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A single plant segmentation method of maize point cloud based on Euclidean clustering and K-means clustering

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ABSTRACT

It is very important to study the correlation between phenotypic information and genetic information of population maize plants for breeding good maize varieties. How to separate single maize plants from population plants to more accurately measure maize phenotypic parameters is still a difficult problem. Therefore, we propose a single plant segmentation method based on Euclidean clustering and K-means clustering. First, three dimensional (3D) point cloud data of two planting density populations of maize (field 1 and field 2) at five-leaf stage (V5) and six-leaf stage (V6) were obtained by terrestrial laser scanning (TLS). Second, the point cloud data of maize plants were preprocessed to extract the point cloud data of the experimental area. Then, plane segmentation, point cloud filtering and Euclidean clustering were used to segment the population maize plants. Finally, the number of plants and center point of point cloud of maize plants after preliminary segmentation were obtained by voxel filtering, and then K-means clustering was used to achieve single segmentation of maize plants. When planting density was sparse, the segmentation results based on Euclidean clustering and K-means clustering showed that the Accuracy* F_1 Score ($A * F_1$) of V5 stage and V6 stage plants were 100.00 % and 99.87 %, respectively; and the $A * F_1$ of V5 stage and V6 stage were 99.59 % and 85.69 %, respectively, when planting density was dense. Compared with the results of Euclidean clustering single plant segmentation, maize single plant segmentation $A * F_1$ increased by 0.00 %, 6.02 %, 12.25 % and 73.41 % at V5 stage and V6 stage in field 1 and field 2, respectively. The results showed that the single plant segmentation based on Euclidean clustering and K-means clustering method could solve the problem that Euclidean clustering single plant segmentation method could not segment the cross-leaf plants. This study provides a simple and reliable method for plant segmentation of population maize for breeders and crop phenotypists.

1. Introduction

Maize is one of the world's three main food crops and is widely grown around the globe. Breeding maize varieties with high yield, high resistance and high quality can improve grain yield and quality and guarantee global food security (Wei et al., 2019; Yang et al., 2021a). Breeding excellent maize varieties requires in-depth understanding of the relationship between genes and phenotypes, so rapid and efficient measurement of maize phenotypic parameters is crucial for maize breeding (Lane et al., 2020; Almeida et al., 2020; Mu et al., 2016; Li et al., 2022; Ma et al., 2023). Manual measurement of crop phenotypic parameters has some problems, such as low efficiency, large subjectivity, high labor cost and great destructiveness. With the development of remote sensing measuring equipment and modern computer technology, crop plant data can be collected through remote sensing measuring equipment such as Light Detection and Ranging (LiDAR), depth camera, color camera, thermal infrared camera and hyperspectral imager (Zhang et al., 2019; Lu et al., 2021; Qiu et al., 2021; Gage et al., 2017; Henke et al., 2020; Wang et al., 2020; Tu et al., 2020). Crop phenotypic parameters can be measured efficiently, non-destructively and quickly by processing crop plant data with computer technology (Cen et al., 2020; Yang et al., 2022; Zhao, 2019).

Crop plant data obtained by various remote sensing measuring equipment can be divided into two dimensional (2D) data and three dimensional (3D) point cloud data, among which 3D point cloud data can accurately reflect the spatial morphology of crops, providing data guarantee for non-destructive and accurate acquisition of crop morphological and phenotypic parameters (Zheng et al., 2022; Su et al.,

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2019a; Miao et al., 2021; Wang et al., 2021; Che et al., 2021; Yang et al., 2021b; Harmening and Paffenholz, 2021). How to segment crop organs from the point cloud of a single crop plant and how to segment a single crop plant from the point cloud of population crop plant are the research hotspots of 3D point cloud processing methods for crops (Su et al., 2019b; Zhu et al., 2021a; Zhu et al., 2021c; Martinez-Guanter et al., 2019).

Jin et al. (2019) used terrestrial laser scanning (TLS) to acquire plant point cloud data of three growth stages of maize, and proposed a median normalized vector growth algorithm to achieve stem and leaf segmentation of maize. However, it required manual intervention to remove ground points and noise points, and false segmentation existed in the top leaves. Zhu et al. (2021b) obtained 3D point cloud data of a single maize plant with a handheld laser scanning (HLS). Aiming at the problem of false segmentation of top leaves, a method of stem and leaf segmentation of maize point cloud was proposed based on point cloud skeleton and optimal transmission distance, and the characteristics of plant height, leaf length and leaf width were measured. Das Choudhury et al. (2020) used cameras to acquire maize plant images of multiple views, constructed maize plant 3D point cloud data through 3D voxel grid reconstruction algorithm, and proposed a new voxel overlap consistency check and point cloud clustering technology to achieve the segmentation of single leaves and stems of maize plants. Elnashef et al. (2019) proposed a new data-driven segmentation model for plant point cloud stem and leaf segmentation for different crops at different growth stages, which described the data by calculating the first-order and second-order tensors of points without pre-defined shape assumptions and constraints to realize the stem and leaf segmentation of plant point cloud. In these studies, stem and leaf segmentation of single plants was realized, but how to segment single plants of population was not involved.

Miao et al. (2022a) used TLS to obtain 3D point cloud data of population plants in multiple growth periods of two maize varieties, and realized the segmentation of a single maize plant through pass filtering. Moreover, they proposed a point cloud image conversion method to successfully segment stem and leaf of point cloud of lower maize plants, thus improving the measurement accuracy of maize plant height and stem diameter. Liang et al. (2020) used self-walking crawler carts to continuously shoot maize plants from different perspectives, and realized three-dimensional reconstruction of population maize plants. The conditional Euclidean clustering algorithm was used to segment single maize plants, and the random sampling consistent cylindrical segmentation algorithm was used to segment maize stem and leaf, realizing the accurate and nondestructive measurement of 11 maize characters such as plant height and leaf area. In these studies, the segmentation of single crop plants and the stem and leaf segmentation of plant point cloud were carried out at the same time. However, there was no crossover among the population plants, so the segmentation of single plant could be realized only by simple point cloud segmentation method. This method is not applicable to the actual planting and growth of crops in the field because there are generally crosses between plants. In the case of plant leaves crossing, how to achieve the single plant segmentation is a research difficulty.

Miao et al. (2022b) used TLS to acquire point cloud data of population banana plants and realized the segmentation of a single banana plant through K-means clustering method, but did not analyze the segmentation accuracy. Lin et al. (2021) used TLS to acquire point cloud data of population plants of rape, maize and cotton from different perspectives, and proposed a columnar space clustering segmentation method, which successfully divided point clouds of the above three crop populations. Compared with Euclidean clustering method, the accuracy of point cloud segmentation was improved by 61.80 %. Jin et al. (2018) used TLS to acquire point cloud data of maize population plants under different planting densities, proposed a method combining deep learning and regional growth algorithm, and successfully separated the maize plant from the population, with the F_1 Score (F_1) of the plant segmentation reaching 94 %. These studies have solved the problem of single plant segmentation. However, there is no further study on single plant segmentation methods adapted to multiple growing stages of crops, and the accuracy of single plant segmentation was mostly measured at the level of single plants, so the effect of single plant segmentation needs to be further analyzed at the level of point cloud.

Leaves crossing is an important factor affecting the accuracy of maize single plant segmentation. At different planting densities and growth stages, the degree of leaves crossing in maize plants varies. Therefore, it is necessary to study a single plant segmentation method that adapts to different degrees of leaves crossing. This paper takes maize plants with two growth stages under two planting densities as the research object, uses TLS to collect point cloud data of maize plants, and carries out research on single plant segmentation method based on Euclidean clustering and K-means clustering. The main work includes: 1) proposed a single plant segmentation method based on Euclidean clustering and K-means clustering; 2) A precision analysis method combining single and point cloud level was used to synthesize the effect of single plant segmentation of maize plants with two planting densities and two growth periods. It provides a simple and reliable method for maize plant segmentation.

2. Materials and methods

2.1. System architecture

To realize the point cloud segmentation of maize plants at the five-leaf (V5) stage and six-leaf (V6) stage, maize plants were taken as the research object. These two growing stages can include a variety of conditions in which the maize plant leaves cross. The system architecture includes three parts: data collection, data processing, and results and analysis. In the data collection part, TLS was used to scan maize plants at V5 stage and V6 stage to obtain 3D point cloud data. In the data processing part, data preprocessing based on Euclidean clustering and K-means clustering, single plant point cloud segmentation were realized.

On the point cloud data, Manual segmentation of single maize plant point cloud was used as the true value of segmentation. In the results and analysis part, the automatic segmentation algorithm of maize point cloud was quantitatively evaluated by comparing automatic segmentation with manual segmentation. Accuracy, precision and recall were used as quantitative evaluation indicators. The system architecture is shown in Fig. 1.

2.2. Data collection

The data collection site was Zhuozhou Experimental Station of China Agricultural University, Baoding City, Hebei Province, China. Maize B73-329 was used as experimental material. The planting scheme of maize was as follows: the planting area was 13.0 m long and 4.8 m wide, and was divided into two planting densities. Planting density 1 (PD1), the spacing between rows was 0.6 m, the spacing between plants in a row was 0.6 m, and three rows were planted; planting density 2 (PD2), the spacing between rows was 0.6 m, the spacing between plants in a row was 0.3 m, and five rows were planted, as shown in Fig. 2. On May 20, 2021, maize was planted according to the planting scheme, filed 1 (F1) was PD1, field 2 (F2) was PD2. The point clouds of the maize plants were collected on June 11, 2021 (V5 stage) and June 17, 2021 (V6 stage).

The Trimble tx8 TLS was used to scan maize plants at V5 stage and V6 stage to obtain 3D point cloud information; its technical specifications are shown in Table 1. Before each scanning, the target balls were set at the edge of the maize growing area, and the unique 3D space was determined. The target balls can identify a unique space within the perspective of the adjacent scanning station. The scan density of The Trimble tx8 was set to level 2 and each scan take 3 min. The scanning stations were located at the four vertices of the experiment area and in the middle of the long side, and the 3D information data of maize from

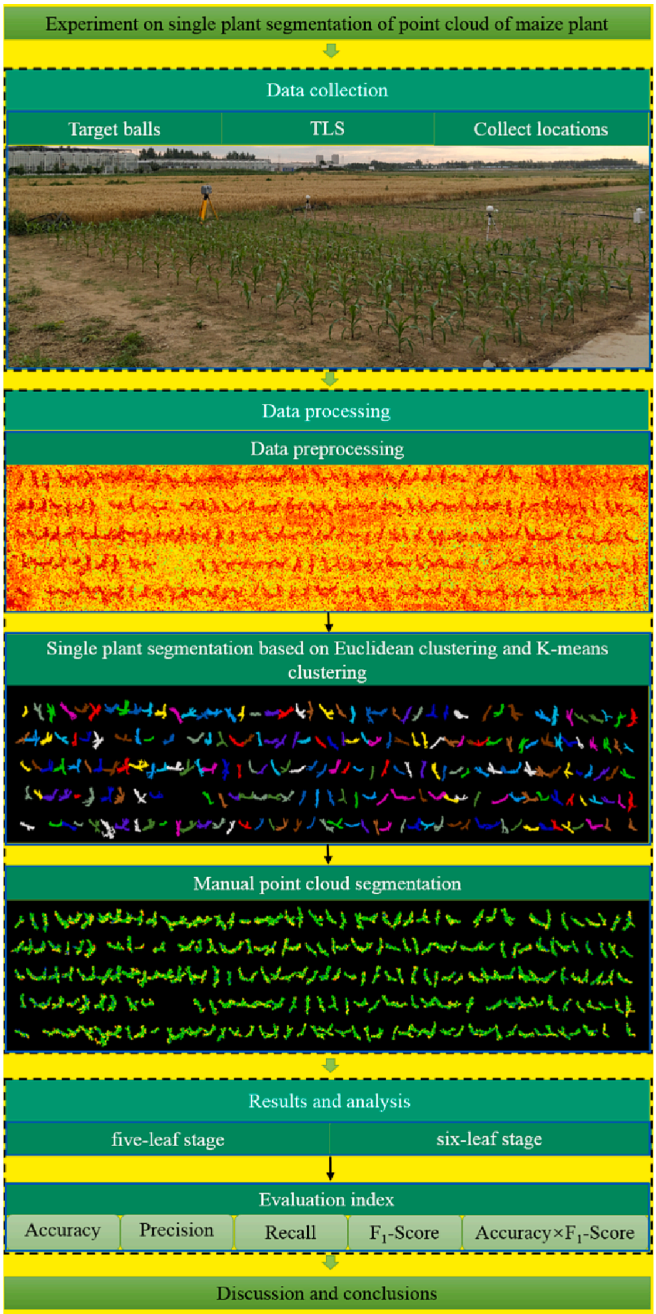


Fig. 1. System architecture.

six stations was collected in each experiment. The positions of the scanning site on the field are shown in Fig. 3.

2.3. Data processing

The data processing method and results are shown in Fig. 4. Data preprocessing and maize plant point cloud single plant segmentation constituted maize plant point cloud data processing. Registration, pass filtering and spatial sampling of point clouds were performed by the Trimble Realworks. The computer operating system is Windows7, with Visual Studio 2013 and Point Cloud Library 1.8.0 installed. The single plant segmentation of maize point cloud at V5 stage and V6 stage was realized by C++ programming based on Euclidean clustering and K-means clustering.

2.3.1. Data preprocessing

Feature point registration, pass filtering and data read and write constituted data preprocessing.

Step 1: The target balls of point clouds at different sites are identified as feature points. The registration matrix was generated from the feature points, and the maize point cloud was registered with Trimble Realworks software. The X-axis is located in the horizontal plane and perpendicular to the maize row, the Y-axis is located in the horizontal plane and parallel to the maize row, and the Z-axis is perpendicular to the horizontal plane. As shown in Fig. 5(a).
Step 2: The polygon segmentation method based on pass filtering was adopted to segment the maize plant and ground point clouds in the F1 and F2 area, and the spatial sampling distance was set as 3 mm. The down-sampled point clouds were shown in Fig. 5(b) and (c).
Step 3: The point cloud data of F1 and F2 area were converted to *.pcd was implemented by a point cloud read-write method.

2.3.2. Single plant segmentation based on Euclidean clustering and K-means clustering

Single plant segmentation based on Euclidean clustering and K-means clustering includes the following steps: plane segmentation, statistical filtering, Euclidean clustering segmentation, voxel filtering and K-means clustering segmentation. The process of single plant segmentation was introduced with the maize point cloud data planted in the V5 stage data of F2 with plant density 2. The single plant segmentation steps are shown in Fig. 6.

Step 1: Plane segmentation. The original point cloud data was segmented into regional point cloud data by grid with a size of 1 m × 1 m. The side length of the edge regional point cloud data was calculated. If the side length was greater than 0.5 m, the number of segmentation was changed; otherwise, the side length of the last grid was changed. Each regional point cloud used the plane segmentation method respectively, and all plant point clouds are merged into one plant point cloud and saved. As shown in Fig. 6 (a). The pseudocode of the plane segmentation step is presented in Method. 1 (shown in Table 2).
Step 2: Statistical filtering. The statistical filtering was performed to remove noise points in point cloud data of maize plants, as shown in Fig. 6 (b).
Step 3: Euclidean clustering segmentation. The Euclidean clustering was performed on maize plant point clouds. Using the X-axis and Y-axis length threshold classification method, the clustering point clouds were classified into multi-maize plants or single maize plant. As shown in Fig. 6 (c) and (d). The pseudocode of the Euclidean clustering segmentation step is presented in Method. 2 (shown in Table 3).
Step 4: Voxel filtering. Multi-maize plants point cloud was projected onto the plane of minimum Z-axis coordinates and voxel filtering was performed. Using Euclidean clustering for the point cloud after voxel filtering, the number of plants in the multi-maize plants point cloud and the central coordinates of each plant were obtained. The results are shown in Fig. 6 (e). The pseudocode of the Voxel filtering step is presented in Method. 3 (shown in Table 4).
Step 5: K-means clustering segmentation. If the number of plants in the multi-maize plants point cloud was 1, the point cloud was labeled as a single plant point cloud. Otherwise, the K-means clustering parameter was set to the number of plants and the coordinates of the center point of the plant. K-means clustering was performed to obtain single maize plant point cloud. The results are shown in Fig. 6 (f). The pseudocode of the K-means clustering segmentation step is presented in Method. 4 (shown in Table 5).

2.3.3. Manual point cloud segmentation

The population maize plant point cloud was read into CloudCompare

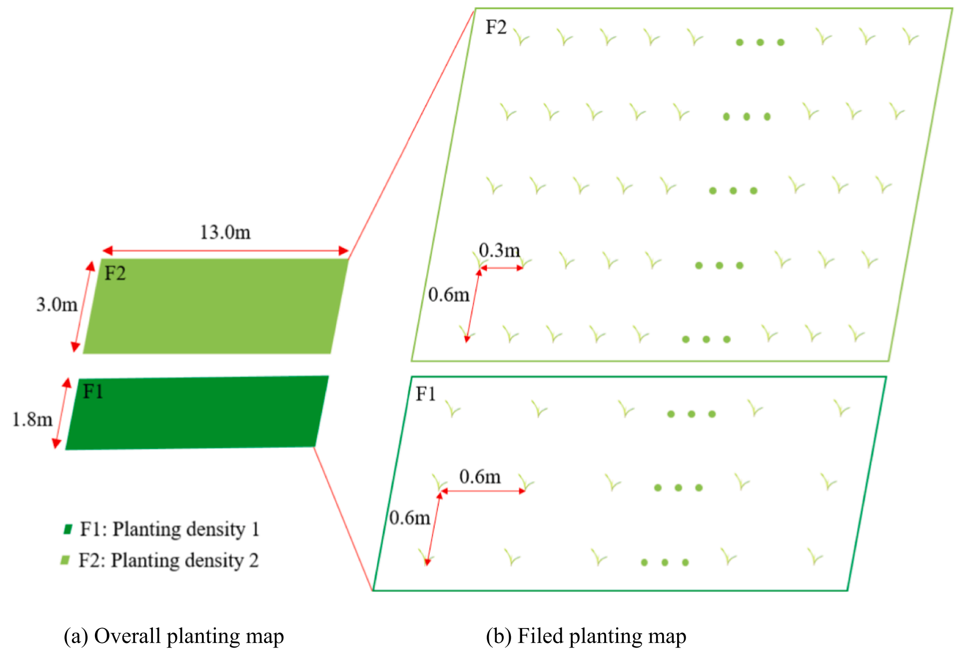


Fig. 2. Maize planting map. Note: Planting density 1: the spacing between rows is 0.6 m and the spacing between plants in a row is 0.6 m. Planting density 2: the spacing between rows is 0.6 m and the spacing between plants in a row is 0.3 m.

Table 1
The Trimble tx8 TLS technical specifications.

technical	specifications	technical	specifications
Min scan distance	0.6 m	Max scan distance	120 m
Field of view	360° × 317°	Scanning accuracy	2 mm
Laser scan resolution	16″	Scan density	Level1/2/3, Extended
Power	72 W	Data storage	USB3.0
Laser wavelength	1.5 μm	Laser class	Class 1 - eye safe

software, and a single maize plant point cloud was manually segmented through the polygonal point cloud segmentation method in the software as the true value of maize plant segmentation.

2.4. Evaluation index

The accuracy of the method proposed in this paper was evaluated by comparing the automatic and manual point clouds of single maize plants. The analysis was made at the level of single maize plants. Two or more complete plants were segmented into one plant, and it was considered that the segmentation of these plants was false. A single plant was basically segmented, and the segmentation was considered true. Accuracy (A) was selected for quantitative evaluation, which could be calculated by formula (1). The plants truly segmented at the single level

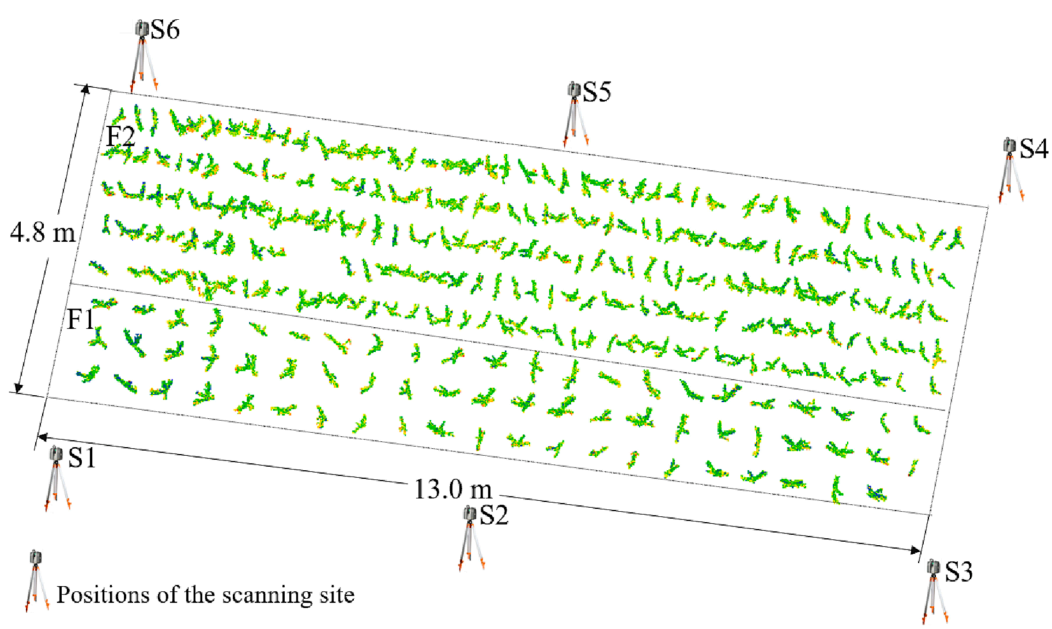


Fig. 3. Positions of the scanning site. Note: The scan stations 1–6 are S1–S6 respectively.

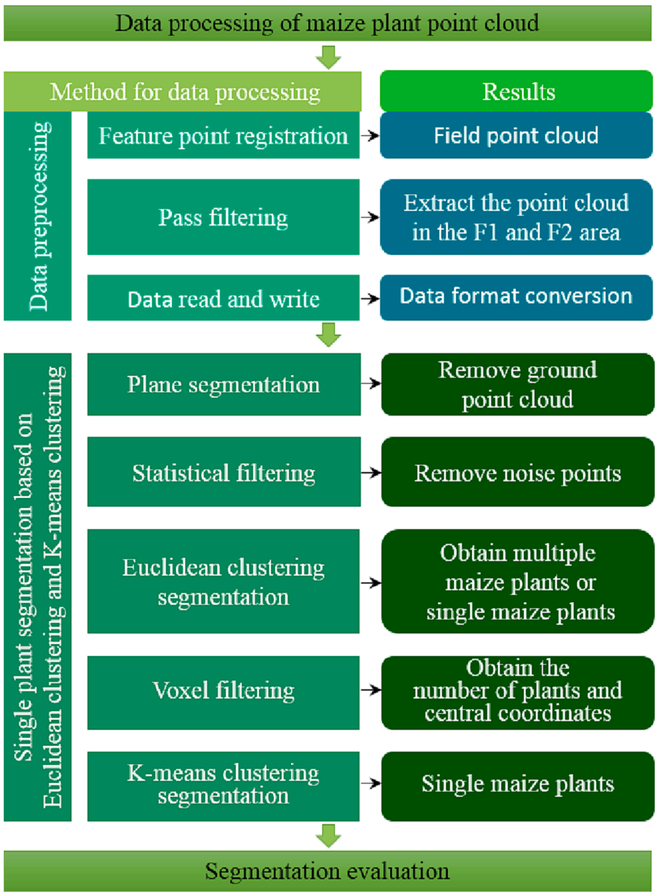


Fig. 4. The data processing method and results.

were analyzed at the point cloud level. Precision (*P*), recall (*R*) and F_1 score (F_1) were used for quantitative evaluation of maize plant segmentation, which could be calculated by formulas (2), (3) and (4). Combining single level and point cloud level, the accuracy multiplied by F_1 score ($A * F_1$) was used for quantitative analysis of maize single plant segmentation method.

$A = TP_P/AC_P$ (1)

Where A, TP_P and AC_P are the accuracy, the number of truly segmented plants and the actual number of plants, respectively.

$P = TP_C/(TP_C + FP_C)$ (2)

$R = TP_C/(TP_C + FN_C)$ (3)

$F_1 = 2 * P * R/(P + R)$ (4)

Where, P, R and F_1 are precision, recall and F_1 score respectively. TP_C, FP_C and FN_C are the number of points truly segmented into the corresponding maize plant, the number of points falsely segmented into the corresponding maize plant and the number falsely segmented into other maize plants, respectively.

3. Results and analysis

The results of single plant segmentation are influenced by the degree of leaf crossing in maize plants. The degree of leaf crossing of some maize plants is shown in Fig. 7. at the V5 and V6 stages in F1 and F2. It can be seen from Fig. 7. At the V5 stage in F1, there is no cross between the leaves of maize plants. At the V6 stage in F1, a few maize plants have cross leaves. At the V5 stage in F2, some maize plants have cross leaves. At the V6 stage in F2, most maize plants have cross leaves.

3.1. *The result of single plant segmentation based on Euclidean clustering*

The Single plant segmentation by Euclidean clustering method (Single plant segmentation based on Euclidean clustering and K-means clustering method) was used for single plant segmentation of maize population point clouds in different fields at V5 stages and V6 stages. The segmentation results are shown in Fig. 8. At the level of single plants, the actual number of plants, the number of clusters, the number of truly segmented plants and the *A* are shown in Table 6. At point cloud level analysis, the *P*, the *R*, the F_1 and $A * F_1$ are shown in Table 7.

It can be seen from Fig. 8, Table 6 and Table 7. The spacing of planting plants in F1 is 0.6 m. At the V5 stage, there is no cross between the leaves of maize plants, and the Euclidean clustering could obtain all single maize plants. At the plant single level, the number of clusters and the number of truly segmented plants were consistent with the actual number of plants, and the *A* reached 100 %. At the point cloud level, the *P*, the *R* and the F_1 all reached 100.00 %. $A * F_1$ also reached 100.00 %. It can perfectly segment all single maize plants. With the growth of maize plants, at the V6 stage, a few maize plants have cross among their leaves, and the Euclidean clustering could obtain most single maize plants. At the plant single level, the number of clusters and the number of truly segmented plants were close to the actual number of plants, and the *A* reached 93.85 %; At the point cloud level, the *P*, the *R* and the F_1 all reached 100.00 %; $A * F_1$ also reached 93.85 %. Most single maize plants can be segmented by the Euclidean clustering method.

The spacing of planting plants in F2 is 0.3 m. At the V5 stage, some maize plants have cross leaves, and the Euclidean clustering can get most single maize plants. At the plant single level, there was a certain error between the number of clusters, the number of truly segmented

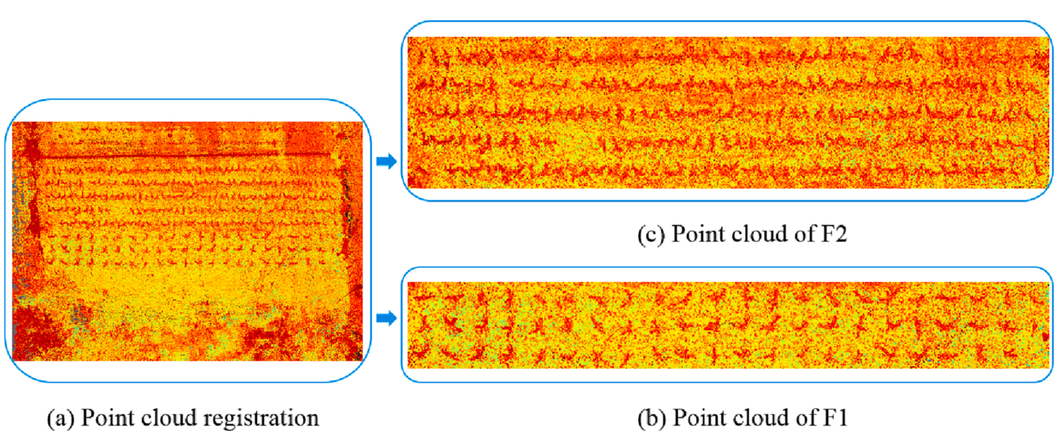


Fig. 5. Point cloud of maize plants data preprocessing.

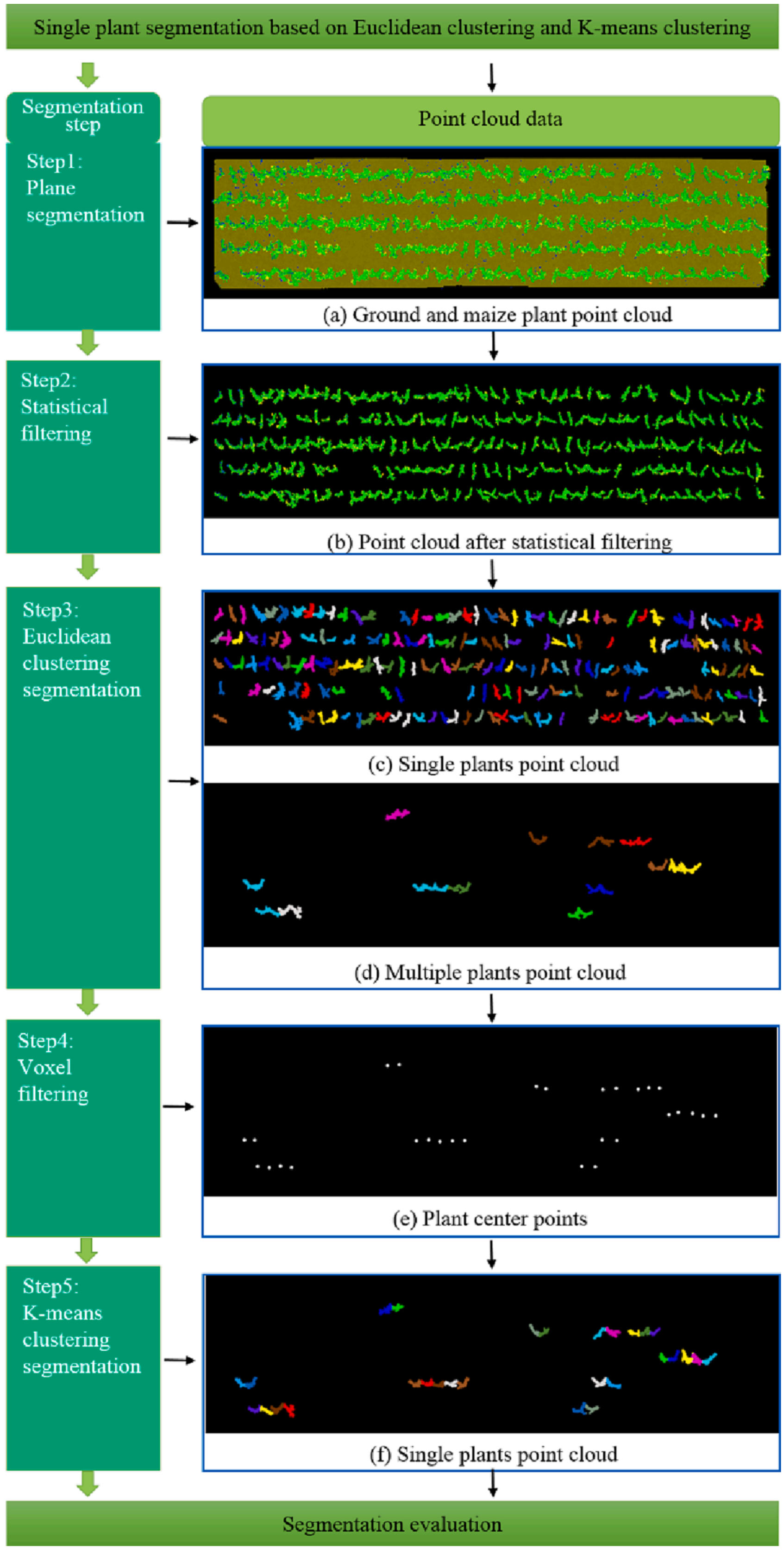


Fig. 6. Point clouds of maize and ground segmentation.

Table 2
Method 1 Plane segmentation method.

```
The original point cloud data is read in
The length Lx of the X-axis of the point cloud is calculated
Qx ← Lx / 1
Rx ← Lx % 1
if (Rx > 0.5) then
    Rx ← 1
else
    Rx ← 0
end if
Initialize the segmentation threshold Tx for the X-axis: Tx ← 1
for i ← 0 to Qx + Rx do
    if (Rx = 0 and i > Qx - 1) then
        Tx ← 2
    end if
    Run threshold segmentation algorithm to generate point clouds P_i
    The length Ly of the Y-axis of the P_i is calculated
    Qy ← Ly / 1
    Ry ← Ly % 1
    if (Ry > 0.5) then
        Ry ← 1
    else
        Ry ← 0
    end if
    Initialize the segmentation threshold Ty for the Y-axis: Ty ← 1
    for j ← 0 to Qy + Ry do
        if (Ry = 0 and j > Qy - 1) then
            Ty ← 2
        end if
        Run threshold segmentation algorithm to generate point clouds P_ij
        Run plane segmentation algorithm to generate maize plant point clouds
        plant point clouds are merged
    end for
end for
Plant point cloud is saved
```

Table 3
Method 2 Euclidean clustering segmentation method.

```
The filtered maize plant point cloud is read in
The Euclidean clustering parameters are set
Run Euclidean clustering algorithm to generate cluster C1
for each cluster point cloud do
    The length Lcx of the X-axis of clustering point cloud is calculated
    The length Lcy of the Y-axis of clustering point cloud is calculated
    Initialize the distance threshold a and b
    if (Lcx > a or Lcy > b) then
        The cluster point cloud is labeled as multi-maize plants
        Multi-maize plants point cloud is saved
    else
        The cluster point cloud is labeled as single maize plant
        Single maize plants point cloud is saved
    end if
end for
```

plants and the actual number of plants, and the A reached 87.34 %. At the point cloud level, the P, the R and the F_1 all reached 100.00 %; $A * F_1$ also reached 87.34 %. Most single maize plants can be segmented. With the growth of maize plants, at the V6 stage, most of the leaves of maize plants have cross, and the Euclidean clustering could obtain a small number of single maize plants. At the level of single plants, both the number of clustering and the number of truly divided plants were significantly different from the actual number of plants, A was only 12.28 %. However, at the point cloud level, the P, the R and the F_1 still reached 100.00 %. The $A * F_1$ was only 12.28 %, and only a small number of single maize plants can be accurately segmented.

The above shows that when there is no cross between leaves of maize plants, the Euclidean clustering method can perfectly segment all single maize plants. When a small number of maize plants have cross leaves, the Euclidean clustering method can also segment most single maize plants, but maize plants with cross leaves have not been truly segmented. When most of the leaves of maize plants have cross, the Euclidean clustering method can only segment a small number of single

Table 4
Method 3 Voxel filtering method.

```
All multi-maize plant point clouds are read in
for each multi-maize plant point cloud do
    The minimum value Z_min for the Z-axis is obtained.
    Multi-maize plants point cloud is projected onto the plane of Z_min
    The voxel filtering parameters are set
    Run voxel filtering algorithm
    The Euclidean clustering parameters are set
    Run Euclidean clustering algorithm
    The number K of Euclidean clusters is obtained
    The center coordinates {Ce_1, Ce_2, Ce_3, ..., Ce_K} of each cluster point cloud are obtained
end for
```

Table 5
Method 4 K-means clustering segmentation method.

```
All multi-maize plant point clouds are read in
for each multi-maize plant point cloud do
    The number K of Euclidean clusters is read in
    The center coordinates {Ce_1, Ce_2, Ce_3, ..., Ce_K} of each cluster point cloud are read in
    if (K = 1) then
        The point cloud is labeled as single maize plant
        Single maize plant point cloud is saved
    else
        The K-means clustering parameters are set
        Run K-means clustering algorithm
        The cluster point clouds are labeled as single maize plant
        Single maize plant point clouds are saved
    end if
end for
```

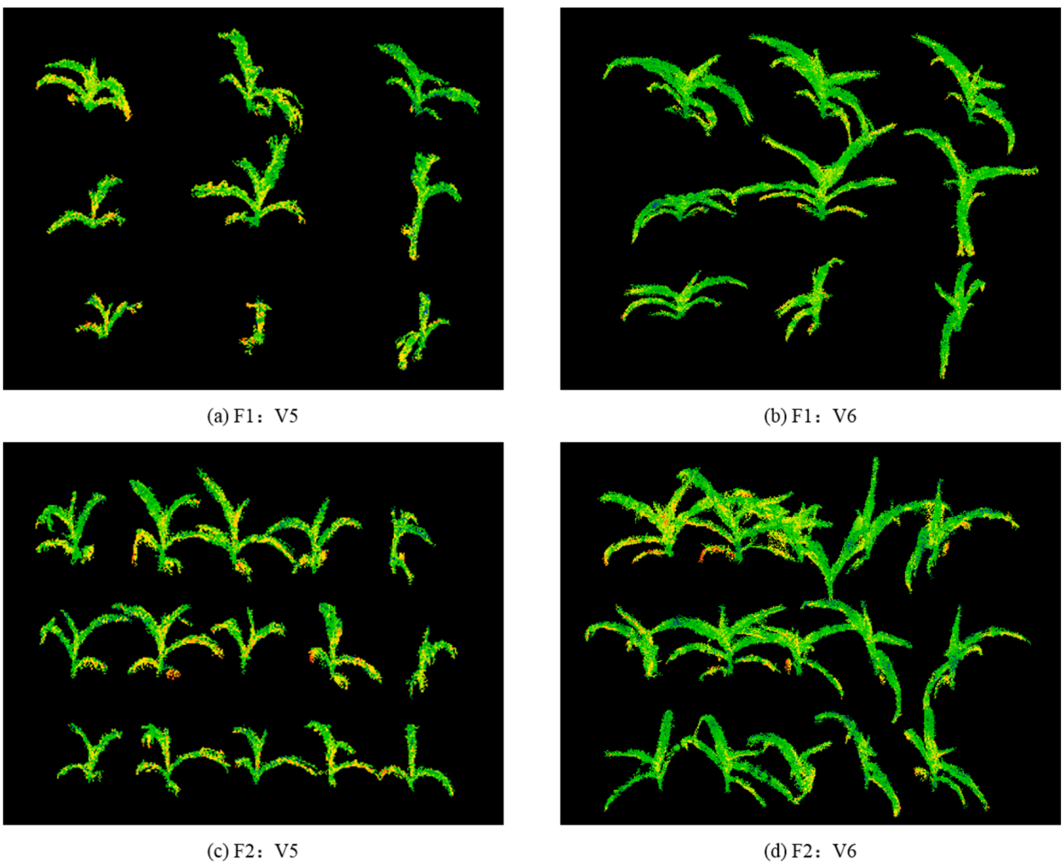


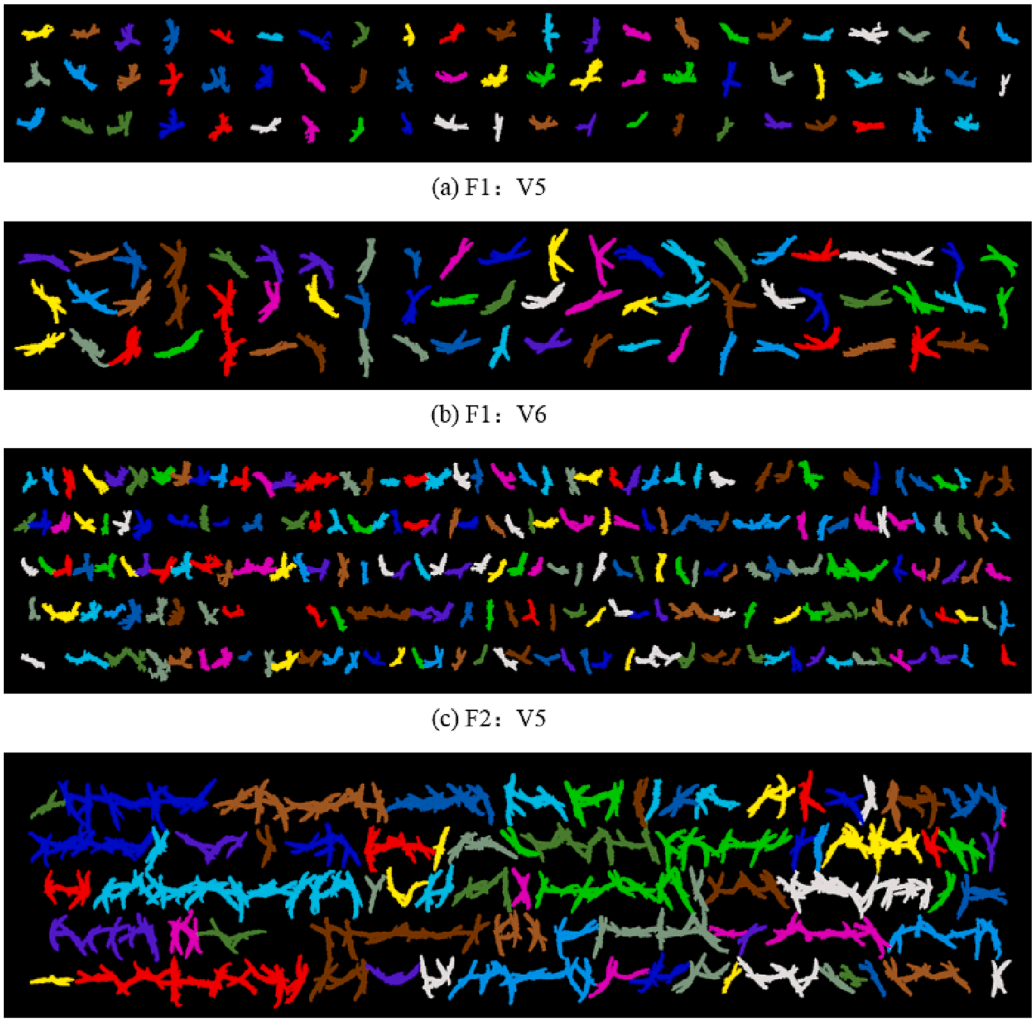
Fig. 7. The degree of leaf crossing of maize plants.

maize plants. Because of cross, most of the maize plants have not been truly segmented. Therefore, the Euclidean clustering method does not adapt to the situation of cross of leaves between maize plants, and has certain limitations in the segmentation of maize plants. In view of the existing problems of the Euclidean clustering method, combined with the characteristics of maize plants, single plant segmentation based on Euclidean clustering and K-means clustering method was used to segment maize plants.

3.2. The result of single plant segmentation based on Euclidean clustering and K-means clustering

To solve the problem that the Euclidean clustering method has poor segmentation effect when maize leaves are cross between plants, single plant segmentation based on Euclidean clustering and K-means clustering was used to segment the above maize population point cloud. The segmentation results are shown in Fig. 9. At the plant single level, the evaluation indexes are shown in Table 8. At the point cloud level, the evaluation indexes are shown in Table 9.

It can be seen from Fig. 9, Table 8 and Table 9. The spacing of planting plants in F1 is 0.6 m. At the V5 stage, there is no cross between the leaves of maize plants, and all single maize plants could be obtained using the single plant segmentation based on Euclidean clustering and K-means clustering method. At the plant single level, the number of clusters and the number of truly segmented plants were consistent with the actual number of plants, and the A reached 100 %. At the point cloud level, the P, the R and the F_1 all reached 100.00 %. $A * F_1$ also reached 100.00 %. It can perfectly segment all single maize plants. At the V6 stage, a few maize plants have cross leaves, and all single maize plants could be obtained by using the single plant segmentation method. At the



(a) F1: V5

(b) F1: V6

(c) F2: V5

(d) F2: V6

Fig. 8. Single plant segmentation based on Euclidean clustering of maize point cloud.

Table 6
Plant level segmentation accuracies of Euclidean clustering method.

Field	Planting density	Stage	AC_P	CL	TP_P	A
F1	PD1	V5	65	65	65	100.00 %
F1	PD1	V6	65	63	61	93.85 %
F2	PD2	V5	229	213	200	87.34 %
F2	PD2	V6	228	72	28	12.28 %

Note: Where AC_P, CL, TP_P, and A are the actual number of plants, the number of clusters, the number of truly segmented plants and the accuracy, respectively.

Table 7
Point cloud level segmentation accuracies of Euclidean clustering method.

Field	Planting density	Stage	Precision/ P	Recall/R	F_1 score/ F_1	$A * F_1$
F1	PD1	V5	100.00 %	100.00 %	100.00 %	100.00 %
F1	PD1	V6	100.00 %	100.00 %	100.00 %	93.85 %
F2	PD2	V5	100.00 %	100.00 %	100.00 %	87.34 %
F2	PD2	V6	100.00 %	100.00 %	100.00 %	12.28 %

plant single level, the number of clusters and the number of truly segmented plants were consistent with the actual number of plants, and the A reached 100 %. At the point cloud level, the P, the R and the F_1 all reached 99.87 %; A * F_1 also reached 99.87 %. All single maize plants can be segment.

The spacing of planting plants in F2 is 0.3 m. At the V5 stage, some maize plants have cross leaves, and all single maize plants could be obtained by using the single plant segmentation method. At the plant single level, the number of clusters and the number of truly segmented plants were consistent with the actual number of plants, and the A reached 100 %. At the point cloud level, the P and the R were not lower than 99.58 %, and the F_1 reached 99.59 %; A * F_1 also reached 99.59 %. All single maize plants can also be segment. At V6 stage, most of the leaves of maize plants have cross, and most of the single maize plants could be obtained by using the single plant segmentation method. At the plant single level, the number of clusters and the number of truly segmented plants were very close to the actual number of plants, and the A reached 96.49 %. At the point cloud level, the P and the R were not lower than 88.47 %, and the F_1 reached 88.81 %. A * F_1 reached 85.69 %. Most of the single maize plants can be segmented.

The above shows that when there is no cross between the leaves of maize plants, the single plant segmentation based on Euclidean clustering and K-means clustering method can also perfectly segment all single maize plants. When a small number of maize plants have cross leaves, the single plant segmentation based on Euclidean clustering and K-means clustering method can still segment all single maize plants, and maize plants with cross leaves can be truly segmented. When most of the leaves of maize plants have cross, the single plant segmentation method

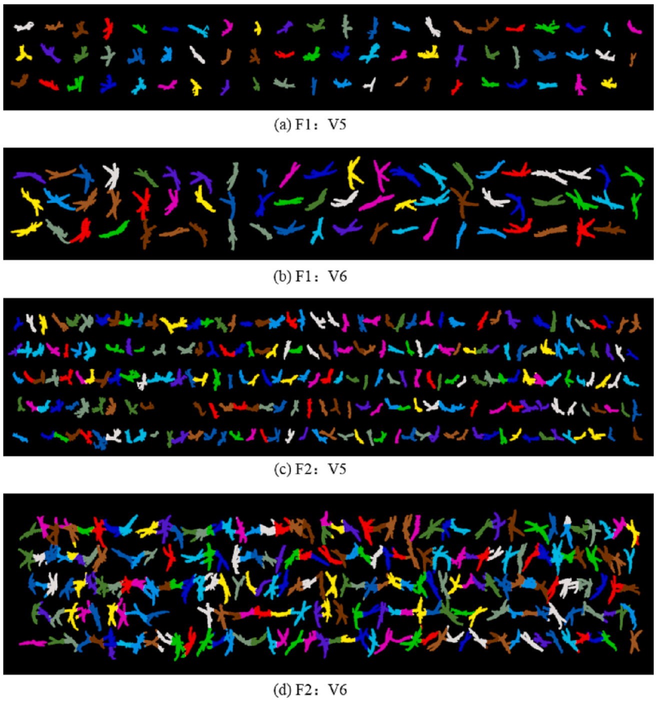


Fig. 9. Single plant segmentation based on Euclidean clustering and K-means clustering of maize point cloud.

Table 8
Plant level segmentation accuracies of Euclidean clustering and K-means clustering method.

Field	Planting density	Stage	AC_P	CL	TP_P	A
F1	PD1	V5	65	65	65	100.00 %
F1	PD1	V6	65	65	65	100.00 %
F2	PD2	V5	229	229	229	100.00 %
F2	PD2	V6	228	230	220	96.49 %

Note: Where AC_P, CL, TP_P, and A are the actual number of plants, the number of clusters, the number of truly segmented plants and the accuracy, respectively.

Table 9
Point cloud level segmentation accuracies of Euclidean clustering and K-means clustering method.

Field	Planting density	Stage	Precision/ P	Recall/R	F_1 score/ F_1	$A * F_1$
F1	PD1	V5	100.00 %	100.00 %	100.00 %	100.00 %
F1	PD1	V6	99.87 %	99.87 %	99.87 %	99.87 %
F2	PD2	V5	99.58 %	99.60 %	99.59 %	99.59 %
F2	PD2	V6	89.16 %	88.47 %	88.81 %	85.69 %

can segment most of the single maize plants. Because of the serious degree of cross of the leaves of maize plants, there were a small number of plant segmentation errors.

3.3. Results analysis of different single plant segmentation methods

The results of different single plant segmentation methods of maize plant point cloud are shown in Table 10.

At the single plant level, the single plant segmentation based on Euclidean clustering method could only segment all single maize plants at the V5 stage of F1. There were some errors in truly segmented the number of plants at the V6 stage of F1 and at the V5 stage of F2. The number of truly segmented plants in V6 stage in F2 was significantly different from the actual number of plants. Using single plant segmentation based on Euclidean clustering and K-means clustering method, all single maize plants could be segmented in V5 and V6 stage of F1 and V5 stage of F2. The number of truly segmented in the V6 stage of F2 was also very close to the actual number of maize plants. It can be seen that the single plant segmentation based on Euclidean clustering and K-means clustering method can not only be applied to the scene where the single plant segmentation based on Euclidean clustering method is used to segment all maize plants, but also can be applied to the scene where the segmentation of maize plants is poor. At the level of comprehensive single and point cloud, the single plant segmentation based on Euclidean clustering and K-means clustering method comparing with the single plant segmentation based on Euclidean clustering method, the $A * F_1$ at the V5 and V6 stages in F1 and F2 increased by 0.00 %, 6.02 %, 12.25 % and 73.41 %, respectively. The results show that the single plant segmentation based on Euclidean clustering and K-means clustering method can solve the problem that the single plant segmentation based on Euclidean clustering method cannot separate the cross leaf plants. It can be seen that the single plant segmentation based on Euclidean clustering and K-means clustering method is superior to the single plant segmentation based on Euclidean clustering method at both plant single level and comprehensive single and point cloud level. In addition, it is suitable for different planting densities and growth stages.

Table 10
Segmentation accuracies of different single plant segmentation methods.

Field	Stage	AC_P	Euclidean clustering		Euclidean clustering and K-means clustering	
			TP_P	$A * F_1$	TP_P	$A * F_1$
F1	V5	65	65	100.00 %	65	100.00 %
F1	V6	65	61	93.85 %	65	99.87 %
F2	V5	229	200	87.34 %	229	99.59 %
F2	V6	228	28	12.28 %	220	85.69 %

Note: Where AC_P, TP_P, A and F_1 are the actual number of plants, the number of truly segmented plants, the accuracy and the F_1 score, respectively.

The Running cost of different single plant segmentation methods of maize plant point cloud are shown in Table 11.

In terms of running time, the two single plant segmentation methods have longer running time in point cloud data programs with larger field areas and later growth periods. The reason is that as the field area increases, the time required for plane segmentation becomes longer; and larger plants results in longer Euclidean clustering time. The running time of the method based on Euclidean clustering and K-means clustering was slightly longer than that of Euclidean clustering. Only at the V6 stage of F2, the program running time increased by 11.4 s, while in other fields and growth stages, the program running time only increased by about 1 s. In terms of running memory, the two single plant segmentation methods have a larger running memory for point cloud data with larger field areas. The main reason for this is that the field area increases, resulting in larger point cloud data and larger running memory. The two single plant segmentation methods have the same amount of running memory. The reason is that there is a large amount of running memory during planar segmentation, and the subsequent point

Table 11
Running cost of different single plant segmentation methods of maize point cloud.

Field	Stage	Euclidean clustering		Euclidean clustering and K-means clustering	
		Running time/s	Running memory/M	Running time/s	Running memory/M
F1	V5	178.43	403	179.11	403
F1	V6	271.66	422	272.49	422
F2	V5	415.20	761	416.51	761
F2	V6	633.51	748	644.91	748

cloud processing requires a small amount of running memory.

4. Discussion

The single plant segmentation proposed in this paper can effectively solve the problem of leaf crossing in maize plants. However, there are still some issues that need further improvement and refinement.

Comparison with other single plant segmentation studies, Lin et al. (2021) used the columnar space clustering segmentation method to achieve single plant segmentation of three crops (rape, maize and cotton), among which the segmentation accuracy of maize reached 96.63 %. In this paper, the lowest and highest accuracy of single plant segmentation were 96.49 % and 100 %, respectively, which improved the segmentation accuracy. The segmentation effect of different planting densities and growth stages was also studied. Jin et al. (2018) used the regional growth algorithm to achieve single plant segmentation of maize plants under three planting densities, and the recalls of dense, medium and sparse were 0.92, 0.93 and 0.95, respectively. In this paper, the accuracies of density and sparsity of maize plants at V6 stage were 96.49 % and 100.00 %, respectively. And the segmentation effect was improved.

The single plant segmentation based on Euclidean clustering and K-means clustering method can effectively segment maize plants with different planting densities at V5 and V6 stages. At the V6 stage of F2, the number of truly segmented maize plants may still be close to the actual number of maize plants; however, the $A * F_1$ of single plant segmentation has decreased. The reason is that with the planting density increased or the plants growth, the cross of leaves between maize plants became more serious. It will lead to the false segmentation of cross leaves during K-means clustering segmentation, which will cause the overall level of the segmentation method to decline. In order to improve segmentation accuracy, point cloud segmentation optimization steps can be added after K-means clustering segmentation. The features such as normal vectors and sizes of maize leaf point cloud are used to optimize the segmentation results.

This method presented in this paper can segment maize plants with a certain degree of cross of leaves, providing technical support for high-quality breeding, scientific planting, and intelligent management of maize. Further research is needed on how to make the single plant segmentation based on Euclidean clustering and K-means clustering method suitable for more severe cross. For example, adding optimization steps for point cloud segmentation or collecting multi-source data to obtain more plant information. It can also be used to study the applicability of the method in other field crops (cotton, soybean and wheat) and expand the application scope.

5. Conclusions

(1) Aiming at the problem that it is difficult to segment a single plant due to leaf crossing, single plant segmentation based on Euclidean clustering and K-means clustering was used to achieve single plant segmentation of maize plant point cloud, which was suitable for different planting densities and different growth stages. Maize plants at different planting densities at the V5 and V6 stages were taken as the research object. The methods of maize single plant segmentation were studied by using TLS.

(2) Comparing with the single plant segmentation based on Euclidean clustering method, using the single plant segmentation based on Euclidean clustering and K-means clustering method the $A * F_1$ at the V5 and V6 stages in F1 and F2 increased by 0.00 %, 6.02 %, 12.25 % and 73.41 %, respectively. The effect of single plant segmentation is significant in dense planting and late growth.

CRediT authorship contribution statement

Yanlong Miao: Performed the experimental work, acquired data, software, and writing – original draft. **Shuai Li:** Performed the experimental work, software, and writing – review & editing. **Liuyang Wang:** Performed the experimental work, and acquired data. **Han Li:** Writing – editing. **Ruicheng Qiu:** Writing – editing. **Man Zhang:** Methodology, writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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