3D Point Cloud Instance Segmentation of Lettuce Based on PartNet

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Abstract

Organ level instance segmentation (e.g., individual leaves) based on computer vision techniques is a key step in the measurement of plant phenotypes. Since plant organs, especially leaves, are self-occluded and emerged-occluded, single-view images affect the acquisition of some effective information. However, 3D global images contain much more plant morphological information than single-view images, and it is of great significance for plant phenotype research. In this paper, lettuce was taken as the research object, its 3D point cloud images were obtained and instance segmentation was carried out based on the deep learning method. The result showed that the 3D point cloud of each leaf was segmented and identified accurately. Specifically, we constructed a lettuce point cloud dataset consisting of 620 real and synthetic point clouds and fused them together to train a 3D instance segmentation network—PartNet, which directly takes 3D point clouds as input and its output is the instance segmentation results of leaves. The experimental results showed that, when tested with 40 point clouds in the validation set, the metric Average Precision (%) with IoU threshold being 0.25 reached 97.2%, and with IoU threshold being 0.5 reached 92.4% respectively, indicating that the constructed PartNet network has the potential to accurately segment the 3D point cloud leaf instances for lettuce.

1. Introduction

People identify, classify, and organize objects based on what they know about their parts [1]. Fine-grained segmentation of different parts of plant organs that belong to the same semantics is very meaningful for plant phenotype research, growth monitoring, and management, such as pruning tree branches and picking specific fruits on fruit trees. Therefore, teaching machines to analyze instance parts belonging to the same semantics is crucial for computer vision, graphics and robotics applications, such as predicting object functions, human-object interaction, shape editing and shape generation [2]. Traditional machine learning methods cannot handle instance segmentation tasks well. With the rise of deep neural network technology in recent years, there have been many pioneering research results in the field of image instance segmentation. Since plants are non-rigid objects with more severe self-obscuration, the items of plant phenotypes that can be obtained based on 2D image instance segmentation methods are limited, so that research on 3D plant phenotype processing methods is needed. PointNet [3] and PointNet++ [4] are regarded as milestones in 3D deep learning models, providing efficient and flexible methods for 3D data classification and segmentation tasks. They have well solved the computational and memory costly problems of directly applying 2D convolutional neural network to 3D volumetric data [5]. 3D instance segmentation networks using PointNet++ as a feature extraction module have emerged in recent years. The proposal of these networks provides new opportunities for 3D plant phenotyping studies [6, 7] and motivates novel work in 3D instance segmentation processing of plants.

One of the main factors hindering the application of 3D deep learning techniques to plant phenotypes is the lack of large annotated 3D plant datasets, which can be used to provide sufficient training data for machine learning frameworks through the strategy of creating synthetic 3D plant models [8]. Instance segmentation dataset requires that each point cloud image contains the complete 3D morphology and requires point cloud with high accuracy so that better results can be obtained during data annotation and network training. Current 3D reconstruction methods based on 2D images include Structure from Motion (SfM) and Multi-View Stereo (MVS) techniques, but they all require the acquisition of a large number of multi-view images and the reconstruction process is slow. At the same time, real plant point cloud images taken based on consumer-grade depth cameras have low accuracy after reconstruction, the results are distorted, and the reconstruction process is also labor-intensive. Although the reconstructed point cloud images based on LiDAR, TLS scanner, X-ray and other methods have high accuracy, the cost of camera equipment is high, and the scanning process is slow, which leads to the small amount of data contained in the dataset and cannot meet the training requirements of deep neural network. Since the 3D instance segmentation dataset needs to label different instances of the same semantic part of each object separately, it needs to consume a lot of manpower and material resources. At present, the most representative, fine-grained and instance-level dataset called PartNet, which belongs to the synthetic dataset, contains 573, 585 part instances over 26, 671 3D models covering 24 object categories. This also provides a new idea to construct a dataset for plant instance segmentation. It should be noted that this dataset has the same name as the PartNet network structure, but belongs to a different work.

The main contributions of this paper are:

(1) Real cultivated lettuce point cloud images are collected and reconstructed to obtain the complete plant point cloud models for dataset construction.

(2) Synthetic point cloud data of leafy plants are generated using Blender software and fused with real data as the training dataset of neural network, and based on this, the point cloud leaves were recombined to enhance the dataset.

(3) In this study, a 3D instance segmentation network model was constructed, using the whole 3D point cloud directly as the input and plant leaves as the output, which reduces the intermediate steps of image processing.

2. Related Work

2.1. Methods based on geometric features and machine learning

Methods based on geometric interpretation and mathematical models, such as model fitting, DBSCAN, K-means [13], region growing [14], most of these methods perform well on man-made objects with fully uniform shapes [9]. When used in plant organ identification, these methods mainly utilize the geometric features of plant images such as RGB color features and morphological features for segmentation, which can achieve semantic segmentation and instance segmentation. Bashar Elnashef *et al.* [10] provided a new tensor-based (first-order and second-order) segmentation algorithm for 3D plant models, which divided the point cloud into points related to leaves and stems and implemented instance segmentation of leaves using DBSCAN. Roberto Ferrara *et al.* [11] used a TLS-based sensor to collect tree point clouds, partitioned them in a cubic voxel manner, and achieved the identification of wood and non-wood voxels by the point density algorithm DBSCAN clustering. Anthony Paproki *et al.* [12] used a morphology-based approach to segment 3D grid images of cotton and estimated phenotypic parameters. Stefan Paulus *et al.* [13] used laser scanning to obtain 3D images of barley and separated organs by a classification algorithm based on histograms of surface features, with 96% accuracy in the separation of leaves and stems.

Machine learning methods based on feature descriptors, such as surface feature histogram (SFH), point feature histogram (PFH) and fast point feature histogram FPFH [10], etc., to distinguish various categories of objects and classify the data based on the resulting model. Helin Dutagaci used Ilastik software to extract local features (intensity, edge and texture features) on rosebush volume data and trained a random forest classifier with ground truth labels to achieve organ-level semantic segmentation of plants, and showed good performance [14]. Paloma Sodhi *et al.* [15] combined local feature descriptors FPFH and global features of point cloud images to train a support vector machine (SVM) classifier to assign a stem and leaf class label to each 3D point to achieve semantic segmentation of sorghum. Paulus *et al.* [10] proposed a plant segmentation method based on point feature histogram descriptors and this new descriptor was used as a support vector machine (SVM) classification of features for segmentation of leaves and stems.

2.2. Deep learning based methods

There are two main ideas of 3D segmentation methods based on deep learning: a multi-view approach that segments 2D and 3D images separately and fuses the results to obtain instances; and a direct segmentation of 3D images that outputs the instance results. Weinan Shi proposed a plant organ segmentation method based on deep learning and a multi-view camera system, which segmented 2D images and integrated information from multiple viewpoints into a 3D point cloud representation of plants [16]. Helin Dutagaci used a 3D U-Net network based on 3D CNN to segment the ROSE-X dataset in voxel form [14], but the results showed that the segmentation accuracy was lower than that of the random forest method.

PointNet++ is a hierarchical network that captures fine geometry from the neighborhood of each point. As the core of the PointNet++ hierarchy, its ensemble abstraction layer consists of three sub-layers: a sampling layer, a grouping layer, and a PointNet-based learning layer. By stacking several ensemble abstraction layers, PointNet++ learns features from local geometric structures and abstracts local features layer by layer. Due to its simplicity and powerful representation, many networks have been developed based on PointNet++ as a backbone network [2, 5, 17], and a large number of subsequent 3D segmentation studies have been based on this network. Jules Morel [18], inspired by PointNet++, proposed a new segmentation method for handling unbalanced and inhomogeneous point clouds of trees, which can directly consume 3D point clouds, and implemented a validation on a large synthetic 3D scan dataset of trees, showing that the method outperforms the existing classifiers on simulated data. Kaya Turgut et. al [6] applied 6 state-of-the-art 3D deep learning network structures: the PointNet, PointNet++, DGCNN, PointCNN, ShellNet and RIConv, and trained and tested the network with a mixture of synthetic images generated by the L-studio software and real images from the ROSE-X dataset, and showed that PointNet++ obtained the best segmentation results.

On the other hand, Yu et. al [17] proposed a top-down recursive decomposition network, PartNet, for fine-grained segmentation of 3D point clouds. With a hierarchical decomposition scheme, the model can obtain fine-grained and accurate segmentation even for highly complex shapes, which provides a new idea for partial instance segmentation of plant point clouds, and in this paper we investigated instance segmentation of lettuce based on the PartNet network.

2.3. 3D dataset

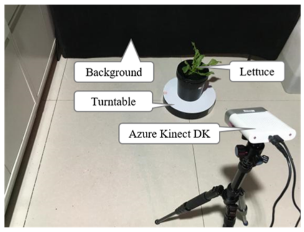
The sources about 3D plant datasets can be mainly divided into real 3D data and synthetic data, based on which real and synthetic datasets can be produced respectively, as well as datasets that mix the two to achieve data augmentation. 3D datasets based on real images are expensive to produce, but since images are captured in the real world, taking into account the effects of lighting and camera acquisition, it is more likely to get better results when testing the trained model on real plant images. H. Dutagaci produced the ROSE-X dataset with 11 3D voxel models of real rosebush plants obtained by X-ray imaging, where each voxel stored the corresponding organ class label [14]. Kaya Turgut et. al [6] also conducted experiments in which the networks were pre-trained using synthetic rosebush models generated by L-studio software and then updated with ROSE-X, and the results show that pre-training with synthetic data can improve the performance of some of the neural networks.

In order to obtain a large number of high-precision 3D images at a low cost, many works have been carried out on the production of synthetic plant dataset. ShapeNet [19] is a richly annotated, large-scale shape repository represented by 3D CAD models of objects. ShapeNet contains 3D models from multiple semantic classes and organizes them according to the Word-Net taxonomy, and provides a large-scale quantitative benchmark for computer graphics and vision research. PartNet [2] is a large-scale 3D dataset with fine-grained, hierarchical, instance-level part annotations. It is selected from ShapeNetCore for the most common categories in indoor scenes. The dataset contains 24 object classes, which also include synthetic data for plants and vases. Ayan Chaudhury took advantage of the classical procedural approach (L-system) to generate plant synthetic model data with annotations that can be used to produce datasets for semantic segmentation and organ-level instance segmentation [8]. Jules Morel et. al [18] used the grove plugin on Blender software to produce a large synthetic dataset of trees and this dataset was expanded by collecting models on the Internet, and point clouds were generated using a simulator in order to mimic the results of images taken in realistic STL.

3. Materials and Methods

3.1. Real data acquisition and 3D reconstruction

The research site was located in the plant factory of the College of Information and Electrical Engineering, China Agricultural University, as shown in Figure 1(a). The variety of lettuce was JingYan lettuce (*Lactuca sativa L. var. youmaicai*); the temperature of the cultivation environment was controlled at 25~28℃; the purple light was irradiated regularly every day to provide a light source



(a) (b)

Figure 1: (a) Growing environment of lettuces. (b) Data collection system.

Feature item	Parameter
Color camera resolution	2048 × 1536 pixels
Depth camera resolution	1024 × 1024 pixels
Points of the raw point cloud	3145728 points
Frame rates	15 FPS

Table1: Key parameters of Azure Kinect DK camera.

for their growth. The Hoagland culture solution was used as the nutrient solution. The cultivation time was 30 days, and the plant height range was 40~188mm.

In this study, an Azure Kinect DK camera (Microsoft Corporation) based on the ToF principle was used to acquire real 3D point cloud data, and the camera parameters are shown in Table 1.

Figure 1(b) is the data collection system: the camera was calibrated in advance; the lettuce was placed on the electric-driven turntable and the turntable was controlled to rotate at an interval of 45°; a single-view picture was taken when the turntable and the plant were in a static state and a total of 8 perspective images were taken for each lettuce plant.

The types of collected images included RGB images and synthesized point cloud images, as shown in Figure 2. The

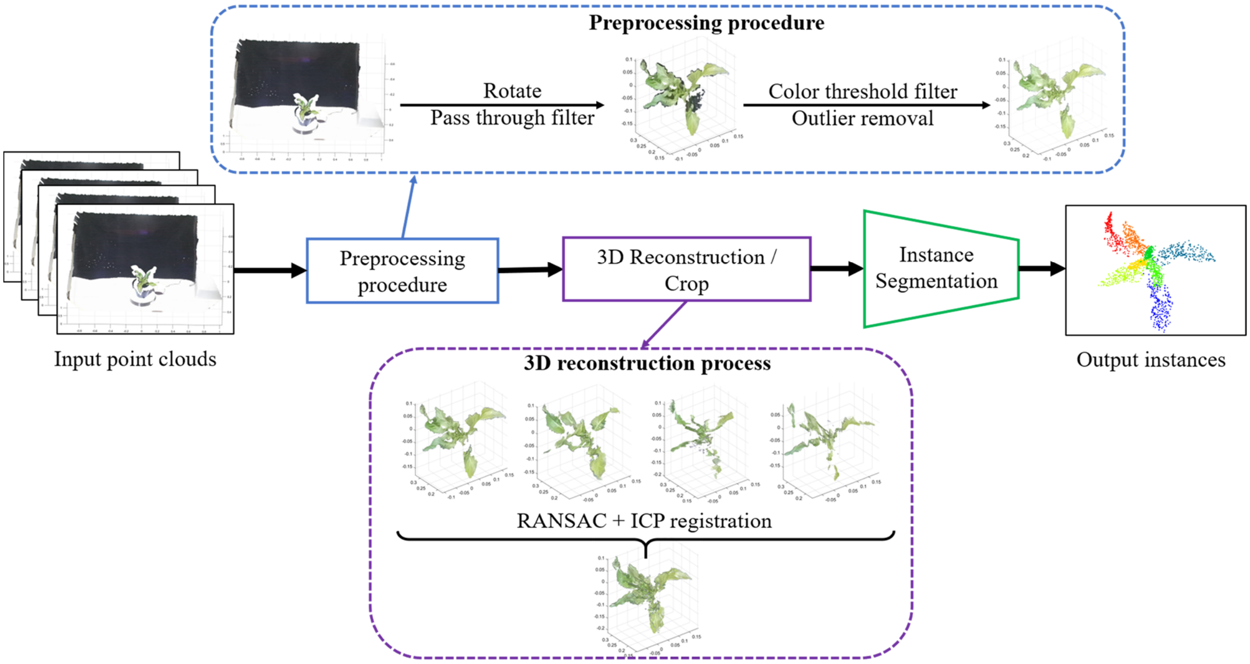


Figure 2: Lettuce point clouds instance segmentation pipeline. The solid arrows point to the flow of point cloud data, and the dashed arrows point to the detailed processing steps of specific sessions.

pre-processing procedure of the original point cloud image is shown in Figure 2(a), using the pass-through filter, color threshold filter, and radius outlier filter to remove background and noise points and obtaining a single-view point cloud image of the lettuce plant. Specifically, according to the shooting distance and lettuce size, pass-through filter parameters were set to x(-0.1, 0.1), y(-0.1, 0.1), z (0, 0.2); the black flowerpot point cloud was removed according to the color filtering method; when using the radius outlier removal algorithm, the minimum amount of points that the sphere should contain was set to 5, the radius of the sphere that would be used for counting the neighbors was set to 0.001. The global point cloud image was obtained by aligning the reconstruction of 4 or 8 viewpoint point clouds according to the RANSAC and ICP algorithms. For lettuce with smaller shape in the early stage of growth, we cropped and combined leaf instances in multiple single-view point clouds to replace reconstruction.

Data acquisition, processing, reconstruction, and neural network modeling were performed on computers configured with Ubuntu 18.04 operating system, AMD Ryzen5 3600 processor, 16GB RAM, NVIDIA GeForce RTX 3060 GPU, and installed with Open3D[20], OpenCV, PCL[21] image processing library and CloudCompare [22], MeshLab open-source software.

3.2. Creating synthetic dataset

Considering that the acquisition of real lettuce 3D point cloud data is a time-consuming and labor-intensive work, including the cultivation of lettuce in the early stage and data acquisition, processing, and 3D reconstruction in the later stage, and that deep learning has high demand for data number, quality and diversity, we introduced synthetic plant point clouds as augmented data to increase the number, quality and diversity of the dataset.

We first used Blender software and its plugin Graswald to produce 100 synthetic complete morphological models similar to lettuce plants [23]. The plugin serves as a framework to design accurate plant models thanks to its intelligent management of leaf arrangement on plant stems. It also presents several presets for handling various leaf characters, allowing us to generate a wide range of plant mesh models and to simulate different plant morphologies by adjusting the random seeds, growth stages, size, and other parameters of the plant model. To increase the number of training data samples, we generated three growth stages, and adjusted the morphological parameters

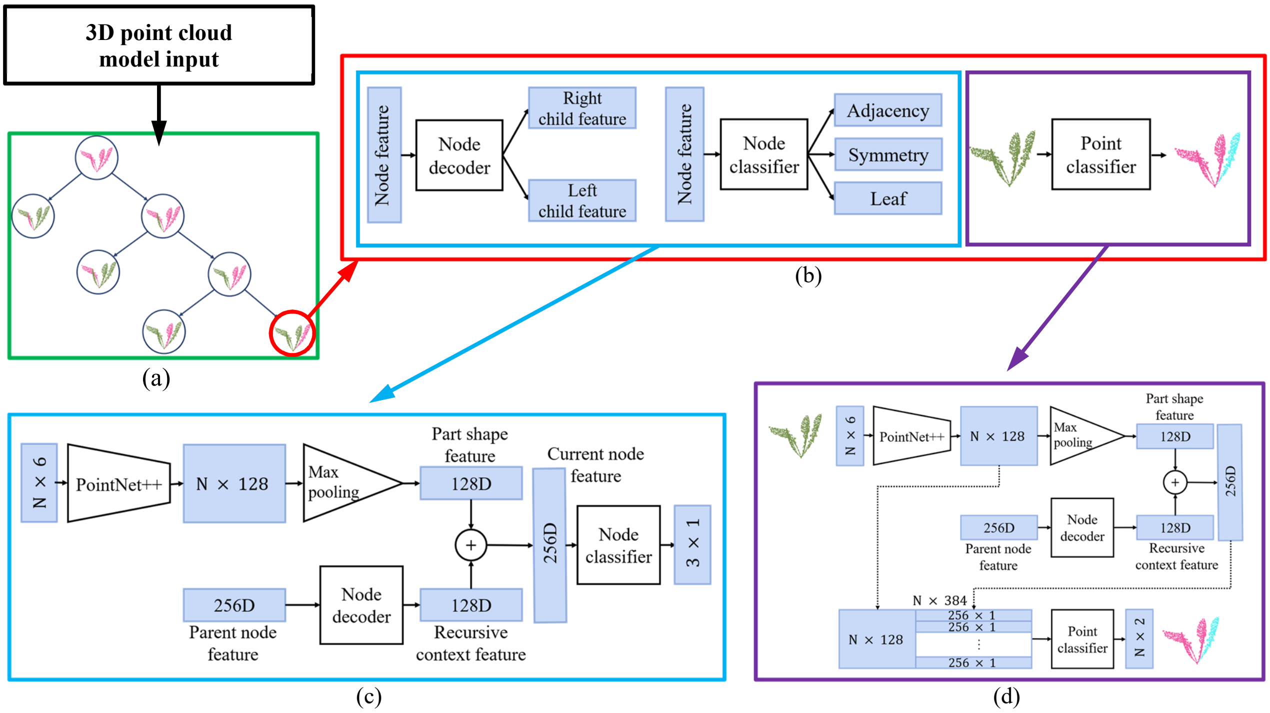


Figure 4: PartNet model pipeline. We used the same network structure as the original PartNet model, with the feature extraction module of PointNet or PointNet++ chosen for the point cloud feature learning network. (a) An overview of the data in the dataset, consisting of a binomial tree of point cloud nodes. (b) The architecture of PartNet. (c) Node decoding module and node classification module. (d) Node segmentation module.

of the plant for each stage. Each generated point cloud contained about 30,000 points. The synthetic data examples are shown in Figure 3.

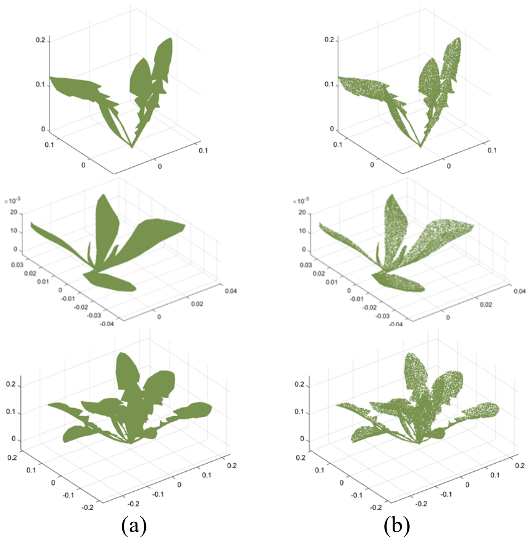


Figure 3: Synthetic dataset (a) Mesh model. (b) Down-sampled point cloud.

3.3. Dataset annotation

The reconstructed point clouds of lettuce were manually segmented into different leaf instances using CloudCompare software, and the segmented point cloud of each instance was down-sampled to 2048 points. For those leaves with less than 2048 points, the Ball pivoting algorithm was used to reconstruct the surface as a mesh model first, and then down-sampled to 2048 points. Then the normal of each point cloud was calculated, so that each point had 6 dimension features with X, Y, and Z coordinate values and a total of 3 directional normals of X, Y, and Z. Each point cloud of a leaf was marked with a unique label serial number. By randomly combining the segmented leaves to generate a new plant model, we achieved further expansion of the dataset.

3.4. Instance segmentation based on PartNet

The architecture of PartNet [2] is shown in Figure 4(a),

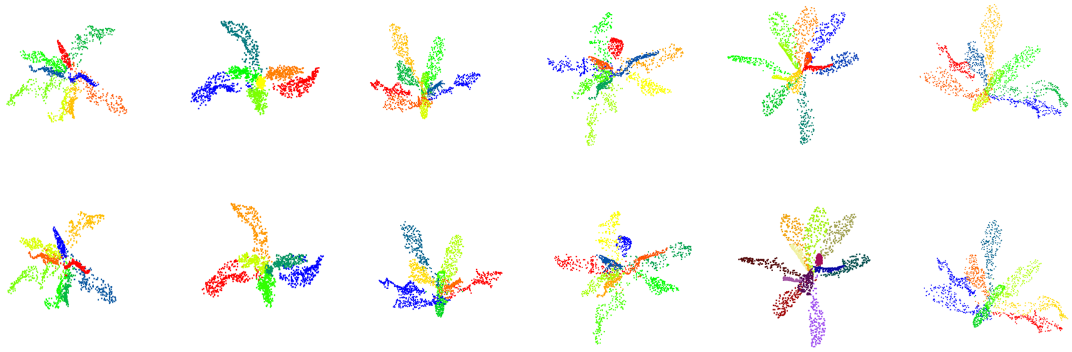


Figure 5: Instance segmentation results on dataset with PartNet. Different colors represent different instances. The color of the same object in ground truth and prediction are not necessarily the same.

which belongs to a recursive neural network that takes a whole point cloud of 3D shape as input, performs top-down decomposition, and outputs the segmented point cloud at the part instance level. During the segmentation process, each point cloud block can be considered as each node in a binary tree traversed using the depth-first search method.

On each point cloud node, three modules were designed: a node of decoding module for context propagation, a node of classification module for hierarchy construction, and a node of segmentation module for point cloud segmentation. As a recursive network, these modules were shared by all nodes in the hierarchy.

The node of decoding module, shown in Figure 4(b), was used to pass global contextual information from a parent node to its child nodes, in which we chose PointNet++ to extract the point cloud feature information.

The node of classification module took the node of a point cloud binary tree as input and predicted the result as either adjacency, symmetry, or leaf types.

The node of segmentation module is shown in Figure 4(c). It concatenated the recursive contextual feature and the part shape feature extracted by PointNet++ and fed the result into the point cloud classification network to achieve two-classification. For comparison with PointNet++, we also used PointNet as the feature extraction network to test its performance in the PartNet recursive network.

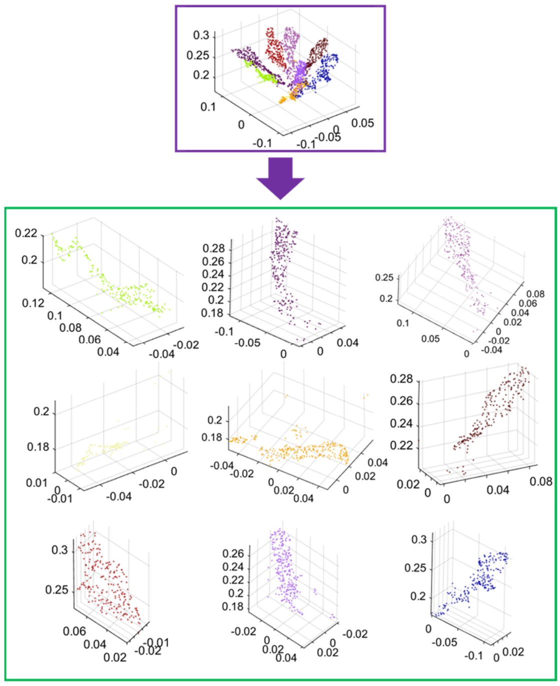


Figure 6: Visualization of different leaf point clouds of lettuce.

3.5. Loss function

The loss function of PartNet consists of the average node label loss (classification loss) and average node segmentation loss, see equation (1).

$$L_{partnet} = \frac{1}{|\mathcal{H}|}\sum_{n\in\mathcal{H}} L_{label}(n) + \frac{1}{|\mathcal{T}|}\sum_{n\in\mathcal{T}} L_{seg}(n) \qquad (1)$$

Where L_{label}, L_{seg} are both the cross-entropy loss. $\mathcal{H}$ is the set of all nodes in the hierarchy, and $\mathcal{T}$ is the set of all non-leaf nodes.

3.6. Training hyperparameters

We did not change the hyperparameters of the original network. PointNet++ for node classification (Figure 4(b)) used 6 point convolutional layers with 64, 128, 128, 256, 256, and 128 filters, respectively, and PointNet++ for node segmentation (Fig. 4(c)) used 4 point convolutional layers with 64, 64, 128 and 128 filters, respectively. In the last three layers of all these networks, 20% random feature dropout was used in every two layers. The Adam optimizer was used for training; the batch size was 10; the initial learning rate was 0.001; the size of the input point cloud was 2048 × 6; and the epoch was set to 500.

3.7. Evaluation metrics

Given a shape point cloud as input, the task of part instance segmentation is to provide several disjoint masks over the entire point cloud, each of which corresponds to an individual part instance on the object. The IoU between each prediction mask and the closest ground-truth mask was calculated and the prediction mask was considered a true positive if the IoU is greater than a certain threshold (e.g., 0.25) [2]. And the average precision (AP) score was used as a measure of the instance segmentation of the point cloud model (with the IoU against ground-truth greater than a threshold) [17].

4. Result and discussion

The instance segmentation results were shown in Figure 5, where the first row was the ground truth point cloud segmentation results, and the second row was the PartNet prediction results. Each point in the segmented lettuce point cloud was assigned a label belonging to a particular leaf instance, and according to the label we extracted different leaf point clouds, and the visualization results of each point cloud are shown in Figure 6.

4.1. Multi-layered leaves of the reconstructed model

Since the accuracy of the consumer-grade depth camera was not high, the collected data had fluctuations, and the point cloud shape of the same leaf of lettuce was not exactly the same when they were collected under multiple

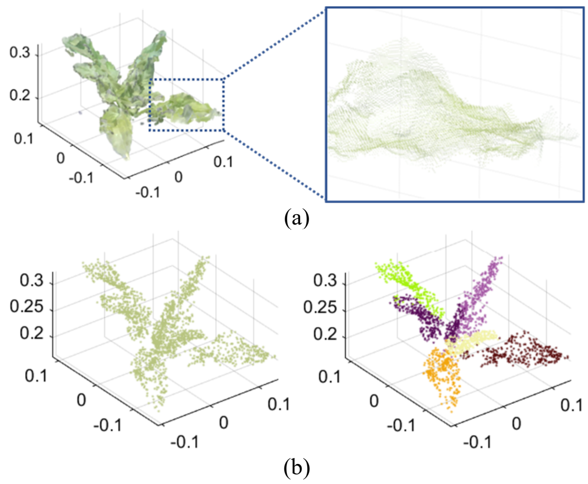


Figure 7: 3D reconstruction of the data with leaf stratification. (a) Visualization of leaf layering. (b) Data segmentation results.

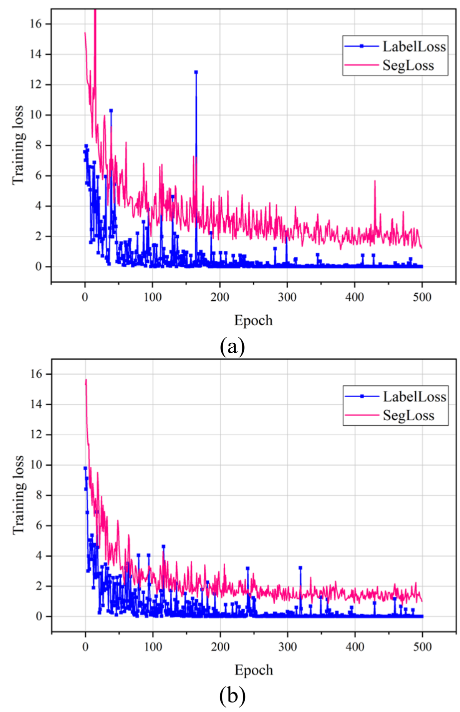


Figure 8: Network training on 500 epoches with labelloss and segloss respectively. (a) PointNet as a feature extraction network. (b) PointNet++ as a feature extraction network.

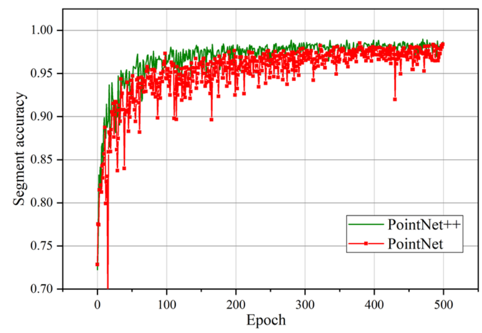


Figure 9: The relationship between segmentation accuracy and epoch in training.

		AP
IoU > 0.25	PointNet	89.0
	PointNet++	97.2
IoU > 0.5	PointNet	81.9
	PointNet++	92.4

Table 2: AP (%) is measured with IoU threshold being 0.25 and 0.5, respectively.

views, so there was a phenomenon of leaf layering in the registration, as shown in Figure 7(a). We reduced the influence of the leaf morphological distortion problem by down-sampling and adding the processed data to the dataset. The comparison of the data before and after segmentation was shown in Figure 7(b), and the results showed that the point cloud of lettuce with multi-layer leaves after reconstruction could still be used as a valid training set data.

4.2. Network performance and accuracy

The relationship between epoch and label loss function, epoch and segmentation loss function were shown in Figure 8. During the training process, the loss function gradually became flat and convergent, indicating that the PartNet network had a relatively stable performance on the lettuce dataset.

The segmentation accuracy of PartNet on the training set versus epoch was shown in Figure 9. The highest accuracy achieved after training 500 epochs is 0.98. We tested the network on 40 untrained images of the test set, and the results were shown in Table 2: When using PointNet++ as the feature extraction network, the Average Precision (AP) of instance segmentation reached 97.2% with an IoU threshold of 0.25, and 92.4% with an IoU threshold of 0.5, respectively. And when using PointNet as the feature extraction network, the AP reached 89.0% and 81.9%, respectively. To some extent, it showed that PointNet ++ learned the local features of the point cloud better than PointNet.

5. Conclusion

In this study, we explored a pipeline to achieve organ-level 3D instance segmentation for lettuce, with the expectation that the trained neural network could segment point clouds of different leaves of plants into separate instances.

(1) A multi-view reconstruction method was used to construct the real lettuce dataset, and although leaf stratification appeared, after down-sampling and adding the processed data to the dataset, the experimental results showed that the dataset could be used for instance segmentation to a certain extent.

(2) Using Blender software to make a synthetic lettuce-like dataset, this method implemented dataset enhancement and ensured that the network was fully trained.

(3) We trained the 3D instance segmentation model PartNet on our 3D plant dataset consisting of a mixture of real and synthetic data and validated the performance of the model on the held-out test set after training for 500 epochs, showing that the AP reached 97.2% when IoU < 0.25 and 92.4% when IoU < 0.5.

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