Sementing the Field of Rapeseed from 3D Laser Point Cloud Using Deep Learning

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Abstract*—Wisdom agriculture is a significant stage goal in the process of agricultural modernization development. Wisdom agriculture promotes the integration of agricultural informatization and intelligence. In recent years, the new models of intelligent agriculture based on artificial intelligence has developed rapidly. In this paper, 3D laser point cloud is used as research data to carry out in-depth research in the field of agriculture based on deep learning technology and point cloud.In this study, the deep learning model Pointnet ++ was used to segment the rapeseed point cloud data in the field:(1) The color enhancement algorithm of HSV color space was used to achieve color threshold segmentation of rapeseed crop point cloud data in complex field environment, and Statistical Outlier Filter and Super-Voxel Clustering were used to segment group rapeseed point cloud respectively.Finally, two groups of pure rapeseed point cloud data were obtained.(2) In this research, six original rapeseed point cloud data sets were used as datasets to train and test the segmentation performance of Pointnet++ (Multi-scale Grouping, MSG) deep learning model for rapeseed point cloud. Intersection over Union(IoU) was taken as the evaluation index of point cloud segmentation accuracy.The IoU of rape point cloud data processed by the three segmentation methods were 0.7748, 0.8019 and 0.8260, respectively.The results show that the segmentation performance of the deep learning model based on Pointnet ++ (MSG) is higher than that of the conventional point cloud segmentation algorithm. Compared with the conventional point cloud segmentation models, the point cloud segmentation based on deep learning framework shows better performance.The construction of a deep learning framework for crop point cloud segmentation and classification in the field requires the corresponding feature extraction processing based on the geometric structure or attributes of specific crops.In the context of the rapid development of agricultural big data, the deep learning framework in the field of agriculture is robust to deal with complex field environment, and the application of deep learning to agricultural research has a good prospect.

Keywords*—3D laser point cloud;Point cloud segmentation;Deep learning;Wisdom agriculture

I. Introduction

The 3D laser point cloud can be used as the data source to realize the 3D virtual simulation of large scene crops. Researchers are able to use the three-dimensional simulation model of crops to extract crop growth parameters and study crop phenotypes, so as to control crop growth situation in real time.

The point cloud target segmentation technology is an important link in the point cloud preprocessing stage. The key of the segmentation process is to quickly and accurately segment the target object point cloud from the original point cloud data. Conventional methods of field crop point cloud segmentation mainly rely on manually checking the target crop point cloud, or dividing the threshold according to the RGB attribute of the point cloud. Checking the point cloud manually is time-consuming and laborious, and visual interpretation cannot take the point cloud structure information into account. Threshold segmentation based on RGB attributes will produce a large number of discrete points, which will bring large errors to subsequent point cloud computing.

In recent years, deep learning framework has become a hot topic in the field of segmentation technology. Deep learning-based segmentation models have also been widely used in many fields and achieved good results. It is worth exploring to apply the promising deep learning technology to the Semantic Segmentation of rapeseed. Prior to the appearance of PointNet and PointNet++, deep learning models on point clouds are mainly divided into the following three categories: The first is the method based on 3D Convolution[1,2,3,4,5]; The second method is based on muti-view projection onto images and 2D convolution[7,8]; The third method is Simply run 1D/2D convolution or even Multilayer Perceptron(MLP) on point cloud.

In 2017, [11,12] proposed two proprietary neural networks for processing point clouds - PointNet and PointNet++. The computation of the neural network is small, and there is no problem of resolution loss. PointNet/PointNet++ is able to simulate any function on the point cloud. But Pointnet lacks layer by layer feature extraction, whereas Pointnet++ implements multi-layer feature extraction.

In this study, a joint algorithm for inter-field rapeseed point cloud segmentation is proposed. Firstly, the RGB information of point cloud data is converted into HSV color space, so as to enhance the RGB properties of point cloud according to the color characteristics of rapeseed crop and minimize the error of threshold segmentation. Statistical Outlier Filter and Super-Voxel Clustering are used to filter the segmented point cloud respectively. The PointNet++ scene semantic segmentation neural network is used to process the original field point cloud data, and the segmentation results are compared with the conventional crop point cloud segmentation methods, so as to

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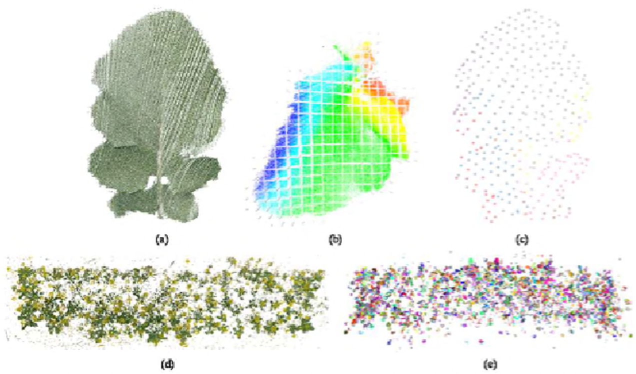


Fig.1: Application of supervoxel clustering algorithm. (a) Point clouds of rapeseed leaf;(b) Adding voxel mesh to the leaf point cloud;(c) Voxelization of leaf point clouds;(d) Field rapeseed point clouds after threshold segmentation;(e) Clustering of Super-voxel in rapeseed

summarize the best segmentation methods for the field rapeseed segmentation. We provide three comparative graphs of the results in Fig.9. Based on the research, the feasibility of applying deep learning to the research of agricultural point cloud is discussed, so as to improve the supply level of artificial intelligence technology in the agricultural field.

In summary, the contributions of our work are:

- a joint algorithm for inter-field rapeseed point cloud segmentation by original algorithms.
- A rapeseed point cloud data set with a capacity of 3000.
- Performance of Pointnet++ deep learning model based on rapeseed point cloud dataset.
- Summarized the best segmentation methods for the field rape segmentation.

II. Materials and Methods

A. Data Acquisition

In this research, flowering rapeseed with the most complex structural information was selected as the research object, and laser scanner was used to collect six groups of point cloud data of rapeseed in the field at the flowering stage in March, when rapeseed flowers were growing well. The collection site was located in the rapeseed planting base of Huazhong Agricultural University (114.36669°E,30.47416°N).

The 3D laser point cloud data of rapeseed in the field environment were obtained by setting up multiple stations in the rapeseed field with FARO Terrestrial Laser Scanner(TLS) - Focus S70. Referring to the study [13], a point cloud registration algorithm based on automatic target ball extraction was adopted. The registration algorithm takes the target ball as the benchmark, the overall registration error is less than the large scene registration error, and the accurate registration of multi-site point cloud is realized.

B. Conventional Point Cloud Segmentation Methods

Since there is no geometric feature of rapeseed in the field, the point clouds that constitute the plant structure are disordered. The single conventional crop point cloud segmentation method cannot do any processing based on the normal vector information of the plant point cloud. Therefore, the segmentation of colonial rapeseed point cloud depends on plant RGB attributes and elevation attributes.

The rapeseed plants and soil under complex field environment have obvious color characteristics: most of the leaves and rhizomes of rapeseed are green; The inflorescence of rapeseed is very obvious yellow; The soil is a darker brown or brown color. However, since there are weeds growing in the field, the segmentation based on point cloud RGB attribute information will retain the weeds. In addition, a large number of outliers will be left after threshold segmentation, so the colonial rapeseed segmentation method based on HSV color space also needs to be used in conjunction with other filtering algorithms.

1) HSV and Statistical Outlier Filter: The HSV color model is useful when it is applied to specify color segmentation. The H and S components represent the color distance, which refers to the numerical difference between two colors. For different color regions, simple color segmentation can be performed by mixing H and S variables and specifying thresholds. In this study, the color enhancement algorithm based on HSV color space was applied to segment the point clouds belonging to green leaves and yellow flower clusters from the original point clouds. The rapeseed point clouds in the field after threshold segmentation were shown in Figure 1(d).

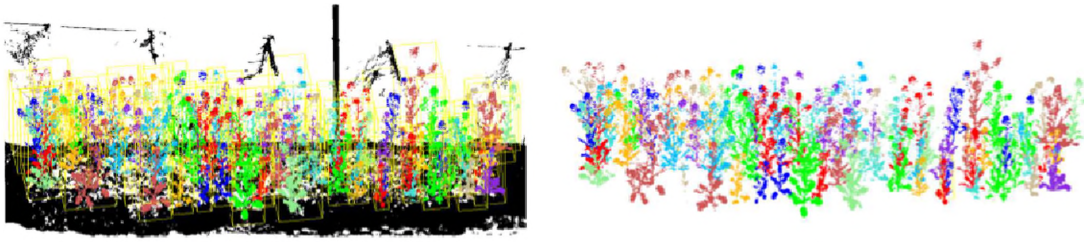
Statistical filters were applied to remove obvious outliers. The field of each point is statistically analyzed, and the distance of all points in the point cloud is set up to form a Gaussian distribution, whose shape is determined by mean value μ and standard deviation σ. Assume that the distance between any point in the point cloud and other points is S_i, and the distance between each point and any point is obtained by traversal. Then, formula (1) for average value and formula (2) for calculation of standard deviation are as follows.

$$\mu = \frac{1}{n}\sum_{i=1}^{n} S_i \tag{1}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - \mu)^2} \tag{2}$$

Set the multiple of standard deviation as m. When the average distance of K points near the target point is within the standard range $(\mu - m\cdot\sigma,\ \mu + m\cdot\sigma)$, the target point is retained; otherwise, the target point is defined as an outlier and eliminated.Thus, the population point cloud data of rapeseed can be basically obtained.

2) HSV and Super-Voxel Clustering: The point cloud separated by HSV color space threshold value was substituted into the supervoxel clustering algorithm, and the specific seed point radius R_{seed} was set. Finally, the point cloud data of colonial rapeseed obtained by the joint processing of HSV color space classification and Super-Voxel clustering was obtained. The application of Super-Voxel clustering algorithm in rapeseed point cloud data in the field is shown in Figure 1.



(a) (b)

Fig.3: (a) Overview of 'AREA_1';(b) Overview of individual rapeseed

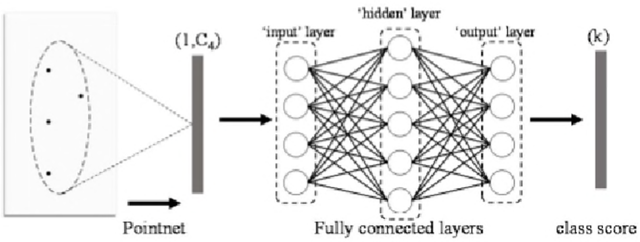


Fig.4: Classification schematic of PointNet++

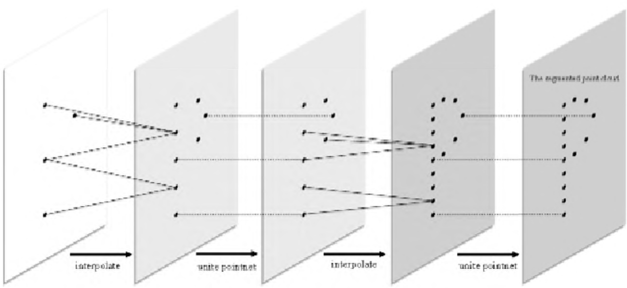


Fig.2: PointNet++ - Segmentation

C. *PointNet++ - Segmentation*

The main operating system used in the experiment of this paper is Ubuntu 20.04. And based on the deep learning framework PyTorch 1.1.0, the Pointnet++ deep learning model was constructed and the corresponding algorithm code was written.

Pointnet++ adds multi-layer feature extraction on the basis of Pointnet, and processes local features in a layered structure [11]. Schematic diagram of PointNet++ segmentation is shown in Figure 2.

1) Data set preparation: In this study, a total of six groups of field point cloud data of seedling rapeseed were used as the source data of the dataset. Firstly, point cloud data of a single rape plant in the data were manually cut, and each group of point cloud data of a single rape plant and complete original data were summarized into a data set with a number of 'AREA', a total of six data sets. Five of the data sets were used as the training set, and the remaining data set was used as the test set to test the training performance of the neural network. Among them, the preview of 'AREA_6' data set is shown in Figure 3.

2) 3D Object Semantic Segmentation Multi-scale grouping (MSG): In the classification process of Pointnet ++ framework, the global feature is obtained after a Pointnet module processing, so as to realize multi-layer feature extraction[12]. The

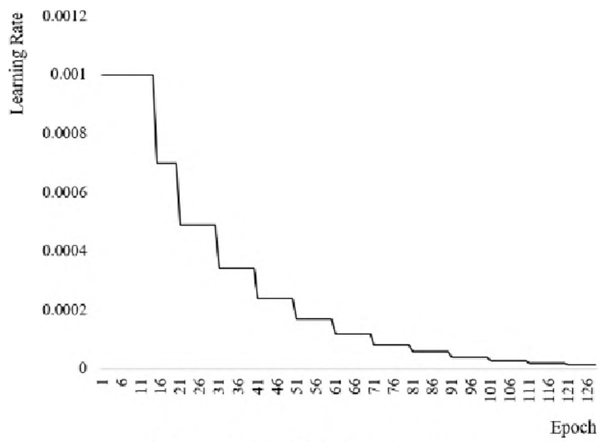


Fig.5: Transformation in Learning Rate

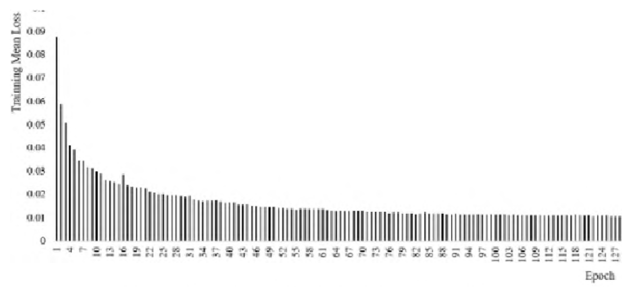


Fig.6: Transformation in Training Mean Loss

Classification diagram of the Pointnet++ framework is shown in Figure 4.

But there are better ways to do multi-layer feature extraction. The researchers proposed a multi-scale grouping method[12]. Multi-layer grouping with different radius is not changed in the sampling section, and each layer of pointnet generates a vector. Finally, the algorithm will concat each feature vector.

III. Results and Analysis

In this research, in the process of target extraction of rapeseed plant point cloud, there are 2632 point clouds in training data and 389 point clouds in test data. The target is a single category of rapeseed per plant.

The initial value of learning rate is set as 0.001. As the training process progresses, the more data are input, the model will fit more slowly. The attenuation value of learning rate is set as 0.7, and the step size is set as 10. Figure 5 shows the change of learning rate in the process of training rapeseed plant point cloud data in this study. At the same time, 128 iterations were carried out in the Epoch period of Training in this paper. As the

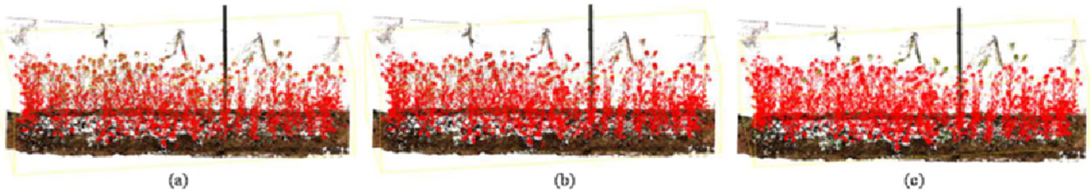


Fig.8: Comparison of three segmentation results.(a) HSV + Statistical Outlier Filter;(b) HSV + Super-voxel clustering;(c)PointNet++(MSG)

number of iterations increased, the Training mean loss function, namely the deviation value between the predicted result and the correct result in Training data, was also decreasing continuously.The change of loss function is shown in Figure 6. The model executed 128 Epochs on a NVIDIA GeForce RTX 3070 GPU, with the batch size set to 2 based on the memory size. In the test set, the classification accuracy of the network is 81.42%.

Intersection over Union (IoU) is taken as a standard measure of segmentation accuracy. IoU algorithm calculates the ratio of the intersection volume of the predicted point cloud bounding box and the real bounding box to the combined collective product, that is, the three-dimensional segmentation accuracy after quantization. Rapeseed is 'Positive', Non-Rapeseed is 'Negative', Correct prediction is 'True' and Error Prediction is 'False', then there is True Positive example(TP)、False Positive example(FP)、False Negative example(FN) and True Negative Example(TN). The confusion matrix example is shown in Figure 7.

The volume of the intersection of the bounding box and the real bounding box predicted by the IoU algorithm is divided by the volume of the union of the two bounding boxes, and the value is [0, 1]. The intersection and union ratio measures the proximity between the predicted bounding box and the real bounding box. The larger the intersection and union ratio is, the higher the overlap degree of the two bounding boxes will be. Equation (3) shows the calculation method of 3D-IoU.

$$IoU = \frac{TP}{TP+FP+FN} \tag{3}$$

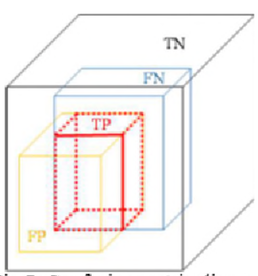


Fig.7: Confusion matrix diagram

Taking 'AREA_6' as the research object, HSV + Statistical Outlier Filter and HSV + Super-Voxel Clustering are respectively used to process point cloud. Thus, the maximum bounding box of the two segmented point clouds is obtained through analysis, as shown in Figure 8. The IoU of point cloud segmentation was calculated by using the spatial location information of the maximum bounding box. The final calculation of segmentation precision is $IoU_{sem\_statistical} = 0.7748$ and $IoU_{sem\_voxel} = 0.8019$ respectively.

Using PointNet++(MSG) deep learning framework to train 'AREA_1', 'AREA_2', 'AREA_3', 'AREA_4' and 'AREA_5', the segmentation neural network of individual rapeseed was obtained. The data set numbered 'AREA_6' was sent into the neural network as the test set, so as to obtain the segmentation result of 'AREA_6' per rapeseed plant, as shown in Figure 8(c). By associating the bounding box of the segmentation result with the standard bounding box, the result is $IoU_{sem\_msg} = 0.8260$.

The results of IoU show that the segmentation accuracy of point-cloud segmentation method based on Pointnet++(MSG) is higher than that of the other two conventional combinatorial algorithms. Figure 8(a) shows that point cloud data in a complex field environment contains point cloud of fallen leaves and weeds that are difficult to remove, and may contain agricultural machinery and facilities with a high similarity to the environment. These non-target point clouds are difficult to be dealt with by traditional algorithms.The segmentation method based on deep learning can well avoid this complex situation, and only classifies and segments the target object.

IV. Conclusion

Agricultural data in the big data environment is faced with many challenges, such as variety, large amount of data, fast updating and iteration, etc. For 3D laser point cloud data, a complete and efficient processing process can meet the timeliness and accuracy of 3D field crop data at the same time. In this research, a set of original algorithm flow that can effectively process the raw crop point cloud data in the field is summarized, and based on IoU, the possibility of semantic segmentation of the Pointnet++ deep learning model in the field scene is explored. In the future, based on the existing deep learning segmentation framework, the feature extraction layer that is more suitable for the segmentation or recognition of specific crops can be added in a targeted way according to the particularity of the attributes of target crops. Finally, the goal of applying the high-efficiency and high-precision deep learning framework based on crops to the future integrated intelligent agriculture platform is realized.

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References

[1] WU Z, SONG S, KHOSLA A, et al. 3d shapenets: A deeprepresentation for volumetric shapes[C]//Proceedings of the IEEE conference oncomputer vision and pattern recognition. Boston, MA, USA: IEEE, 2015:1912-1920.

[2] MATURANA D, SCHERER S. Voxnet: A 3d convolutionalneural network for real-time object recognition[C]//2015 IEEE/RSJ InternationalConference on Intelligent Robots and Systems (IROS). Hamburg, Germany: IEEE,2015: 922-928.

[3] QI C R, SU H, NIEßNER M, et al. Volumetric andmulti-view cnns for object classification on 3d data[C]//Proceedings of theIEEE conference on computer vision and pattern recognition. Las Vegas, NV, USA:IEEE, 2016: 5648-5656.

[4] RIEGLER G, ULUSOY A O, GEIGER A. Octnet: Learning deep3d representations at high resolutions[C]//Proceedings of the IEEE Conferenceon Computer Vision and Pattern Recognition. Honolulu, HI, USA: IEEE, 2017:3577-3586.

[5] WANG P S, LIU Y, GUO Y X, et al. O-cnn: Octree-basedconvolutional neural networks for 3d shape analysis[J]. ACM Transactions onGraphics (TOG), 2017, 36(4): 72.

[6] J. Li, X. Liang, Y. Wei, T. Xu, J. Feng and S. Yan, "Perceptual Generative Adversarial Networks for Small Object Detection," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 1951-1959, doi: 10.1109/CVPR.2017.211.

[7] SU H, MAJI S, KALOGERAKIS E, et al. Multi-viewconvolutional neural networks for 3d shape recognition[C]//Proceedings of theIEEE international conference on computer vision. Santiago, Chile: IEEE, 2015:945-953.

[8] KALOGERAKIS E, AVERKIOU M, MAJI S, et al. 3D ShapeSegmentation With Projective Convolutional Networks[C]//The IEEE Conference onComputer Vision and Pattern Recognition (CVPR). Honolulu, HI, USA: IEEE, 2017.

[9] LAFFERTY J, MCCALLUM A, PEREIRA F C. Conditional randomfields: Probabilistic models for segmenting and labeling sequence data[J].,2001.

[10] Landrieu, Loic and Martin Simonovsky. "Large-Scale Point Cloud Semantic Segmentation with Superpoint Graphs." 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (2018): 4558-4567.

[11] R. Q. Charles, H. Su, M. Kaichun and L. J. Guibas, "PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 77-85, doi: 10.1109/CVPR.2017.16.

[12] Charles R. Qi, Li Yi, Hao Su, and Leonidas J. Guibas. 2017. PointNet++: deep hierarchical feature learning on point sets in a metric space. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17). Curran Associates Inc., Red Hook, NY, USA, 5105–5114.

[13] Lin Chengda, Xie Liangyi, Han Jing, Hu Fangzheng.Identification of maize planting plant number based on laser point cloud [J/OL]. Laser Technology:1-11[2021-06-09].

[14] P. Junietz, W. Wachenfeld, K. Klonecki and H. Winner, "Evaluation of Different Approaches to Address Safety Validation of Automated Driving," 2018 21st International Conference on Intelligent Transportation Systems (ITSC), 2018, pp. 491-496, doi: 10.1109/ITSC.2018.8569959.

[15] O. Schumann, M. Hahn, J. Dickmann and C. Wöhler, "Semantic Segmentation on Radar Point Clouds," 2018 21st International Conference on Information Fusion (FUSION), 2018, pp. 2179-2186, doi: 10.23919/ICIF.2018.8455344.

[16] M. Simonovsky and N. Komodakis, "Dynamic Edge-Conditioned Filters in Convolutional Neural Networks on Graphs," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 29-38, doi: 10.1109/CVPR.2017.11.

[17] Zhang, H., Lu, G., Zhan, M. et al. Semi-Supervised Classification of Graph Convolutional Networks with Laplacian Rank Constraints. Neural Process Lett (2021). https://doi.org/10.1007/s11063-020-10404-7