High-throughput analysis of maize azimuth and spacing from Lidar data

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Abstract: Efficient leaf azimuth angles and plant spacing are crucial for enhancing light interception efficiency in maize, thereby increasing yield per unit area. Traditional methods for measuring these traits are labor-intensive and prone to error. This study aimed to develop an accurate and efficient method for determining leaf azimuth angles and plant spacing in maize to improve understanding of field competition and support breeding programs. Utilizing light detection and ranging (Lidar) technology, 3D point cloud data of maize plants were collected, enabling effective 3D morphological reconstruction through multi-frame stitching. Principal component analysis (PCA) was employed to determine the leaf azimuth angles of individual maize plants. Additionally, a method based on point density analysis was developed to identify the central axis position of single maize plants. Specifically, point density in the neighborhood of each point in the maize point cloud was calculated, with the central axis determined along the direction of highest point density. The integration of PCA-based leaf azimuth detection and point density analysis provided a robust framework for accurately determining leaf azimuth angles and plant spacing. In the detection of leaf azimuth angles, this method achieved an R^2 of 0.87 and an RMSE of 5.19°. For plant spacing detection, the R^2 was 0.83 and the RMSE was 0.08 m. This approach facilitates parameterized modeling of field competition, significantly enhancing the efficiency of breeding programs by providing detailed and precise phenotypic data. Despite the high accuracy demonstrated by the proposed methods, further investigation is needed to evaluate their effectiveness under varying environmental conditions and across different maize varieties. Additionally, challenges related to partial occlusions and complex canopy structures may impact the accuracy of point cloud data analysis, necessitating further refinement of the algorithms.

Keywords: Lidar, maize azimuth angle, 3D point cloud, principal component analysis
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1 Introduction

In China, maize is the primary edible material and a highly used cash crop. It occupied a key position in the international agricultural trading market. Timely, accurate and detailed information on crop growth and development as well as dynamic monitoring data during the growth period are an important part of implementing crop yield management and timely regulation[1]. Maize is a monocotyledonous plant, its leaves are directional. In the middle and late stages of growth, leaf cross-shading will affect the efficiency of photo-synthesis. Phenotypic parameters such as plant spacing, row spacing and leaf growth direction are important for maize yield[2,3]. Maize phenotypic traits, especially plant growth azimuth and plant spacing, have a wide range of applications value for improving crop yield. Moreover, the growth azimuth of maize leaves is closely related to photosynthesis rate, and it can effectively serve as a phenotypic parameter for crop competition in the field[4].

In recent years, computer vision technology has advanced quickly in intelligent agriculture[5,6]. Currently, RGB images with features such as low cost and convenience are mainly used to analyze maize biomass, leaf morphology, and cob traits[7,8]. However, in real fields, the RGB images which acquired through a single perspective contain a limited amount of information. Maize plants usually have complex growth patterns and heavily overlapping leaf shading. The information on plant morphology that can be used for analysis is incomplete when obtained through RGB images. Three-dimensional data can provide more detailed and comprehensive plant phenotype information than RGB images[9]. Therefore, the advent of 3D digitizing technology has greatly facilitated the study of 3D structural modeling of crops[10,11]. Unfortunately, 3D digitizing technology requires physical contact and interaction with the plant during data collection, which can disturb the plant and the measurement process tends to be time-consuming.

With the rapid development of Lidar sensors, collecting 3D point cloud data of plants by Lidar and conducting phenotypic studies has become an effective means to obtain plant morphological and structural phenotypes in high throughput[12]. Lidar sensors can obtain 3D information of crops instantly, accurately and on a large scale, and they are an important technological tool for monitoring the growth status of crops. Michael et al.[13] measured canopy height of maize and wheat using ground-based Lidar scanning technology in the field. And then the growth pattern of canopy height over time was analyzed by these measurements. Jin et al.[14] used Lidar to collect maize point clouds, and proposed a median normalized-vector growth (MNVG)

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algorithm, which can segment stem and leaf with four steps, i.e., pre-processing, stem growth, leaf growth, and post processing. Gao et al.[15] combined seedling detection and clustering algorithms to segment single maize plants from UAV airborne Lidar and RGB images. Digital orthophotography of maize seedlings was used to locate individual maize plants and calculate maize plant height. Zhou et al.[16] acquired RGB images of maize plants using a downward photography approach using ground vehicles and UAVs, and they obtained several plant parameters characterizing the maize seedling stage from the RGB images. The principal component analysis (PCA) is used to determine the direction of the principal axis of the maize-seedling skeleton. The principal axis is then introduced as a reference to identify the direction angle of the plant in binary images. Using 3D reconstruction and skeleton extraction, Lei et al.[17] calculated the leaf base angles and inclination angles by extracting geometric features from the entire point cloud and skeleton. A phenotype extraction method using end-to-end segmentation networks from a top-view image of maize seedlings was proposed by Li et al.[18] that automatically retrieved phenotypic data, including maize canopy cover and plant azimuth plane angle. Lin et al.[19] created a field maize organ hierarchy model using data collected from point clouds of maize plants using terrestrial Lidar. They used the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering algorithm for individual segmentation of maize in the field, and used the multi-conditional identification method to separate various maize organs from the point cloud. Sheng et al.[20] used Laplace algorithm and adaptive algorithm for skeleton extraction of three varieties and 24 different growth stages of maize. The proposed approach successfully generates accurately extracted skeleton from 3D point cloud and estimate phenotyping parameters with high precision of maize plants (leaf length, leaf inclination angle, leaf azimuthal angle and plant height). Su et al.[21] used terrestrial Lidar to study maize phenotype dynamics under drought stress. They collected Lidar data at six growth stages using a FARO Focus3D X120 scanner from five fixed positions around the maize, at a height of 1.5 m. High-reflectance target balls were used for accurate point cloud registration. Lei et al.[22] investigated the effect of leaf occlusion on maize leaf area index (LAI) inversion using UAV- Lidar data. Data were collected on 28 August and 14 September 2018 with a Riegl VUX-1 sensor flown at 15 m above ground at a speed of 3 m/s. The scanning frequency was 550 kHz, with a spot diameter of 0.0075 m and an average ground point distance of 0.0239 m. The data were acquired using pendulum scanning, and point cloud density and incidence angles were consistent across both dates. Jin et al.[23] used terrestrial Lidar to estimate maize biomass non-destructively. In 2018, they used a FARO Focus3D X 330 HDR scanner mounted on a tripod, collecting data from 10 m×10 m plots and individual plants. In 2019, the same sensor was mounted on a high-throughput phenotyping system called Crop3D, which moved on tracks to cover larger areas. Data were collected in "Helical Mode" for higher efficiency, allowing for detailed phenotypic trait extraction at various levels, including plot and individual plant. Drouet et al.[24] demonstrated that the maize plant leaves' growth-related azimuth shift led to a more dispersed distribution of leaves in the plant's top leaf position without a discernible trend to move the distribution between rows. The phenomenon of azimuth shift of plant leaves during growth causes the canopy structure of maize populations to change over time[25,26]. At present, the research about leaf azimuth during maize growth is not deep enough and the conclusions still vary widely. Thus, there is a need for further research on leaf azimuth during maize plant growth through improved monitoring and analysis methods.

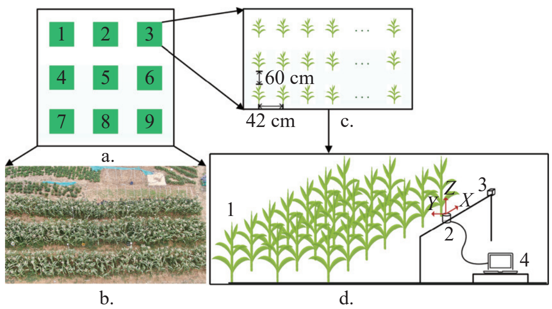
This study aimed to develop an automated method for determining maize growth parameters from multi-temporal 3D point cloud data. A new method is proposed to automatically determine maize growth azimuth and central axis based on multi-temporal point cloud data using principal component analysis (PCA). Laser scanning was first performed to acquire 3D point clouds of maize plants from different time points in the field. After cropping the point clouds using a region of interest, Gaussian mixture modeling was applied to stitch the fragmented point clouds back together. Individual plant segmentation and outlier removal were then conducted on the stitched point clouds. The key innovation lies in using PCA and point density method to extract the azimuth information from 3D point clouds.

2 Materials and methods

2.1 Study area and data acquisition device

2.1.1 Study area

The experiment was carried out from April to June 2022 at the experimental farm located in Baohe District, Hefei City, Anhui Province (31°N, 117°E). The maize was planted into nine plots with a plot spacing of 0.5 m. Nineteen plants were planted on each row with a plant spacing of 0.3 m to 0.8 m, for a total of fifteen 13 m long rows. Point cloud data were acquired on June 8, 2022 at 5 pm using a High-resolution Lidar. This Lidar collects point cloud data at the pixel level based on the Time of Flight principle, with up to 1 500 000 points collected per second and a 45° horizontal×25° vertical field of view. Data collection took place during daylight hours in calm weather conditions to prevent shadows and target motion effects. Communication for data acquisition was conducted via Ethernet. Besides using Lidar to gather plant data, manually measured plots on the ground were also utilized for validation purposes. The experimental layout is illustrated in Figure 1.



a. Plots 1 through 9 the experiment area and nine plots; b. Picture of the experiment site; c. An enlarged view of a plot and its planting; d. Data acquisition process diagram: 1. Maize plant of field, 2. 16-line Lidar, 3. Slide sensors, 4. Laptop.

Figure 1 Sketch of the field experiment

2.1.2 Data acquisition

The point cloud data acquisition system consists of a 16-line Lidar (Velodyne VLP-16, Velodyne Lidar, Inc., San Jose, USA), a slide rail, and a radar mount. The slide rail device includes of a sensor and a 1-meter-long aluminum track, with the Lidar mounted on the slide rail located south of the experimental area. The radar mount is equipped with two liftable tripods, allowing the system to capture point cloud data at various heights steadily and clearly. The Velodyne VLP-16, a commercial product renowned for its reliability and high performance, is utilized in this study. Table 1 is a summary of the key specifications of the VLP-16 Lidar.

Table 1 Performance parameters of VLP-16 Lidar

Specifications	Parameters
Laser line number	16
Measurement accuracy	±3 cm
Field of view (Vertical)	30°
Field of view (Horizontal)	360°
Measuring range	0.5-100.0 m

For the data acquisition process, the Lidar was mounted on the slide rail, which was positioned parallel to the rows of maize. The slide rail enabled the Lidar to move horizontally along the length of the rail, facilitating the acquisition of point cloud data. For each of the nine plots, the Lidar was placed at one end of the plot and moved horizontally along the rail to scan the entire plot. This procedure was repeated for each plot. The Lidar was oriented perpendicularly to the ground, ensuring a comprehensive vertical scan of the maize plants from top to bottom.

2.2 Overall process flow for calculating growth azimuth and plant spacing

This study proposed a PCA-based method to calculate the growth azimuth of maize plants. Furthermore, a local maxima-based approach is developed to precisely determine maize plant spacing and row spacing. Through these newly developed methods, leaf azimuth and plant spacing for maize can be efficiently determined.

The first step was using 16-line Lidar to capture the original 3D point cloud of maize. Then, in order to obtain 3D data of maize plants in the area, a uniform data file type and pre-processing operations like cropping and stitching of the 3D point cloud were used. This prevented the large amount of redundant data generated by the Lidar scan and the interference of multiple types of data storage, as well as further improved the speed of data processing. The 3D data of maize plants in the region were manually cropped based on this to produce point cloud data of single corn plants. To reduce the influence of multiple data on the accuracy of the growth azimuth of maize plants, PCA was employed to measure the growth azimuth of single maize plants. Furthermore, structural information such as plant spacing and row spacing were determined using the maximum local approach based on an exact calculation of maize plant growth's azimuthal angle. In the last step, the effectiveness of the method described in this study was verified using linear regression analysis of generated and measured phenotypic data. Figure 2 shows the flow chart for calculating maize plants' leaf azimuth and spacing.

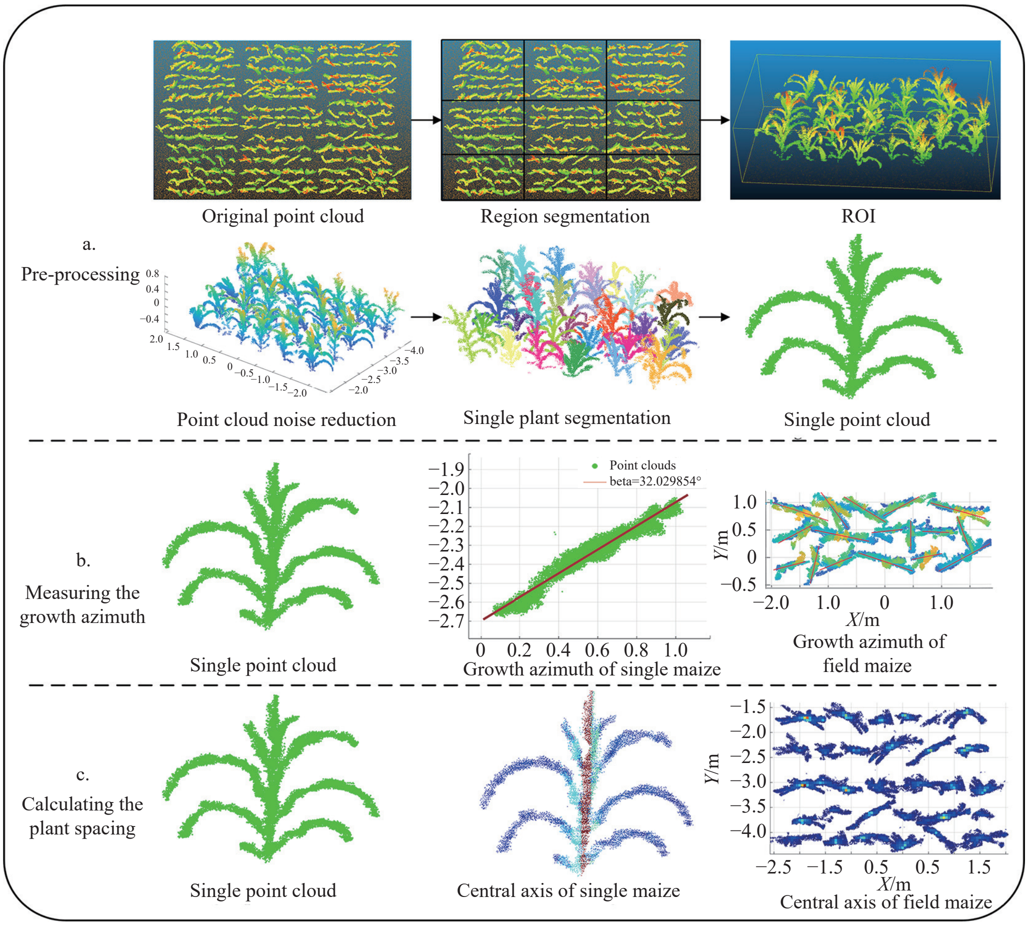


Figure 2 Flow chart for calculating the azimuth and spacing of maize plants

2.3 Data pre-processing

The point cloud data obtained by high-resolution Lidar contains a significant amount of ground and field information, necessitating preprocessing to isolate the maize plants. Initially, the point cloud data is cropped to remove irrelevant information by defining the spatial range of the target plants and discarding points outside this range. During this cropping stage, ground data is removed based on depth information, excluding points identified as belonging to the ground.

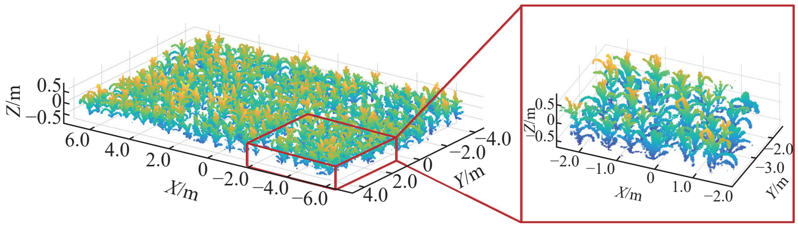
The region of interest (ROI) is established according to the experimental settings, specifying the sections of the experimental cornfield where the study is focused. Point clouds falling outside this ROI are considered invalid and deleted. Once the ROI data is obtained, redundant information is removed using statistical filtering to eliminate noise and outliers. The specific steps are as follows:

1) Calculate the average distance (d_i) of each point to all K-neighborhood points;

2) Calculate the mean (μ) and sample standard deviation (σ) of the distance container of the whole point set;

3) Compare the distance threshold with the distance of each point in turn, and the points that satisfy $d_i - \mu > k\sigma$ (where k is an empirical parameter) are marked as outliers and removed.

Following this process, the remaining point cloud data is free from ground points, noise, and redundant information. This refined data is used for further analysis (Figure 3). By providing detailed steps of the preprocessing procedures, this description ensures clarity and reproducibility of the methods used.



a. Raw data b. Data clipped in region of interest

Figure 3 Point cloud data clipped in region of interest from the raw data

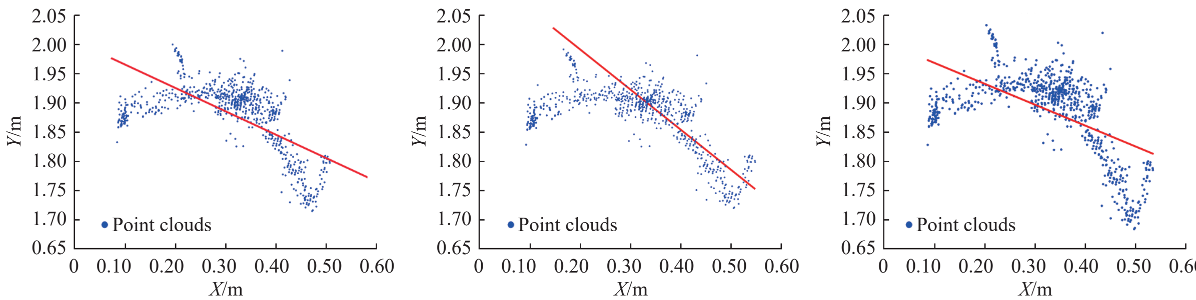
2.4 Splitting single plants to measure plant azimuth

The azimuth of maize growth is crucial in determining how maize plants grow their leaves[27]. With the development of maize, all the unfolded leaves will move toward and be uniformly distributed along a plant azimuthal plane. The azimuth of the maize is the angle formed by this plane and the direction of the planting row. The point cloud data can be projected in two dimensions to depict better the plant azimuthal plane and the growth azimuth angle. This study evaluates three commonly used methods for assessing the azimuth of maize growth azimuth from point cloud data (Figure 4): principal component analysis (PCA), random sample consensus (RANSAC) and least squares (LS). PCA projects the multi-dimensional cloud into a linear subspace, with the primary component representing growth azimuth. The steps for PCA are as follows:

Step 1: First, transform the point cloud data into a matrix with 3 columns and n rows. Calculate the centroid of the point cloud. The centroid calculation formula is as follows:

$$\text{Centroid} = \frac{1}{n}\sum_{i=1}^{n} P_i \tag{1}$$

where, P_i represents the coordinates of each point, and n is the number of points in the point cloud set.



a. PCA b. RANSAC c. LS

Figure 4 Three methods for determining maize growth azimuth

Step 2: Decentralize the point cloud data. Specifically, perform zero-mean normalization on each row of P, subtracting the mean of the row from each data point within the row to obtain a new matrix P'.

Step 3: Compute the covariance matrix C of the new matrix P', as shown in the following equation:

$$C = \frac{1}{n-1} P'^{\mathrm{T}} P' \tag{2}$$

Step 4: Calculate the eigenvalues and eigenvectors of the covariance matrix C. The eigenvector corresponding to the largest eigenvalue represents the direction of the principal component, which is the direction of the growth azimuthal plane.

RANSAC iteratively estimates model parameters from random subsets, while least squares finds the azimuth minimizing residual errors. To compare the methods, fifteen maize plant datasets are collected for a rotation experiment. The plant azimuth fitted by each algorithm are compared against manually measured values to analyze error plots (Figure 5).

Due to the point cloud data of maize plants being collected from different angles using Lidar, there would be varying degrees of missing data points. The point cloud data of maize plants whose growth azimuth angle is 90° suffers the most data loss, hence the largest errors of the three algorithms occur in this case. The results showed that PCA achieved the smallest error range of 2.0°-9.5° among the algorithms and demonstrated the most stable accuracy across angles. PCA achieved the highest fitting accuracy of R^2=0.87 for modeling growth azimuth, with RMSE of 5.19°. PCA yielded the minimum error in determining growth azimuth for point clouds

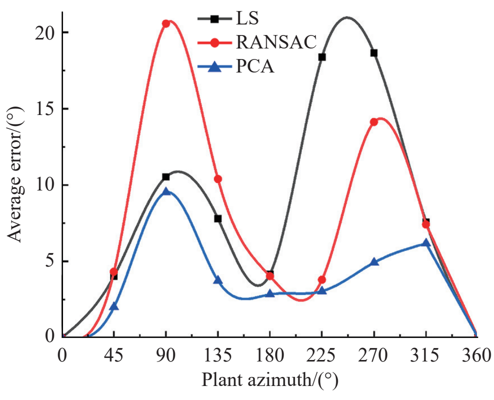


Figure 5 Error plots of the three methods

containing missing data, exhibiting optimal precision and stability. Therefore, PCA was selected for computing the growth plane in this research.

2.5 Maize plant spacing measurement

The location of individual maize stalks is determined by calculating the number of points in the projected point cloud area of the maize plant in a large field. Then, the plant spacing is calculated by calculating the plant spacing and row spacing of the maize in the field from the relative positions of the individual maize stalks.

The point cloud data are first gridded to ensure that each grid has a point cloud with a certain amount of data within it. The size of each small grid is a set fixed parameter. The total number of grids is calculated by counting how many grids have projection points in them. The number of point clouds within each grid is also calculated to obtain the coordinates of the grid area with the largest point density. The coordinates of this highest density grid area represent the location of the maize stalk. Colors are then assigned to the points within the largest grid area to distinguish the maize stalk position (Figure 6).

After determining the central axes of the maize plants, the plant spacing is then calculated based on the average distance between all plants.

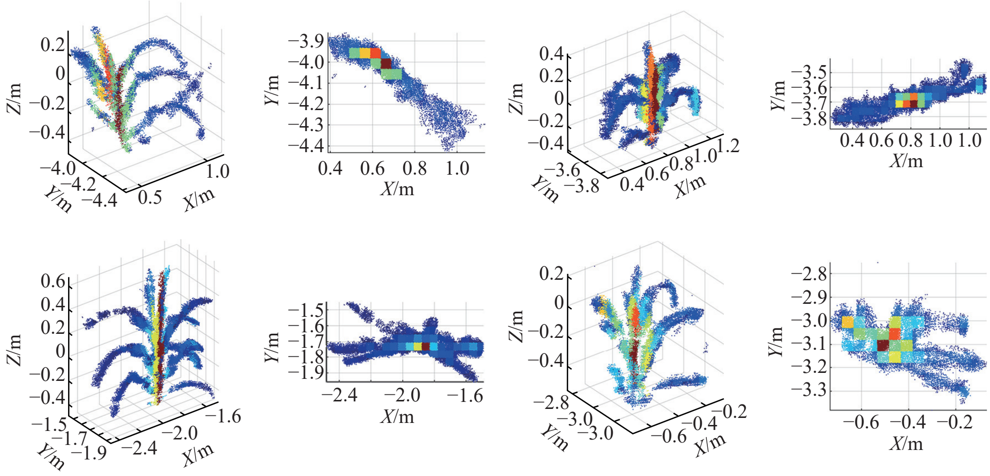


Figure 6　Stalk position of maize by point density method

3 Analysis and discussion

This study aimed to use point cloud data for growth azimuth discrimination and spacing calculation of maize and to determine the growth direction of maize plants in the field. This study is achieved by the method, which determines the plant leaf growth azimuth by projecting the maize plant point cloud data as two-dimensional data and determining its PCA principal axis azimuth. However, accurate validation using the point cloud data method is challenging. Although the PCA can obtain more stable leaf growth azimuths, another validation method: i.e., manual observation is chosen.

3.1 Results and analysis of leaf azimuth discrimination based on PCA

First, single plant point cloud data needs to be obtained to determine the leaf azimuth of maize plants. The point cloud data of maize plants in the ROI area are manually segmented into single plants. Some of these single plant point cloud data are incomplete due to environmental factors during field collection. After acquiring the separated single plant data from the field, methods are applied to calculate the leaf growth azimuth of the plants and determine the location of the plant growth azimuth axis (Figure 7).

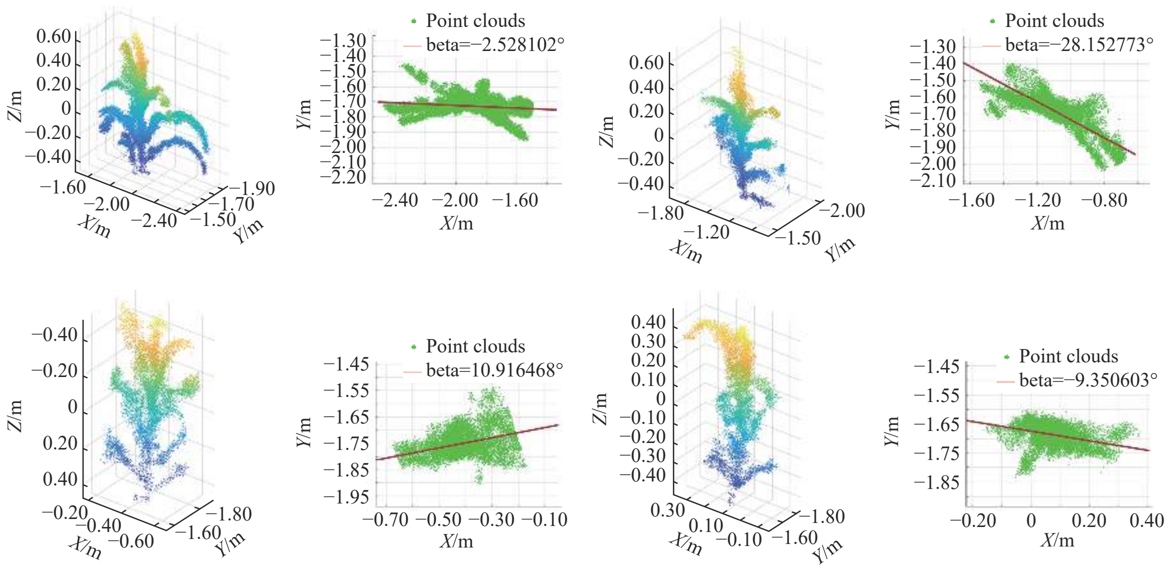


Figure 7　Calculation of maize growth direction angle by PCA

To evaluate the accuracy of our method, we calculated the leaf growth azimuth for each segmented plant using principal component analysis (PCA). The results indicate that the proposed method achieves a high degree of accuracy, with an R^2 value of 0.87

and a root mean square error (RMSE) of 5.19°. Figure 8 shows a scatter plot comparing the measured azimuth values against the predicted values, highlighting the strong correlation between the two sets of data.

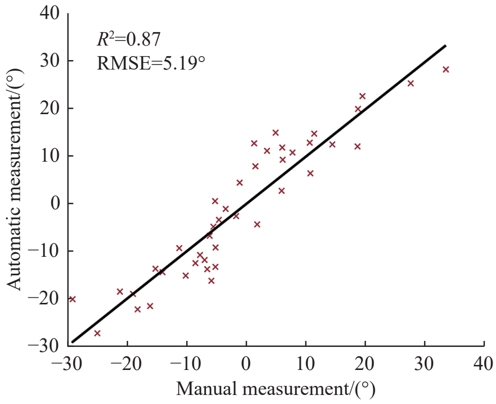


Figure 8 Relationship of manual vs automatic measurements compared

3.2 Results and analysis of calculating maize plant spacing

To evaluate the effectiveness of the maize plant spacing calculation method based on stalk positions, this study used manual measurement and computational methods to measure maize leaf azimuth in the field, and compared and analyzed the measurement values from the two methods. Specifically, the manual measurement values were obtained through in-field measurement using tools such as tape measures, while the calculated values were derived through the projected point density method. The calculation method shown in Section 2.5 was used to calculate the number of maize plants in the nine groups of fields.

The comparison results, as illustrated in Figure 9, demonstrate that the proposed method closely aligns with the manual measurement results. The analysis of plant spacing shows a strong agreement between the two methods, further validating the accuracy of the computational approach.

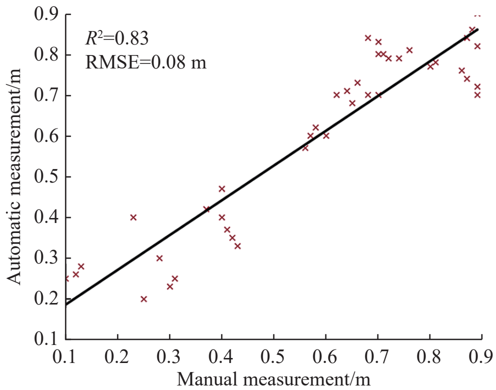


Figure 9 Relationship of manual vs automatic measurements compared

4 Discussion

A new method for determining the growth azimuth and plant spacing of maize plants using Lidar point clouds is described in this study. In the test area, maize plants were densely distributed, and as they grew, their leaves intertwined and tended to overlap, particularly in the later stages of growth. The technique for determining plant growth azimuths using PCA enables the nondestructive detection of the growth azimuths of 255 maize plants in the experimental area.

Comparing our results with existing literature, He et al.[28] utilized UAV imagery combined with deep learning algorithms to accurately detect the leaf azimuth angle of maize at different growth stages, achieving an RMSE of 6.1°. He's study, which developed the Swin-Roleaf tool incorporating Swin Transformer and Circular Smooth Label for detecting oriented bounding boxes (OBBs) of maize leaves, demonstrated a high correlation between the system-derived leaf azimuth angles and ground truth. This approach significantly improved the efficiency of measuring leaf azimuth angles compared to traditional manual methods.

While He's method is innovative and effective, it has certain limitations. The UAV-based image analysis can struggle with precision in dense and overlapping plant structures. In contrast, our Lidar-based approach not only achieves a superior RMSE of 5.19°, indicating higher accuracy, but also offers enhanced precision in handling dense and complex plant architectures. The quantitative detection accuracy expressed as coefficient of determination and root mean square error is presented in Table 2. By leveraging Lidar technology, the method of this study overcomes some of the challenges associated with UAV-based imagery, providing a more robust and accurate solution for analyzing maize plant architecture.

Table 2 Detection accuracy of the distance between two maize plants under different conditions

Measured parameters	R^2	RMSE
Leaf azimuth	0.87	5.19°
Plant spacing	0.83	0.08 m

The proposed method's effectiveness is highlighted by its high accuracy and efficiency in determining the leaf azimuth and plant spacing. By utilizing PCA for azimuth calculation and the projected point density method for spacing measurement, this approach ensures robustness against incomplete point cloud data, which is common in field conditions.

In the experiment, the acquired Lidar point cloud data showed that the majority of maize plant stalks were growing perpendicular to the ground. However, a tiny percentage of maize plants still have stalks that are not parallel to the ground. The most significant causes of plant stalks that are not perpendicular to the ground are phenomena involving shade and inversion. Meanwhile, maize plants with poor perpendicularity to the ground may connect with neighboring maize plants for shading, resulting in incorrect identification of the stalks site and a more significant measurement error for plant distance and row distance.

Figure 8 and Figure 9 provide visual evidence of the strong correlation between the measured and predicted values, reinforcing the method's reliability. Additionally, this method's ability to handle large datasets efficiently makes it suitable for high-throughput agricultural analysis.

The results of this study demonstrate the potential of Lidar data-based plant monitoring in the field. Obtaining plant growth azimuths using a portable 3D digital scanner is less efficient than the approach described in this study. Because of the limitations of this 3D digital scanner, it can only identify individual plants in a narrow area. In this study, individual maize plants were in the field using Lidar to scan them, and their growth azimuth and plant spacing were then assessed using point clouds data. The findings demonstrate that the Lidar system can effectively and non-destructively extract single and multiple crop structural metrics in the field.

In real-world conditions, our method can be adopted for various applications such as precision agriculture, crop monitoring, and automated phenotyping. The method's robustness to incomplete data ensures it remains effective even in less controlled field environments. However, there are limitations to consider. The accuracy of point cloud data segmentation plays a critical role in the overall effectiveness of this method. Environmental factors such as lighting conditions and sensor noise can affect the quality of the point cloud data. Future work should focus on improving segmentation algorithms and integrating more advanced sensors to mitigate these issues. By addressing these aspects, it is believed that this proposed method offers a significant contribution to the field and holds potential for wide adoption in practical agricultural applications.

5 Conclusions

In this study, terrestrial Lidar scanning was utilized to acquire 3D point cloud data of maize populations, enabling investigation of leaf azimuth discrimination and spacing calculation. Principal component analysis (PCA) achieved the highest fitting accuracy of R^2=0.87 for modeling growth azimuth, with RMSE of 5.19°. Gridding of point clouds facilitated geolocation of plant stalks across experimental plots for plant spacing analyses. The proposed method of determining the central axis based on point density achieved an R^2 of 0.83 and an RMSE of 0.08 m for maize growth modeling. This novel Lidar-enabled workflow for non-destructively assessing azimuthal and structural traits establishes an automated process with applications for scientific maize cultivation management and yield forecasting.

Despite the promising results, there are several limitations to this study. Firstly, the accuracy of point cloud data segmentation is critical for the overall effectiveness of this method. Environmental factors such as lighting conditions and sensor noise can affect the quality of the point cloud data, leading to potential errors in azimuth and spacing calculations.

Future research should focus on improving segmentation algorithms to enhance the accuracy of point cloud data interpretation. Integrating more advanced sensors that can reduce the impact of environmental noise will also be beneficial. Additionally, dynamic monitoring of changing leaf azimuths over developmental phases can further optimize precision agriculture approaches through improved spatiotemporal characterization of crop structure and growth. By addressing these aspects, this proposed method will offer a significant contribution to the field and hold potential for wide adoption in practical agricultural applications.

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