3D Point Cloud Instance Segmentation of Lettuce Based on Adaptive DBSCAN

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1. Introduction

Leaf instance segmentation plays a crucial role in obtaining plant phenotypic parameters [1]. Utilizing three-dimensional (3D) images allows for a higher level of detail compared to two-dimensional (2D) images, making it highly significant for plant phenotype extraction. This abstract focuses on the research of lettuce, using 3D point clouds as the primary data form.

At present, a large number of studies have implemented leaf instance segmentation and counting based on traditional machine learning or deep learning algorithms [6, 4, 3, 5]. However, there are few unsupervised, adaptive and simple instance segmentation algorithms for limited sample dataset. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a density-based algorithm [2]. It is unsupervised and also can discover clusters of any arbitrary shape and size in datasets containing even noise and outliers. However, DBSCAN is sensitive to the parameters of Eps and MinPts, so it is important to improve the algorithm to achieve self-adaptation of the two parameters. In this abstract, the idea of ANNA (Average Nearest Neighbor Analysis) and mathematic expectation are introduced to improve DBSCAN. It aims to achieve self-adaptation of the two important parameters Eps and MinPts of DBSCAN.

2. Proposed Method

Eps and MinPts of DBSCAN were dynamically selected according to the distribution characteristics of the lettuce point cloud dataset, so that the improved algorithm could better adapt to datasets with different densities and noise, improve the accuracy of instance segmentation. In order to improve the efficiency and accuracy of improved DBSCAN, downsampling 3D point cloud data at first.

ANNA first calculated the distance between the target point and its nearest neighbor point, and then acquired the average of all these nearest neighbor distances in order to reflect the density of the data. Therefore, the idea of ANNA was introduced to improve DBSCAN in order to determine Eps. The steps of the algorithm are as follows:

(1) Calculate the Euclidean distance from each point to all other points in the 3D point cloud dataset and form the distance matrix.

(2) Sort the calculated distance of each point.

(3) Calculate the average of distances with the same sort number (K) as the value list of Eps. The K represents the number of neighborhood points around the target point.

For the calculated list of Eps, traverse the distance matrix to find out the points whose distance was less than Eps and the mathematic expectation of the number of the points was calculated, then MinPts list was acquired. The formula is shown in formula (1). P_i represents the number of points whose distance was less than Eps of point i, and n is the number of point clouds in dataset.

$$MinPts = \sum_{i=1}^{n} \frac{1}{n} \times P_i \tag{1}$$

3. Result and Discussion

Figure 1(a) and 1(b) showed the trend of Eps and MinPts with changing K. The Eps and MinPts of different K were input into DBSCAN to obtain the cluster number. When the generated cluster number was the same for many times, the cluster number was defined as the optimal clustering result, and the two parameters corresponding to the maximum K value in the stationary phase were used as the optimal parameters of DBSCAN. As shown in figure 1(c), when the value of K was 8, the cluster number was 8, and the clustering result began to enter a stationary phase until the value of K was 82. Therefore, the Eps and MinPts corresponding to K=82 were taken as the optimal parameters.

The segmentation effect was evaluated by accuracy and accuracy refers to the proportion of the correctly segmented and total number of point clouds. The accuracy was shown in Table 1. The accuracy of improved DBSCAN had been greatly increased.

Visualize the point cloud instance segmentation results in figure 2. When the number of leaves increased, DBSCAN had serious segmentation errors and more noise points, and the segmentation accuracy could not be guaranteed. Because the improved DBSCAN found the optimal parameters, the segmentation accuracy was higher and noise

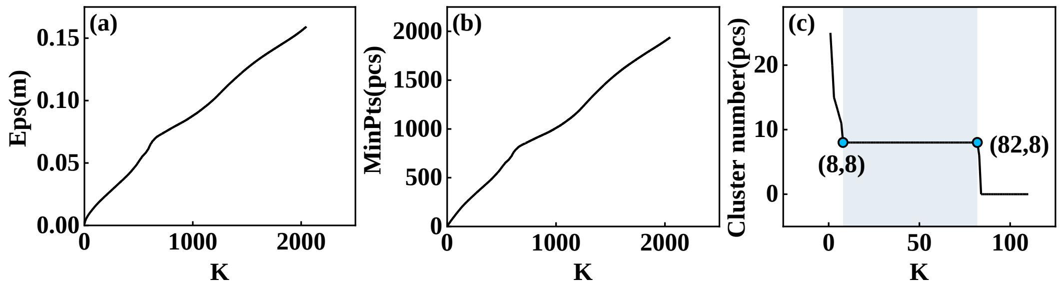

Figure 1. The trend of Eps, MinPts and Cluster number with K. (a) The values of Eps with different K. (b) The value of MinPts with different K. (c) The value of cluster number with different Eps and MinPts corresponding to K.

Methods	Average accuracy (%)
DBSCAN	80.91
Ours	91.80

Table 1. Comparison of DBSCAN and improved DBSCAN.

points were fewer. However, some parts of leaves were undivided when the occlusion was severe. On the whole, the segmentation results were within the acceptable range.

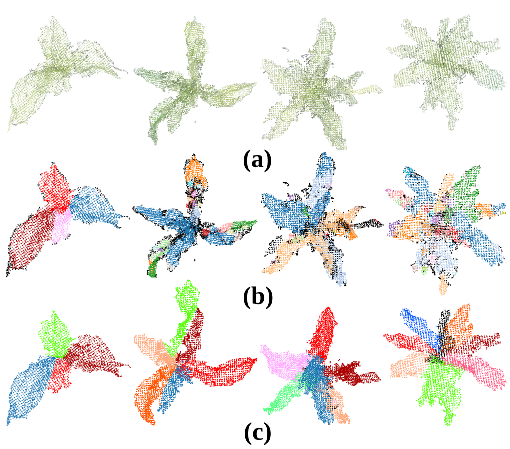

Figure 2. Instance segmentation results of lettuce. (a) 3D point cloud after downsampling. (b) Instance segmentation based on DBSCAN. (c) Instance segmentation based on ours.

The results of segmentation were taken as the number of leaves. As shown in figure 3(a), R^2 of DBSCAN was 0.637, and the correlation degree was weak. Figure 3(b) showed that R^2 of improved DBSCAN reached 0.940 with strong correlation, indicating that improved DBSCAN could realize leaf count of lettuce more accurately. Both MAE and RMSE were smaller when using improved DBSCAN.

4. Conclusion

In this abstract, our research contributes to the field of instance segmentation of lettuce leaves. We proposed an improved DBSCAN algorithm for leaf instance segmentation, incorporating the concepts of ANNA and mathematical expectation to determine the crucial parameters, namely Eps and MinPts. By applying this algorithm, the accuracy of instance segmentation significantly increased from 80.91% to 91.80%. Moreover, we achieved an R^2 value of 0.940, indicating a strong correlation between the ground truth and the predicted leaf count. Our method provides valuable insights for nondestructive phenotype acquisition in lettuce research.

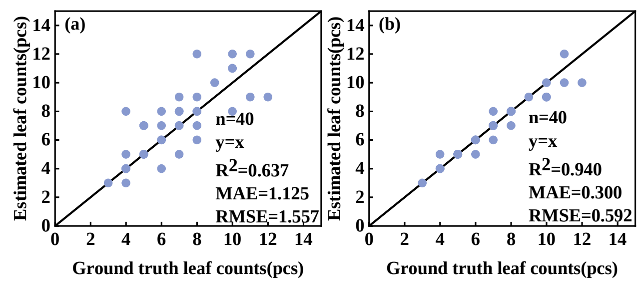

Figure 3. The correlation degree between the estimated leaf number and ground truth. (a) Estimated result based on DBSCAN. (b) Estimated result based on ours.

References

[1] Charlene M Grahn, Chris Benedict, Tom Thornton, and Carol Miles. Production of baby-leaf salad greens in the spring and fall seasons of northwest washington. *HortScience*, 50(10):1467–1471, 2015. 1

[2] Kamran Khan, Saif Ur Rehman, Kamran Aziz, Simon Fong, and Sababady Sarasvady. Dbscan: Past, present and future. In *The fifth international conference on the applications of digital information and web technologies (ICADIWT 2014)*, pages 232–238, 2014. 1

[3] Yinglun Li, Weiliang Wen, Teng Miao, Sheng Wu, Zetao Yu, Xiaodong Wang, Xinyu Guo, and Chunjiang Zhao. Automatic organ-level point cloud segmentation of maize shoots by integrating high-throughput data acquisition and deep learning. *Computers and Electronics in Agriculture*, 193:106702, 2022. 1

[4] Luhan Wang, Lihua Zheng, and Minjuan Wang. 3d point cloud instance segmentation of lettuce based on partnet. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1647–1655, 2022. 1

[5] Luhan Wang, Lihua Zheng, and Minjuan Wang. 3d point cloud instance segmentation of lettuce based on partnet. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1647–1655, 2022. 1

[6] Lele Xu, Ye Li, Yuanyuan Sun, Lei Song, and Shan Jin. Leaf instance segmentation and counting based on deep object detection and segmentation networks. In *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*, pages 180–185, 2018. 1