/min, then the plants were scanned at 360° using the scanner. The angle between the scanner lens and the plant was in the range of 45° to 60°.

Point cloud alignment and denoising

Point cloud alignment was performed using the Iterative Closest Point (ICP) algorithm, which found the corresponding point pair set between the two sets of point cloud data and calculated the transformation matrix between them by iterating continuously to obtain the matching relationship between the target and source point cloud sets. Each truncated maize plant had two-point cloud outputs. The two acquired point clouds were

104 denoted as point cloud 1 and point cloud 2. The rotation and translation matrices R and
105 T to be solved by the ICP algorithm can be expressed as Eq:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = R \begin{bmatrix} X_i \\ Y_i \\ Z_i \end{bmatrix} + T \quad (1)$$

106 After obtaining the matrices R and T, the next step was to convert each point in
107 point cloud 2 with the current R and T, i.e. point cloud 2 and point cloud 1 to the same
108 3D coordinate system, thus completing the stitching process.

109 Point cloud denoising was performed using an irregular triangular network
110 encryption algorithm, which created a sparse irregular triangular network from seed
111 points, where the number of neighboring points (K=5) of all points within a user-
112 defined search radius r=5 mm, and if less than K neighboring points were found, one
113 point was removed as noise until all invalid points were identified and removed. This
114 method effectively reduced the number of noisy points without losing the true surface
115 points.

116 **Point cloud segmentation**

117 The stem and leaf point cloud of a single maize plant was segmented based on a random
118 sampling consistency (RANSAC) algorithm. The equations are shown below:

119 $$(x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2 = \frac{\left[l(x-x_0)^2+m(y-y_0)^2+n(z-z_0)^2\right]^2}{l^2+m^2+n^2} \quad (2)$$

120 where $(x_0,\ y_0,\ z_0)$ was a point on the cylindrical axis, $(l,\ m,\ n)$ was the direction
121 vector of the cylindrical axis.

122 **Plant parameters extraction**

Define the vertical distance from the junction of the base of the stem with the soil to the highest point of the plant as the plant height, and:

$$H = z_{max} - z_{min} \quad (3)$$

where z_{max} and z_{min} were the z-axis coordinates of the highest and lowest points in the single plant point cloud, respectively.

The leaf length and width were the sums of the Euclidean distances between the leaf skeleton points, and the leaf skeleton model was obtained by extracting the leaf vein points with greater curvature in the triangular mesh model.

The maize blade was divided and firstly triangulated using the greedy projection triangulation algorithm. The blade model after faceting was composed of several spatial triangulation facets, then the area of a single spatial triangulation facet was calculated through the Helen formula, and finally, the area of a single blade was calculated through the area summation formula, which was calculated as follows:

$$S_i = \sqrt{p_i(p_i - a_i)(p_i - b_i)(p_i - c_i)} \quad (4)$$

$$S = \sum_{i=0}^{n} S_i \quad (5)$$

where: p_i was half the perimeter of the faceted triangle, a_i, b_i, c_i were the lengths of the sides of the faceted triangle, *n* was the total number of facets, and *i* was the facet index number.

Plant parameter measurement

The plant height was the shortest distance from the rootstock to the tip of all target plants using a straightedge. The leaf length was the distance from the base of the leaf to the tip of the leaf with a straightedge. The leaf width was the maximum width of the

leaf. The single leaf area was determined using the formula: leaf area = leaf length * leaf width * 0.85. The total leaf area was the sum of the individual leaf areas of the whole plant.

Application of the data set

Linear regression analysis was performed between manually measured data and data extracted through the point could model. A scatter plot of 1:1 was created to test the model fit. The independent data from Experiment 2020 was used to test the line equations by comparing the differences in the estimation accuracy with the coefficient of determination (R^2) and root mean square (RMSE). R^2 and RMSE were calculated using Eqs. (6) and (7), respectively:

$$R^2=\frac{\sum_{i=1}^{n}(x_i-\bar{x}_i)^2\times(y_i-\bar{y}_i)^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2\times\sum_{i=1}^{n}(y_i-\bar{y}_i)^2} \quad (6)$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(y_i-x_i)^2}{n}} \quad (7)$$

where x_i, $\bar{x}$, y_i, $\bar{y}$ were the measured value, the mean of measured values, the predicted value, and the mean of predicted values, respectively, *n* was the number of measurements.

Results and analysis

Crop 3D reconstruction based on point cloud data

Point cloud triangulation

The results shown in Fig. 1 (b, d) were based on the greedy projection triangulation algorithm to reconstruct the point cloud data on a grid. The results showed that the algorithm used could effectively complete the grid reconstruction of the plant point

166 cloud data, and lead to good reconstruction results.

167 ***Point cloud splicing***

168 Due to the great height of the maize plants after the elongation stage, it was difficult to
169 use the laser scanner to acquire all the plant point cloud data at once, so the plants
170 needed to be truncated and acquired segmented, and then the segmented point clouds
171 needed to be spliced together. Fig. 2 showed the splicing effect of the 3D point cloud
172 splicing of truncated maize plants. As the figure showed, the point clouds obtained
173 under the rotating platform were completely spliced of the maize plants. Since the three
174 varieties exhibited a similar splicing effect, that of VB was only presented for
175 conciseness.

176 ***Point cloud segmentation***

177 Fig. 3 showed the 3D point cloud and plant conformation segmentation results of maize
178 plants, where individual leaf skeletons are visualized with random colors. The leaf
179 visualization of the 3D model represented a maize leaf *in vivo*, and the segmentation
180 results of individual leaves matched well with the maize plants in real growth conditions.
181 The results showed that the organ segmentation method used in this study could
182 effectively extract each leaf from the 3D point cloud of the maize plant.

183 ***Plant leaf midrib fitting***

184 The stems were extracted according to the random sampling consistency algorithm
185 mentioned above, and then each leaf was separated by using the Euclidean clustering
186 algorithm. This fitting was done with three different maize varieties (VA, VB, and VC).
187 Fig. 4 showed the dense point cloud (a-c), skeleton (d-f), and leaf midrib (g-i) of the

reconstructed maize plants at the growth stage of 35 days after seedling emergence. Leaf midrib of different leaves was represented by different colors, and the leaf blade midrib was accurately fitted by using the method of this study.

Phenotype parameter extraction and accuracy analysis

Plant height extraction and accuracy analysis

The model accuracy was verified by comparing the predicted plant height extracted by the model and the measured plant height. As shown in Fig. 5, there was a good correlation between the predicted and measured values, and for all three varieties R^2 was greater than 0.95. The R^2 and RMSE were 0.969 and 2.718 cm for VA, 0.954 and 2.994 cm for VB, and 0.967 and 2.732 cm for VC, respectively. The R^2 and RMSE were 0.964 and 2.818 cm for three varieties together. This indicates that the method used in the present study could represent the plant height *in vivo*. Since the method was not sensitive to varieties, the leaf phenotypic parameters were no longer analyzed separately for varieties.

Extraction and accuracy analysis of leaf phenotypic parameters

Taking a maize plant 25 days after emergence as an example, and at this time, all six spreading leaves of the plant were visible. As shown in Fig. 6, the predicted and observed values of leaf length, leaf width and leaf area showed highly significant positive correlations. The average R^2 and RMSE of tested varieties were 0.938 and 2.596 cm of leaf length, 0878 and 0.273 cm of leaf width, and 0.956 and 4.494 cm^2 of leaf area respectively. Although the edge of the leaf is poorly reconstructed in the process due to the long and slender leaf tip of maize leaves, it could still provide a

reference for obtaining phenotypic parameters based on the point that could reconstruct plants.

Discussion

With the development of 3D scanning equipment and 3D reconstruction technology, 3D scanning technology finds a wide range of applications in various aspects of agricultural production research, especially in crop 3D reconstruction and phenotype research [14]. Reik *et al*. developed a multi-scale method using airborne laser scanning data with point densities to determine the number and vertical extent of canopy layers [15]. Gaillard *et al*. used a laser scanner combined with a movable measuring arm to acquire 3D point cloud data of barley to achieve organ-specific growth monitoring of barley plants [16]. Tsoulias *et al*. mounted a laser scanning system on a tractor to obtain the 3D structural parameters of apple trees [17]. Chang et al. developed a method for detecting sorghum spikes using unmanned aerial vehicle (UAV) images to extract 3D point clouds, and the results showed that the correlation coefficients between the spike length and width measured by the UAV and those measured on the ground were 0.61 and 0.83, respectively [18]. In the above-mentioned studies, either the accuracy of the data obtained was not high or the equipment was too expensive for most researchers to afford. These studies were suitable for high throughput acquisition of phenotypic data under field conditions. However, for some indoor experiments requiring higher precision analysis of phenotypic properties, particularly in plant breeding programs, the present study provided a feasible solution. Field maize or other crops could also be reconstructed by the method established in this study.

Although the 3D reconstruction of plants based on laser scanning data had high accuracy, there were still many drawbacks due to the movement of instruments and human factors during the scanning process, and the use of laser scanners to obtain high-precision 3D models of plants required obtaining point cloud data from different angles [19-20]. When performing point cloud data acquisition, plant shaking during acquisition due to the exposure of the scanner's lens exposure or the rotation of the turntable could cause the loss of point cloud data, resulting in the degradation of the quality of the grid generated later [21]. In the present study, the lens was fixed to avoid the loss of accuracy caused by the movement of the lens, and the platform rotated slowly to ensure the integrity and accuracy of the point cloud acquisition.

In this paper, we achieved 3D reconstruction of maize plants through the processes of point cloud data acquisition, alignment, denoising, and segmentation. In addition to the point cloud information, we also obtained information on the color and texture of the plants, which could be very useful for analysis of plant properties related to crop nutrition, disease or yield, which will be focused on in the future. The collection of plant point cloud data using laser scanners were insufficient in the large-scale automated measurement of phenotypic information, so the studies of algorithms for automated acquisition of phenotypic information were one of the next steps. This could be done by means such as adding a robotic arm, or by proposing a deep learning framework to acquire object point cloud data from multi-view images for 3D reconstruction, which in turn improved the reconstruction efficiency [16, 22].

The 3D model of maize plants obtained from laser point cloud 3D reconstruction

had a high reconstruction accuracy and could describe the plant structure and characteristics in detail, meeting the requirements for accurate measurement of plant phenotypic data. In this study, the correlation coefficients between the predicted values and observed values of plant height, leaf length and leaf area were above 0.93, and the correlation coefficient of leaf width reached 0.87 (Fig. 5 and 6). Compared with the conventional leaf area measurement method (length times width times factor), the leaf area measured in this study has theoretically higher accuracy and no damage to the plant. In addition, it was convenient to collect point cloud data by a laser scanner, but the subsequent processing consumed some time. With the development of graphics processing unit computing, the post-processing time was greatly reduced, but it still could not meet the need for real-time reconstruction. With the rapid development of simultaneous localization and mapping technology, a more efficient reconstruction algorithm would become a hot spot for future research.

Conclusion

We proposed a 3D reconstruction method for maize plants based on laser point cloud data, which effectively reconstructed the detailed features of the plants and accurately reflected the plant morphology. Through the iterative closest point algorithm and the random sampling consistency algorithm, the point cloud data were aligned and segmented to further improve the maize 3D reconstruction model. The plant parameters obtained by the reconstructed model showed high consistency with the observed values, which could provide a reference for obtaining phenotypic parameters based on the reconstructed plants.

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Not applicable for that section.

Authors' contributions

Conceptualization, CJ and CS; methodology, TL and XZ; software, FW and TY; formal analysis, YZ and RL; data curation, YZ and TY; writing—original draft preparation, FW and RL. writing— review and editing, CJ and FY. All authors were involved in preparing and revising the manuscript.

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Availability of data and material

All data analyzed during this study are presented in this published article.

Declarations

Ethics approval and consent to participate

Not applicable for that section.

Consent for publication

All authors have seen the manuscript and approved to submit to your journal. All authors agree to publish.

Competing interests

The authors declare that they have no competing interests.

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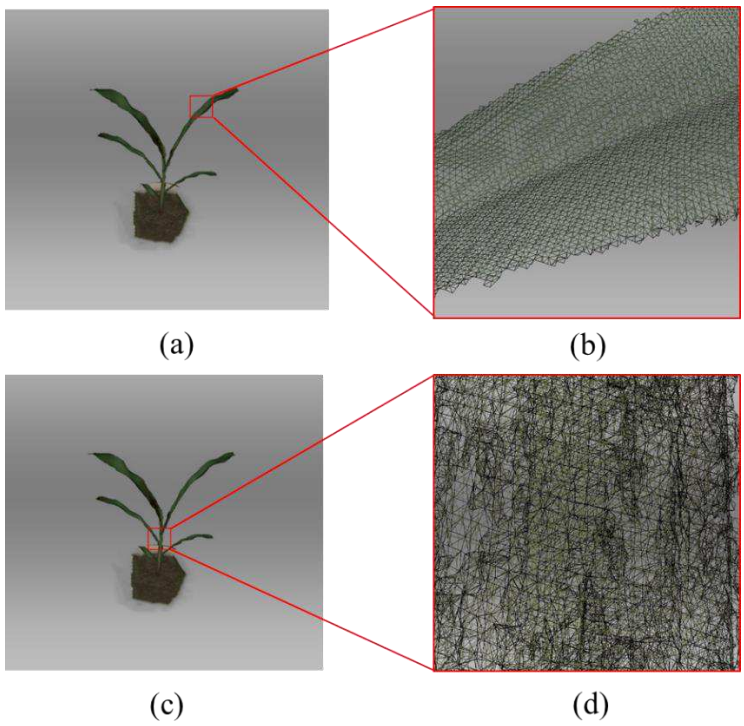

Fig. 1 Leaf (a-b) and stem (c-d) mesh effect based on greedy projection triangulation algorithm

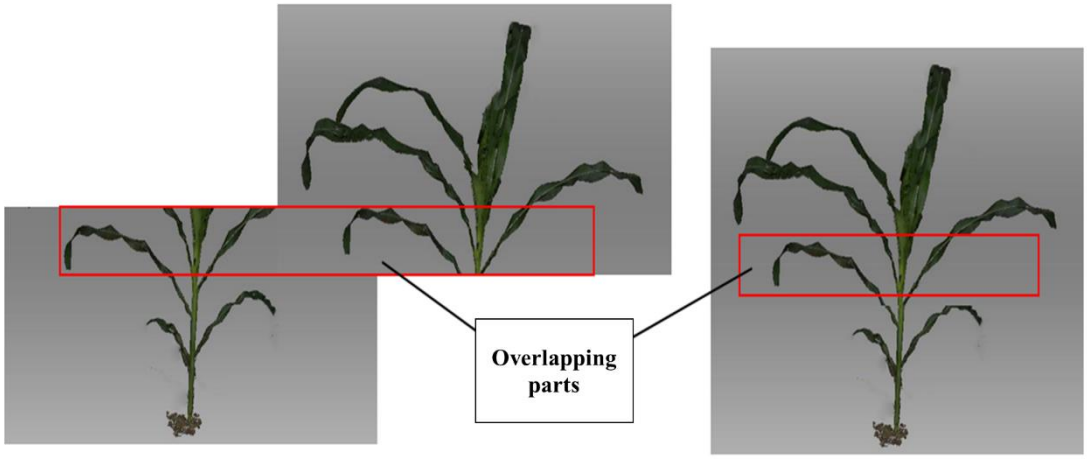

Fig.2 Reconstruction of point cloud splicing of truncated maize plants

Fig. 3 Maize three-dimensional point cloud segmentation

(a) Maize plant point cloud, (b) Stem point could, (c) Leaf point cloud, (d) Single leaf point cloud

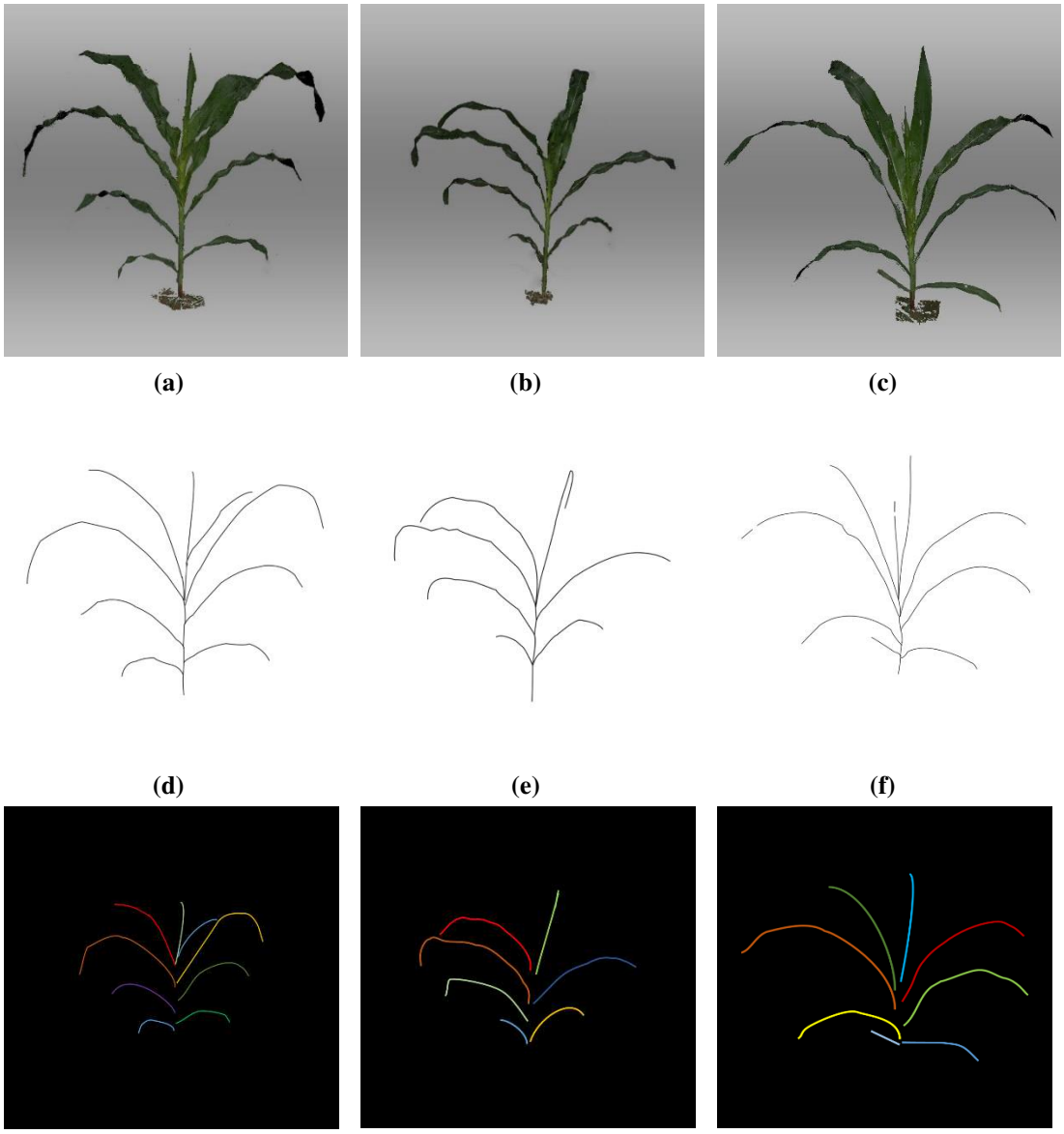

Fig. 4 Dense point cloud (a-c), skeleton (d-f), and leaf midrib (g-i) of maize plants (a, d, g) VA, (b, e, h) VB, (c, f, i) VC

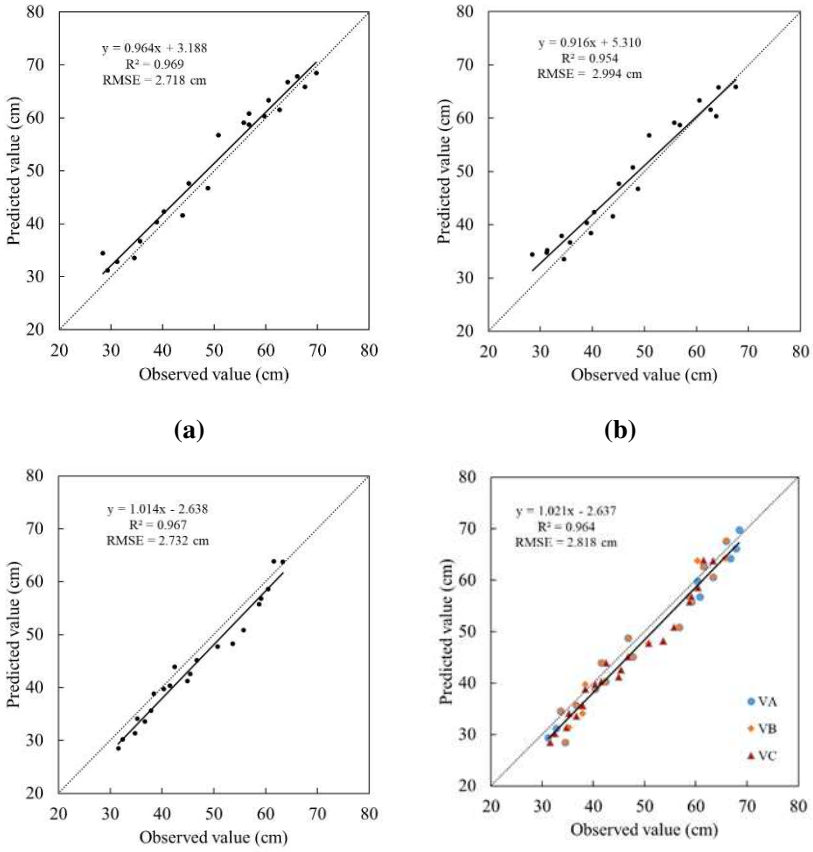

Fig. 5 Precision analysis of maize plant height of VA (a), VB (b), VC (c) and three maize varieties (d)

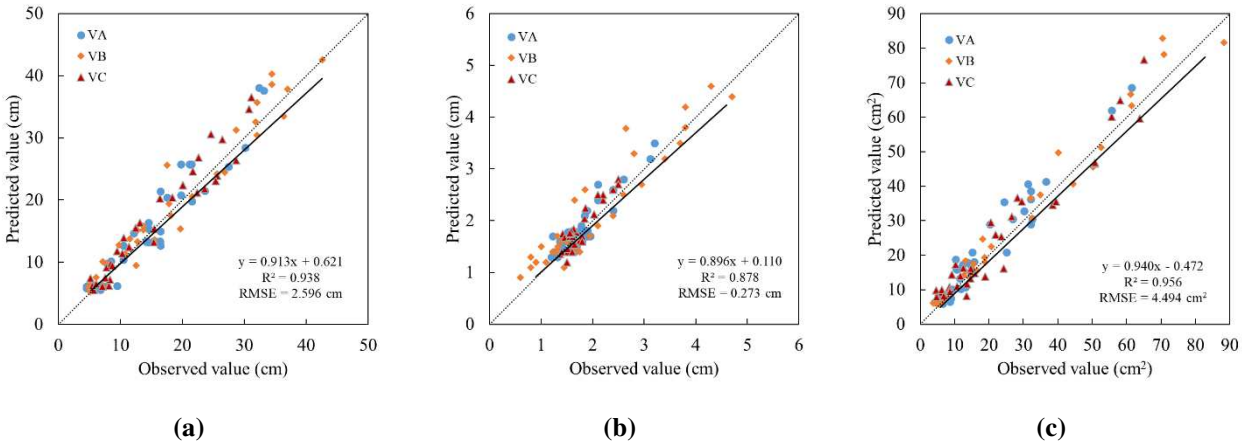

Fig.6 Analysis on the precision of phenotypic parameters of leaf length (a), leaf width (b) and leaf area (c) of three maize varieties