Postprint of Maize Plant Point Cloud Tassel Segmentation Based on Supervoxel Clustering and Local Features

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Abstract

To address the challenge that current 3D point cloud processing methods face in recognizing tassels within corn plant point clouds, this study proposes a tassel segmentation method for corn plant point clouds based on supervoxel clustering and local features. Initially, an undirected graph of the corn plant point cloud is constructed through edge connection operations, where edge weights are computed based on normal vector differences, and the plant point cloud is decomposed into multiple supervoxel subregions via spectral clustering. Subsequently, the top subregions of the plant are extracted by integrating principal component analysis with point cloud linear features. Finally, tassel point clouds are identified within these top subregions by leveraging the planar local features of corn plant point clouds. The method was evaluated on 15 mature corn plant point clouds across three density levels, using F1-score as the metric for segmentation accuracy. Compared with manually segmented ground truth data, the average F1-scores for tassel point cloud segmentation were 0.763, 0.875, and 0.889 at point cloud densities of 0.8, 1.3, and 1.9 points/cm, respectively, indicating that segmentation accuracy increases with point cloud density. The results demonstrate that the proposed method based on supervoxel clustering and local features is capable of extracting tassels from corn plant point clouds, thereby providing technical support for research and applications in high-throughput corn phenotyping and three-dimensional reconstruction.

Full Text

Preamble

Tassel Segmentation of Maize Point Cloud Based on Super Voxels Clustering and Local Features

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Abstract: Accurate and high-throughput maize plant phenotyping is vital for crop breeding and cultivation research. Tassel-related phenotypic parameters are important agronomic traits. However, fully automatic and fine tassel organ segmentation of maize shoots from three-dimensional (3D) point clouds is still challenging. To address this issue, a tassel point cloud segmentation method based on point cloud super voxels clustering and local geometric features was proposed in this study. Firstly, the undirected graph of the maize plant point cloud was established, the edge weights were calculated by using the difference of normal vectors, and the spectral clustering method was used to cluster the point cloud to form multiple super voxel sub-regions. Then, the principal component analysis method was used to find the two end regions of the plant and based on the observation of the straight direction of the bottom stem regions, the top and bottom regions were distinguished by the point cloud linear features. Finally, the tassel points were identified based on the plane local features of the point cloud. The sub-regions of the top region of the plant were classified into leaf regions, tassel regions, and mixed regions by plane local features of the point cloud, the tassel points in the tassel sub-region, and the mixed region were the finally segmented tassel point clouds. In this study, 15 mature maize plants with 3 point cloud densities were tested. Compared with the ground truth segmented manually, the average F1 scores of the tassel segmentation were 0.763, 0.875 and 0.889 when the point cloud density was 0.8/cm, 1.3/cm, and 1.9/cm, respectively. The segmentation accuracy of this method increased with the increase of plant point cloud density. The increase of point cloud density and the number of point clouds mainly affected the calculation results of point cloud plane features in tassel segmentation. When the number of point clouds was small, the top leaf point cloud was relatively sparse. Therefore, the difference between the plane feature of the leaf point and the plane feature of the tassel point was not obvious, which led to the increase of the misclassification of the point cloud. However, the time complexity of the algorithm was $O(n^3)$, so the increase in the density and number of point clouds would lead to a significant increase in the running time. Considering the segmentation accuracy and running time, the research obtained the best effect on the mature maize plants with a point cloud density of 1.3/cm and an average number of 15,000. The segmentation F1 score reached 0.875 and the running time was 6.85 s. The results showed that this method could extract tassels from maize plant point cloud, and provided technical support for the research and application of high-throughput phenotyping and three-dimensional reconstruction of maize.

Keywords: maize tassel; 3D point cloud segmentation; phenotyping; super voxels clustering; local features; principal component analysis

1 Introduction

Maize is an important food crop, and its yield is crucial for ensuring global food supply [1]. Maize tassel-related phenotypic parameters are important agronomic traits for maize breeding [2-4]. Traditional tassel parameter extraction methods mainly rely on manual measurement, which is inefficient, subjective, and destructive. In recent years, the development of computer vision technology has provided conditions for automatic measurement of crop phenotypic parameters [5,6].

Two-dimensional image-based visual technology was first applied to tassel phenotyping. Gage et al. [7] developed an image-based maize tassel phenotypic analysis system that could obtain standard images of detached tassels and extract phenotypic parameters such as tassel length and width. Some research focused on identifying tassels in maize plant or canopy images. Ye et al. [8] combined Histogram of Oriented Gradients features and a Support Vector Machine classifier to identify tassel regions, and then used a saliency detection method to achieve tassel pixel segmentation. Kurtulmus and Kavdr [9] combined color features and a Support Vector Machine classifier for tassel localization, and used hierarchical clustering to achieve tassel segmentation. Lu et al. [10] used multi-angle images to improve tassel segmentation accuracy and achieved rough measurement of parameters such as tassel color and branch number. Lu et al. [11] constructed a deep learning network called TasselNet for tassel recognition, achieving accurate counting of tassels in maize canopy images. However, two-dimensional images are only a projection of three-dimensional space. While 2D images can be used for tassel counting, the extraction results for parameters such as tassel length and width are not accurate.

With the popularization of 3D sensors such as 3D laser scanners [12], Time-of-Flight cameras [13], and LiDAR [14], 3D point cloud-based visual technology has been used for crop phenotyping research, including crop species identification [15], dynamic monitoring of crop growth [16], canopy 3D reconstruction [17,18], and measurement of various phenotypic parameters [19-22]. These studies have demonstrated that extracting crop phenotypes from 3D space has higher accuracy [23,24]. However, current research on maize tassel phenotyping based on 3D point clouds is still limited. Han et al. [25] used stereo vision technology for 3D point cloud reconstruction of detached tassels and employed a density-based clustering algorithm for tassel segmentation to extract phenotypic parameters. At present, extracting tassel phenotypic parameters from maize plant or population point clouds remains challenging, with accurate segmentation of tassel point clouds being a technical difficulty. To address this problem, this study proposes a maize plant point cloud tassel segmentation method based on super voxels clustering and local features, which can directly segment and identify tassel point clouds on maize plants, providing a technical foundation for high-throughput phenotyping and 3D geometric reconstruction of maize.

2 Materials and Methods

2.1 Test Materials and Point Cloud Data Acquisition

Field experiments were conducted from May to October 2019 in the maize test field of Shenyang Agricultural University (116.16°E, 39.56°N). Mature maize plants with row spacing of 60 cm and plant spacing of 25 cm were selected as research objects. A FreeScan X3 handheld laser scanner was used to acquire 3D point clouds of maize plants. The field-grown mature maize plants were transplanted into pots and moved indoors for point cloud acquisition. Since the FreeScan X3 laser scanner requires laser-sensitive plates for 3D positioning, during data collection, the photosensitive plates were first attached to auxiliary brackets that were placed around the measured plants to ensure that the laser line could scan both the plant and the photosensitive plates simultaneously. The data acquisition process is shown in Figure 1 Figure 1: see original paper. Using CloudCompare software, the pot and mobile bracket point clouds were manually removed, retaining only the maize plant point cloud data.

To verify the segmentation effect of the proposed algorithm on plants with different point cloud densities, 15 mature maize plants with different morphologies were selected as test samples. Each maize plant point cloud was sampled to 3 point cloud densities (as shown in Figure 1(b)), namely 0.8, 1.3, and 1.9 points/cm, where point cloud density indicates how many points exist per centimeter. The average numbers of points for the three densities were approximately 6,000, 15,000, and 30,000 points, respectively, with average tassel point cloud numbers of about 140, 360, and 890 points. CloudCompare software was used to manually segment the tassel point clouds from the test maize plants to obtain ground truth segmentation.

2.2 Tassel Point Cloud Segmentation Method

The proposed method takes scattered maize plant point clouds as input and achieves tassel point cloud recognition through three main steps: point cloud super voxels clustering, plant top sub-region extraction, and tassel point cloud identification.

2.2.1 Point Cloud Super Voxels Clustering This study first decomposes the plant point cloud into multiple point cloud sub-regions through super voxels clustering. These sub-regions are formed by integrating local region point clouds with geometric similarity, and they well preserve the boundary information between plant organs, facilitating subsequent tassel point cloud segmentation. This study uses a spectral clustering algorithm to achieve point cloud super voxels clustering. Assuming the input 3D maize point cloud is P = {p |i = 1, 2, ···, n} with n points, the specific steps for super voxels clustering of P are as follows.

(1) Edge connection operation. All points in P undergo edge connection operations to form an undirected graph. For any point p , the K-nearest neighbor spatial search method [26] is first used to obtain the k nearest neighbor points to p in P in terms of Euclidean distance, forming the point set A = {a |j = 1, 2, ···, k, a   P}. Then, all points in A are traversed to determine whether each point can connect with p to form an edge. If the k nearest neighbor points of a in P do not include p , then p and a cannot be connected; otherwise, they can be connected to form an edge, and the weight of this edge is calculated through formula (1):

$$\theta_{ij} = \arccos(n_i \cdot n_j)$$

$$e = \begin{cases} 0.1 & \theta_{ij} < \theta_{threshold} \\ 0.9 & \theta_{ij} \geq \theta_{threshold} \end{cases}$$

where n and n represent the unit normal vectors of points p and a , respectively;   is the angle between n and n in radians. This study uses the normal vector estimation module in the Point Cloud Library (PCL) [27] to calculate point cloud normal vectors. This module first uses Principal Component Analysis (PCA) [28] to estimate normal vectors. The initial normal vectors have inconsistent orientation, causing adjacent point cloud normal vectors to point in opposite directions. The module adjusts normal vector directions through viewpoint position by providing a 3D viewpoint coordinate to orient all normal vectors toward the viewpoint direction.

(2) Construction of normalized Laplacian matrix. Construct the adjacency matrix W of plant point cloud P, which is an n×n square matrix. Its element w   in row i and column k represents the connection relationship between points p and p . If there is no edge connection between p and p , then w   = 0; if there is an edge connection, then w   equals the weight of that edge. Construct the n×n degree matrix D, whose element d   in row i and column k is calculated through formula (2):

$$d_{ik} = \begin{cases} \sum_{j=1}^{n} w_{ij} & i = k \\ 0 & i \neq k \end{cases}$$

From formula (2), it can be seen that the diagonal elements of degree matrix D are non-zero, while all other elements are zero. After obtaining adjacency matrix W and degree matrix D, the normalized Laplacian matrix L is calculated through formula (3):

$$L = D^{-1/2} \times (D - W) \times D^{-1/2}$$

(3) Point cloud clustering. The singular value decomposition method is used to calculate the eigenvalues and eigenvectors of normalized Laplacian matrix L, and the K eigenvectors u (i = 1, 2, ···, K) corresponding to the K smallest eigenvalues are selected. Each eigenvector u is an n-dimensional column vector, where K is a user-input category number parameter, and this study sets K = 80. The above K eigenvectors are combined into an n×K feature matrix F = [u_1, u_2, ···, u_K], and F is row-normalized. If each K-dimensional row vector in F is regarded as a data sample, then there are n data samples in matrix F. The K-means clustering method is used to cluster these n data samples into K categories, where the category of the i-th data sample is the category of point p in plant point cloud P. Finally, points with the same category are grouped into the same sub-region, and the plant point cloud is ultimately divided into K sub-regions. Let Ø denote the sub-region point set, and the m-th sub-region is denoted by Ø (m = 1, 2, ···, K). This study uses point cloud normal vectors as features to cluster neighboring points with similar normal vectors into the same sub-region.

The point cloud super voxels clustering results for different plant types are shown in Figure 2 [Figure 2: see original paper]. It can be seen from the figure that each organ of the plant is decomposed into multiple sub-regions with smooth boundaries, and the overall morphology of each sub-region is relatively simple, making it convenient to represent and identify with simple geometric features. For example, sub-regions on leaves are approximately planar, while sub-regions on stems are approximately cylindrical. However, at some organ junctions, there are cases where point clouds belonging to different organs are mistakenly grouped into the same sub-region, such as some leaf collar point clouds forming the same sub-region as the stem, and some tassel point clouds forming the same sub-region as the top leaf.

2.2.2 Plant Top Sub-Region Extraction The tassel is located in the top region of the maize plant, so the tassel point cloud can be roughly located through the relative position of the point cloud in the plant. Some studies use depth cameras to obtain plant point cloud data [29,30]. During data acquisition, the camera position can be adjusted so that a certain coordinate axis of the plant point cloud coordinate system coincides with the growth direction of the maize plant, allowing preliminary identification of the top sub-region through point cloud coordinate values. However, point cloud data obtained using handheld laser 3D scanners or multi-angle image reconstruction methods belongs to scattered point clouds, whose relative position to the coordinate axes of the space coordinate system is random, thus increasing the difficulty of extracting the plant top region. This study uses the following steps to locate the plant top region.

(1) Fit the principal component vector of the plant point cloud. Principal component analysis is used to extract the principal component direction of plant point cloud P. First, the center point p_c of the plant is calculated:

$$p_c = \frac{1}{n}\sum_{i=1}^{n} p_i$$

Then, the covariance matrix C is constructed using formula (5):

$$C = \frac{1}{n}\sum_{i=1}^{n}(p_i - p_c)^T(p_i - p_c)$$

where matrix C is a 3$×$3 symmetric real matrix. The singular value decomposition algorithm is used for eigenvalue decomposition of C to obtain three non-negative eigenvalues λ_1, λ_2, λ_3 ($\lambda_1 \geq \lambda_2 \geq \lambda_3$) and their corresponding three eigenvectors I_1, I_2, I_3. The eigenvectors I_1, I_2, and I_3 are the first, second, and third principal component vectors of the plant point cloud, respectively.

(2) Extract candidate top sub-region sets. Using the first principal component vector I_1 of the plant point cloud as the direction vector, the parametric equation L(t) of the line passing through the plant center point p_c is:

$$L(t) = I_1 t + p_c$$

The projection coordinate t of each point p in P on line L(t) is calculated using formula (7):

$$t_i = (p_i - p_c) \cdot I_1$$

The maximum value t_1 and minimum value t_2 of all point projection coordinates are found, and then two thresholds t_3 and t_4 are calculated using formulas (8) and (9) to extract point clouds at both ends of the plant:

$$t_3 = 0.9t_1 + 0.1t_2$$

$$t_4 = 0.9t_2 + 0.1t_1$$

Sub-region sets V_1 and V_2 are defined, and all point cloud sub-regions are traversed. If a sub-region contains points with projection coordinates > t_3, the sub-region is added to set V_1. If a sub-region contains points with projection coordinates < t_4, the sub-region is added to set V_2. Both V_1 and V_2 are candidate plant top sub-region sets, representing the two ends of the maize plant, one being the bottom region and the other the top region. The process of extracting candidate top regions is shown in Figure 3 Figure 3: see original paper.

(3) Identify the top sub-region. The stem in the bottom region of mature maize plants is cylindrical with obvious straight linear features. In contrast, the top region of the plant contains the tassel, which presents a certain broom-like shape with weak straight linear features. Based on these characteristics, this study selects the top sub-region set from V_1 and V_2 by calculating the straight linear features of point clouds in the sub-regions.

The straight linear feature of a sub-region point set is defined as the average of the straight linear features of all points in the set. To calculate the straight linear feature of a point p in sub-region point set Ø, all points in Ø within a distance less than r_1 from point p are first found to form point set B_1, where r_1 is a user-adjustable parameter and this study sets $r_1 = 10$ cm. Then, Principal Component Analysis is used to calculate the three eigenvalues λ_1, λ_2, λ_3 ($\lambda_1 \geq \lambda_2 \geq \lambda_3$) of point set B_1. If λ_1 is significantly larger than λ_3 (i.e., λ_1 - λ_3 is large), the straight linear feature f_1 of point p is calculated through formula (10):

$$f_1(p) = \frac{\lambda_1 - \lambda_3}{\lambda_1}$$

The straight linear features of each sub-region in V_1 and V_2 are calculated using the above method, and the average straight linear feature f_{v1} of all sub-regions in V_1 and the average straight linear feature f_{v2} of all sub-regions in V_2 are computed. By comparing the magnitudes of f_{v1} and f_{v2}, the sub-region set with the smaller value corresponds to the plant top region, while the set with the larger value corresponds to the plant bottom region. The heat maps of straight linear features for sub-regions in V_1 and V_2 are shown in Figure 3(b). It can be seen from the figure that the tassel sub-regions in the top region have very small straight linear feature values, causing the average straight linear feature of this candidate region to decrease significantly. In contrast, the stem has a larger straight linear feature value, keeping the feature value of the bottom region at a relatively high level.

2.2.3 Tassel Point Cloud Recognition The top sub-region set extracted in the previous section (Figure 4 Figure 4: see original paper) contains three types of sub-regions: tassel sub-regions containing only tassel points, leaf sub-regions containing only leaf points, and mixed sub-regions containing both tassel and leaf points. To achieve accurate segmentation of tassel point clouds, it is necessary to identify tassel sub-regions in the top region and identify tassel point clouds in mixed sub-regions. Since leaves have more obvious planar features than tassels, this study identifies tassel point clouds and leaf point clouds through the planar features of points within sub-regions. The specific steps are as follows.

(1) Extract planar features of points within sub-regions. To calculate the planar feature of a point p in sub-region point set Ø, all points in Ø within a distance less than r_2 from point p are found to form point set B_2, where r_2 is a user-adjustable parameter. Then, the three eigenvalues λ_1, λ_2, λ_3 ($\lambda_1 \geq \lambda_2 \geq \lambda_3$) of point set B_2 are calculated. If λ_2 is significantly larger than λ_3 (i.e., λ_2 - λ_3 is large), the planar feature f_2(p) of point p is calculated through formula (11):

$$f_2(p) = \frac{\lambda_2 - \lambda_3}{\lambda_1}$$

The planar feature f_2(Ø) of sub-region point set Ø is the average of the planar features of all points in the set. The heat map of planar features of plant top point clouds is shown in Figure 4(b), where larger feature values indicate weaker planar features.

(2) Point cloud classification. The mean f_2 and variance S_2 of planar features of all sub-regions are calculated. If the planar feature of a sub-region is greater than $f_2 + 0.5S_2$, the sub-region is classified as a leaf sub-region. If the planar feature of a sub-region is less than f_2 - $0.5S_2$, the sub-region is classified as a tassel sub-region, and its internal points are classified as tassel points. If the planar feature of a sub-region satisfies f_2 - $0.5S_2$ < f_2(Ø) < $f_2 + 0.5S_2$, the region is a mixed sub-region. In mixed sub-regions, points with planar features f_2(p) less than f_2 are classified as tassel point clouds. The point cloud classification process is shown in Figure 4(c).

(3) Denoising. In mixed sub-regions, the planar features of leaf edge points are also small, so they are easily classified as tassel points during classification. However, these misclassified points are usually far from the entire tassel point cloud. Therefore, this study uses a statistical outlier removal method to eliminate isolated noise points in the segmented tassel point cloud.

The final tassel segmentation results and ground truth results are shown in Figures 4(d) and 4(e), respectively. It can be seen from the figures that the proposed method segments most of the tassel point clouds. However, the point cloud classification method in this study has misidentification of sub-region categories, which reduces the segmentation accuracy of tassel point clouds. For example, sub-region 1 in Figure 4(a) is a mixed sub-region, but its internal leaf point clouds are far more numerous than tassel point clouds. Therefore, the planar feature value of this sub-region reflects more characteristics of leaf point clouds, causing the sub-region to be misclassified as a leaf sub-region and resulting in missing tassel points in the final segmentation result. In mixed sub-region 2 in Figure 4(a), the numbers of leaf point clouds and tassel point clouds are similar, so the sub-region category can be correctly identified through planar feature values, and most tassel point clouds in this sub-region can be identified.

2.3 Segmentation Accuracy Evaluation

This study uses Precision, Recall, and F1 score to evaluate segmentation accuracy. For tassel point clouds, TP represents the number of points belonging to the tassel that are correctly segmented as tassel, FP represents the number of points not belonging to the tassel that are mistakenly segmented as tassel, and FN represents the number of points belonging to the tassel that are mistakenly segmented as other organ point clouds. Precision, Recall, and F1 score are calculated as shown in formulas (12) to (14):

$$Pr = \frac{TP}{TP + FP}$$

$$Re = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Pr \times Re}{Pr + Re}$$

where Pr represents precision, Re represents recall, and F1 represents the F1 score. Generally, segmentation precision and recall are contradictory, so the F1 score is often used for comprehensive consideration of segmentation algorithm effectiveness. A higher F1 score indicates better segmentation performance.

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3 Results and Discussion

3.1 Segmentation Efficiency and Accuracy

Algorithm testing was conducted on a laptop workstation configured with a 2.2 GHz CPU and 32 GB DDR memory. During point cloud super voxels clustering, the singular value decomposition method was used for eigenvector decomposition of the n×n normalized Laplacian matrix, resulting in an overall algorithm time complexity of O(n^3). Therefore, as point cloud density and point cloud quantity increase, algorithm running time increases significantly. When the point cloud density was 0.8 points/cm, the number of mature maize plant point clouds averaged about 6,000, and the average total running time was 2.26 s. When the point cloud density was 1.3 points/cm, the average plant point cloud quantity was about 15,000, with an average total running time of 6.85 s. When the point cloud density increased to 1.9 points/cm, the average plant point cloud quantity increased to about 30,000, and the total running time increased to 27.37 s. The specific running times of the proposed method are shown in Table 1 .

The segmentation accuracy of the proposed algorithm is shown in Table 2 . When the point cloud density was 0.8 points/cm, the average F1 score, average precision, and average recall for tassel segmentation were 0.763, 0.746, and 0.832, respectively. When the point cloud density was 1.3 points/cm, these three metrics were 0.875, 0.898, and 0.867, respectively. When the point cloud density was 1.9 points/cm, the three segmentation metrics were 0.889, 0.950, and 0.849, respectively. From the F1 score metric, it can be seen that the segmentation accuracy of this study gradually increases with point cloud density, but the difference in segmentation effect between point cloud densities of 1.3 and 1.9 points/cm is not significant.

The increase in point cloud density and point cloud quantity mainly affects the calculation results of point cloud planar features in the tassel segmentation step. When the number of point clouds is small, the top leaf point cloud is relatively sparse, and the difference between the planar features of leaf points and tassel points is not obvious, leading to increased point cloud misclassification. However, when the number of point clouds increases, the planar features of leaf point clouds become more prominent, thus increasing the distinction between tassel points and leaf points and reducing the leaf point clouds included in the segmented tassel point clouds, significantly improving segmentation precision. From the precision metrics in Table 1, it can be seen that as point cloud density increases, precision improves significantly, while recall changes little. The increase in F1 score mainly comes from the increase in precision.

The visualization results of tassel segmentation for maize plants with a point cloud density of 1.9 points/cm and different F1 scores are shown in Figure 5 [Figure 5: see original paper]. It can be seen from the figure that most test samples exhibit incomplete tassel segmentation, indicating that the proposed method has an under-segmentation problem. When the tassel is completely above the top leaves or far from the leaves, the segmentation accuracy of this study is very high (as shown in Figures 5(m) to 5(o)). Conversely, when the tassel is wrapped by leaves or close to leaves (as shown in Figures 5(a) to 5(c)), the segmentation accuracy is lower. The reason for this phenomenon is that if the tassel is close to leaves, the boundary point clouds between them have very similar normal vectors and planar local features, making accurate segmentation difficult through point cloud super voxels clustering and planar features.

3.2 Algorithm Parameters

The parameters affecting the proposed algorithm are mainly the K parameter in the point cloud super voxels clustering step, the r_1 parameter in the plant top sub-region extraction, and the r_2 parameter in the tassel point cloud recognition. The K parameter affects the number of sub-regions obtained from point cloud super voxels clustering; larger K values result in more sub-regions. In subsequent plant top sub-region extraction and tassel point cloud recognition operations, sub-regions are used as point cloud sets to calculate the straight linear features and planar features of points. Smaller K values result in fewer sub-regions per organ, increasing the probability that each sub-region contains point clouds from multiple organs, reducing the discriminative power of straight linear features and planar features for stem, leaf, and tassel points, and decreasing segmentation accuracy. However, larger K values significantly increase the computation time of super voxels clustering. In this study, K = 80 was determined through experiments, which is applicable to mature maize point clouds of different plant types and densities, decomposing each organ into multiple sub-regions with smooth boundaries and simple morphology that can be easily judged using straight linear features and planar features.

The r_1 parameter affects the calculation results of point straight linear features. If r_1 is small, when calculating the straight feature of a stem point in the bottom sub-region, the neighboring points found may only include one side of the stem cylinder surface, reducing the calculated straight feature value. Conversely, larger r_1 values result in larger straight feature values for stem point clouds, making the contrast between straight features of bottom and top sub-regions more obvious. However, excessively large r_1 values increase the number of neighboring points and reduce the computational efficiency of feature values. This study sets $r_1 = 10.0$ cm. Since the diameter of maize stems usually does not exceed 10.0 cm, this value ensures that the neighboring point set of each stem point forms a relatively complete cylindrical point cloud set, resulting in large straight feature values for stem points while not excessively reducing computational efficiency.

The r_2 parameter affects the calculation results of point planar features, thereby changing the recognition results of tassel point clouds. The planar features of maize leaves are local—while the entire leaf surface shows obvious bending characteristics, local small areas are relatively flat. As r_2 increases, the neighborhood point range searched for each point increases, increasing the planar feature values of leaf points and reducing the contrast in planar features between leaf points and tassel points. Therefore, the r_2 value should not be too large. Since the leaves in the top sub-region are all tip areas of upper leaves, the width of these areas usually does not exceed 6.0 cm, and the top leaves often curl along the leaf veins, the r_2 value should be less than 3.0 cm to ensure that the planar features of leaf point clouds are obvious. However, too small an r_2 value results in too few neighboring points, making it difficult to describe the geometric characteristics of local regions and reducing the accuracy of planar feature calculations. At the same time, each branch of the tassel may also present certain planar features in extremely small regions, so the r_2 value must not be smaller than the width of tassel branches. The width of each branch of maize tassel is usually less than 1.0 cm, so the r_2 value should be greater than 1.0 cm.

When setting the specific parameter value of r_2 in this study, for each point cloud density, parameter selection tests were started from $r_2 = 1.0$ cm, gradually increasing r_2 by intervals of 0.1 cm until $r_2 = 3.0$ cm. The r_2 parameter with good segmentation effect was selected for calculation. When multiple parameter values had similar segmentation effects, the minimum value was selected as the

r_2 parameter to reduce the number of neighboring points as much as possible and improve the computational efficiency of planar features. Through this method, this study determined that when point cloud density = 0.8 points/cm, r_2 is set to 2.4 cm; when point cloud density = 1.3 points/cm, r_2 is set to 1.8 cm; and when point cloud density = 1.9 points/cm, r_2 is set to 1.0 cm. As point cloud density decreases, the r_2 parameter value increases significantly. This is because when point cloud density is low, the neighborhood search radius needs to be increased to find enough neighboring points to describe local planar features. When given a new plant point cloud density, the r_2 values provided in this study can be used as references to improve parameter selection efficiency. For example, if the plant point cloud density is 1.6 points/cm, the r_2 value can be tested between the parameter values for point cloud densities of 1.9 and 1.3 points/cm, i.e., starting parameter selection from r_2 = 1.0 cm and gradually increasing r_2 by intervals of 0.1 cm to 1.8 cm.

3.3 Outlook

The current algorithm cannot handle cases where the tassel is wrapped by leaves or close to leaves. In such cases, the normal vectors and planar local features of boundary point clouds between leaves and tassels are very similar, causing decreased segmentation accuracy. Jin et al. [31] developed a region-growing stem-leaf segmentation algorithm based on median normalized vectors, using Euclidean distance as a feature and a heuristic region-growing strategy to completely segment organ point clouds from seed points at the bottom of organs. This method proves the effectiveness of distance features in maize organ segmentation. In future work, combining the tassel point clouds segmented in this study as seed points with distance-constrained region-growing methods is expected to optimize the final tassel point cloud segmentation results.

The algorithm in this study can only segment tassels from single maize plant point clouds. To obtain single plant point clouds, maize plants need to be transplanted into pots and manually scanned with a laser scanner, resulting in low data acquisition efficiency. The MVS Pheno platform can quickly and automatically obtain multi-angle images of maize plants and use structure-from-motion methods to obtain high-quality single plant point clouds [32]. The next step is to combine the proposed method with the MVS Pheno platform to accelerate tassel phenotyping speed.

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4 Conclusion

This study proposes a maize plant 3D point cloud tassel segmentation method based on super voxels clustering and point cloud local features, verifying the possibility of identifying and segmenting tassels on mature maize plant point clouds. By analyzing the experimental results of this study, the following conclusions are drawn:

(1) The segmentation accuracy of the proposed method increases with plant point cloud density. When the point cloud densities are 0.8, 1.3, and 1.9 points/cm, the average F1 scores of tassel point cloud segmentation are 0.763, 0.875, and 0.889, respectively.

(2) The time complexity of the algorithm is $O(n^3)$, so as point cloud density and point cloud quantity increase, the running time increases significantly.

(3) Considering both segmentation accuracy and running time, the method achieves the best performance on mature maize plant point clouds with a density of 1.3 points/cm and an average quantity of about 15,000 points, with a segmentation F1 score of 0.875 and a running time of 6.85 s.

The results demonstrate that the proposed method has the capability to extract tassel point clouds from scattered maize plant point clouds and can provide technical support for research and applications in high-throughput maize phenotyping and 3D reconstruction.

References

[1] TESTER M, LANGRIDGE P. Breeding technologies to increase crop production in a changing world[J]. Science, 2010, 327: 818-822.

[2] DUNCAN W G, WILLIAMS W A, LOOMIS R S. Tassels and the productivity of maize[J]. Crop Science, 1967, 7: 7-9.

[3] MEGHJI M R, DUDLEY J W, LAMBERT R J, et al. Inbreeding depression, inbred and hybrid grain yields, and other traits of maize genotypes representing three eras[J]. Crop Science, 1984, 24(3): 545-549.

[4] BROWN P J, UPADYAYULA N, MAHONE G S, et al. Distinct genetic architectures for male and female inflorescence traits of maize[J]. PLoS Genet, 2011, 7(11): ID e1002383.

[5] ZHANG Y, ZHANG N. Imaging technologies for plant high-throughput phenotyping: A review[J]. Frontiers of Agricultural Science and Engineering, 2018, 5(4): 406-415.

[6] FERNANDA D M, GEMMA M, CAROLINA R A, et al. Yielding to the image: How phenotyping reproductive growth can assist crop improvement and production[J]. Plant Science, 2018, 282: 73-82.

[7] GAGE J L, MILLER N D, SPALDING E P, et al. TIPS: A system for automated image-based phenotyping of maize tassels[J]. Plant Methods, 2017, 13(1): 1-11.

[8] YE M, CAO Z, YU Z. An image-based approach for automatic detecting tasseling stage of maize using spatio-temporal saliency[C]// SPIE Conference

on Multispectral Image Processing and Pattern Recognition. Washington, USA: SPIE Digital library, 2013.

[9] KURTULMUŞ F, KAVDIR Ş. Detecting corn tassels using computer vision and support vector machines[J]. Expert Systems with Applications, 2014, 41(16): 7390-7397.

[10] LU H, CAO Z, XIAO Y, et al. Fine-grained maize tassel trait characterization with multi-view representations[J]. Computers and Electronics in Agriculture, 2015, 118: 143-158.

[11] LU H, CAO Z, XIAO Y, et al. TasselNet: Counting maize tassels in the wild via local counts regression network[J]. Plant Methods, 2017, 13(1): 1-17.

[12] MAKANZA R, ZAMAN-ALLAH M, CAIRNS J E, et al. High-throughput method for ear phenotyping and kernel weight estimation in maize using ear digital imaging[J]. Plant Methods, 2018, 15(1): ID 49.

[13] WANG C, GUO X, WU S, et al. Three dimensional reconstruction of maize ear based on computer vision[J]. Transactions of the CSAM, 2014, 45(9): 274-279.

[14] WEN W, GUO X, YANG T, et al. Point cloud segmentation method of maize ear[J]. Journal of System Simulation, 2017, 29(12): 3030-3034, 3041.

[15] WEN W, WANG Y, XU T, et al. Geometric modeling of maize ear based on three-dimensional point cloud[J]. Journal of Agricultural Science and Technology, 2016, 18(5): 88-93.

[16] YU Z, ZHOU H, LI C. An image based automatic recognition method for the flowering stage of maize[C]// International Symposium on Multispectral Image Processing and Pattern Recognition. Washington, USA: SPIE Digital library, 2019.

[17] BRICHET N, FOURNIER C, TURC O, et al. A robot-assisted imaging pipeline for tracking the growths of maize ear and silks in a high-throughput phenotyping platform[J]. Plant Methods, 2017, 13(1): ID 96.

[18] JIA H, QU M H, WANG G, et al. Dough-stage maize (Zea mays L.) ear recognition based on multiscale hierarchical features and multifeature fusion[J]. Mathematical Problems in Engineering, 2020, 2020(2): 1-11.

[19] PAULUS S, SCHUMANN H, KUHLMANN H, et al. High-precision laser scanning system for capturing 3D plant architecture and analysing growth of cereal plants[J]. Biosystems Engineering, 2014, 121: 1-11.

[20] PAULUS S, DUPUIS J, RIEDEL S, et al. Automated analysis of barley organs using 3D laser scanning: An approach for high throughput phenotyping[J]. Sensors, 2014, 14(7): 12670-12686.

[21] CHÉNÉ Y, ROUSSEAU D, LUCIDARME P, et al. On the use of depth camera for 3D phenotyping of entire plants[J]. Computers and Electronics in

Agriculture, 2012, 82: 122-127.

[22] BUSEMEYER L, MENTRUP D, MÖLLER K, et al. BreedVision—A multi-sensor platform for non-destructive field-based phenotyping in plant breeding[J]. Sensors, 2013, 13(3): 2830-2847.

[23] LIN Y. LiDAR: An important tool for next-generation phenotyping technology of high potential for plant phenomics?[J]. Computers and Electronics in Agriculture, 2015, 119: 61-73.

[24] GARRIDO M, PARAFOROS D S, REISER D, et al. 3D maize plant reconstruction based on georeferenced overlapping lidar point clouds[J]. Remote Sensing, 2015, 7(12): 17077-17096.

[25] HAN D, YANG G, YANG H, et al. Three dimensional information extraction from maize tassel based on stereoscopic vision[J]. Transactions of the CSAE, 2018, 34(11): 166-173.

[26] MILLER F P, VANDOME A F, MCBREWSTER J. KD-TREE[M]. San Francisco, California, USA: Alpha Press, 2009.

[27] RUSU R B, COUSINS S. 3D is here: Point cloud library (PCL)[C]// IEEE International Conference on Robotics & Automation. New Jersey, USA: IEEE Press, 2011.

[28] GROTH D, HARTMANN S, KLIE S, et al. Principal components analysis[J]. Methods in Molecular Biology, 2013, 930: 527-547.

[29] XIANG L, BAO Y, TANG L, et al. Automated morphological traits extraction for sorghum plants via 3D point cloud data analysis[J]. Computers and Electronics in Agriculture, 2019, 162: 951-961.

[30] QIU R, ZHANG M, WEI S, et al. Method for measurement of maize stem diameters based on RGB-D camera[J]. Transactions of the CSAE, 2017, 33(S1): 170-176.

[31] JIN S, SU Y, WU F, et al. Stem-leaf segmentation and phenotypic trait extraction of individual maize using terrestrial LiDAR data[J]. IEEE Transactions on Geoscience and Remote Sensing, 2019, 57(3): 1336-1346.

[32] WU S, WEN W, WANG Y, et al. MVS-Pheno: A portable and low-cost phenotyping platform for maize shoots using multiview stereo 3D reconstruction[J]. Plant Phenomics, 2020, 2020(2): ID 1848437.

Note: Figure translations are in progress. See original paper for figures.