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Point cloud based iterative segmentation technique for 3D plant phenotyping

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***Abstract*— The segmentation of 3D point clouds is an important prerequisite step for many plant phenotype and data analysis. One of the main challenges is high resolution 3D plant model segmentation. In this paper, we present an iteration based approach for 3D segmentation directly from the dense point clouds that are reconstructed from multi-view images. We extend the existing euclidean distance and spectral clustering (SC) algorithms and using iteration approach to segment the 3D point clouds into elementary shape units that could represent the plant organs (stems, branches, leaves, etc.). Such approach only requires the 3D coordinate data information. Experimental results show our approach can effectively segmented the obtained point cloud for various plant species.**

***Index Terms*— Plant phenotyping, Point cloud segmentation, Spectral clustering, Plant segmentation**

I. Introduction

Plant phenotyping refers to a quantitative description of the plant's anatomical, ontogenetical, physiological and biochemical properties [1]. Our study focus on plants' physiological process and analyze traits to understand their mechanistic basis [2]. In the recent years, a large growing requirement of tools to study the genetic structure of plants (the genotype) and analysis of plant structure and phenotype. The emerging discipline of plant phonemics aiming to extract the quantitative and qualitative measurement of key plant feature, such as main stem height, size and inclination, petiole length and initiation angle and leaf width, length, thickness, area, and biomass [3]–[6]. The resulting information is vital to understanding the plant growth and development, and to ensure global food requirement in the face of climate change, resource depletion and population increasing in the coming decades.

The common procedure to collect plant morphological data consists of many laborious manual measurements, often using different type of equipment like ruler, protractor and tape in [7]–[10], which is impractical, especially to analysis large amount of plants. As notice in recent study, performing the plant phenotyping research has seen in the ultra high resolution scanning platform. The scanning data are used to generate 3D surface mesh reconstruction and involve developing advanced software provides features such as plant limbs recognition (branches, leaves, stem, etc.) and accurate data extraction such as stem size, leaf width, length, and area. Thus, 3D plant point clouds segmentation is the fundamental step in processing such data.

The segmentation process aims to cluster points with similar characteristics into homogeneous regions for the given set of point clouds. These clustered the points should be meaningful and have similar geometrical feature. A recent survey [11] by Nguyen on point cloud segmentation techniques generally classified into two categories: 1. Using purely mathematical model and geometric reasoning techniques such as region growing [12] or model fitting [13]; 2. Using feature descriptor and machine learning techniques to separate the different classes of object types and then classify the data by the resultant model. Such segmentation process is one of the most important steps for plant phenotyping analyzing. Most of them are well designed for man-made objects that can be almost completely decomposed into uniform geometric shapes. However, plants have a particularly challenging subject, with large amounts of self-occlusion, and, depending on the plant species, leaves that lack of texture necessary to perform robust feature matching, either to separate leaves from one another, or locate specific leaves across multiple views [14]. Recovering the branching structure of a plant or leaf-on tree is a specific issue that has been addressed by Bayer, Seifert, and Pretzsch [15].

Some approaches use geometric distance information [17] or intensity information [18]. Yin's [19] approach requires manually cutting and then scanning each leaf individually. Lou [20] proposed using spectral clustering approach is performed on the neighborhood graph between the 3D plant's points. In above methods, some of them is not straightforward in general, especially when the leaves are most overlapping, some of them are time consuming process and not able to work on large amount of 3D point cloud, or require manually cutting of the plant leaves.

Our study focus on processing the prototype plant point cloud previously reconstructed from multi-view 3D scanning. We investigate the feasibility of developing an automatic and robust point cloud based segmentation pipeline to process the

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large amount of data (millions of 3D points in single point cloud model) acquired using the high resolution camera. The rest of paper is organized as followed: A brief description the pipeline of 3D plant data acquisition in Sect.II. We propose a iterative based segmentation approach using spectral clustering(SC) and euclidean clustering(EC) in Sect.III. Finally, the experimental result in Sect.IV and conclusion in Sect.V.

II. Plant data acquisition and Preprocessing

In the past few years, numbers of methods and principles have been developed to capture the plant in 3D, such as LIDAR (Light Detection And Ranging) [21], [22], laser light scanning [23], structured light [24], stereo vision [25] and space carving [10]. As Lu proposed in [26], multi-view 3D reconstruction algorithm usually produce much better result that other methods. It can generate the complete point clouds with color information using multi-views images capture by high resolution camera. Normally, such process require at least six images to create a reasonable result.

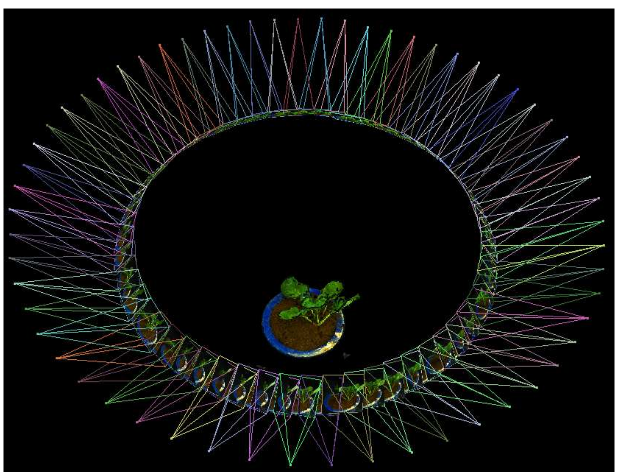

Fig. 1: Cameras position around a brassica. Rotation step: 6°

In our experiment, we place the plant in center and take the picture in a rotation angle. To make sure we have dense point cloud and full 3D model of the scanning plant, we took images in every 6 degree as shown in Fig.1. We used the multi-view stereo(PMVS) [27] and VisualSFM [28] system to perform automatic camera calibration. It is likely that additional points are contained in the model which comprise from the background or other non-plant material. In addition, they are using SIFT [29] GPU acceleration based feature detection. Normally the VisualSFM has much faster performance in a Nivdia graphic card installed PC/Laptop.

Once we have finished the reconstruction by multi-views images, we have the dense 3D plant model. Such 3D plant model usually contain over millions points with color information. It is necessary to perform the preprocessing before segmentation. As mentioned above, VisualSFM may brings noise and some outliers. In addition, the model may contains registration error and redundant points. Hence, without losing the important 3D information the preprocessing should be performed as follows in orders:

A. *Noise removal*

The noise may come from the camera lens or the process during image feature extraction and mapping. We are using black curtain as background to separate any other objects beside the green plant. Hence, a simple color filter will remove most of the 3D noisy points.

B. *Outliers removal*

The 3D model may contains some outliers which cause by the processing of multi-view reconstruction, such as noise, miss match points and registration error. Such sparse outliers might cause the segmentation failure.

However, it is possible to trim the irregularities which do not meet some certain criteria by performing statistical analysis on each point's neighborhood [30], [31]. We are using statistical analysis to remove the outliers which implement in PCL library. As shown in Fig.2 are the 3D plant before and after the outliers removal.

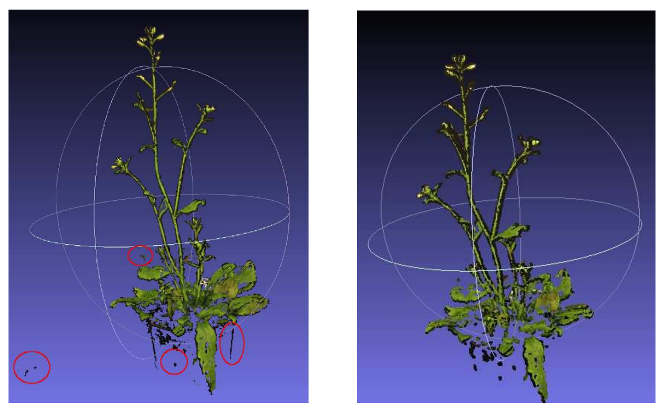

Fig. 2: Left: original cloud with outliers; Right: after outliers removal

C. *Down-sampling*

Generally, the scanned 3D plant model is dense and detailed, it is time and memory consuming to process and analyze, particular in segmentation process. Lu [26] proposed to down sampling the 3D point cloud using Merge Close Vertices filter with $0.5\% \sim 10\%$ of the diagonal length of the enclosing box that surrounds the 3D points. However, such down-sample may lose some of the detail, such as the buds, small leaf. Hence, without losing too much details, we using smaller threshold $0.1\% \sim 1\%$, depends on the different plants.

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III. 3D PLANT POINT CLOUD SEGMENTATION

Spectral clustering (SC) is powerful technique in data analysis. Numbers of algorithms based on spectral clustering has been proposed in the past few years, such as [32]. The detail of introduction can be found in [33]. In generally, the spectral clusterings have similar steps [34].

Recently, spectral clustering has been implemented in 3D point cloud segmentation, such as [20], [34] with well segmented results, specailly for the 3D plant point cloud. The algorithm can be summarized as followed:

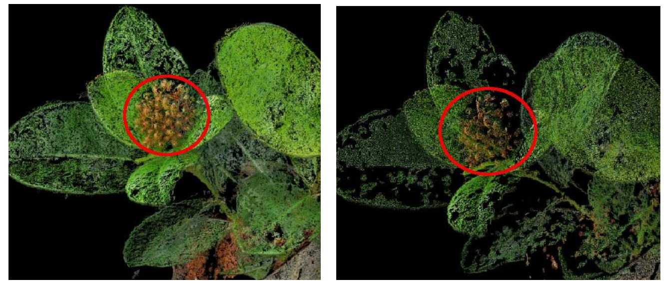
Algorithm 1 Spectral clustering for 3D point cloud

Require: Point cloud $P = \{p_i \in \mathbb{R}^3, 1 \leq i \leq n\}$. Let k be the desired number of clusters.

using K-NN distance to construct similarity matrix $\mathbf{S} \in \mathbb{R}^{n \times n}$, let $\mathbf{W}$ be its weighted adjacency matrix and $\mathbf{D}$ is the degree matrix.
compute the Laplacian matrix $\mathbf{L} = \mathbf{D} - \mathbf{W}$.
compute the first k eigenvectors $u_1, \ldots, u_k$ of $\mathbf{L}$.
let $\mathbf{U} \in \mathbb{R}^{n \times k}$ be the matrix containing the vectors $u_1, \ldots, u_k$ as columns.
for $i = 1, \ldots, n$, let $y_i \in \mathbb{R}^k$ be the vector corresponding to the i-th row of $\mathbf{U}$.
cluster the points $(y_i)_{i=1,\ldots,n} \in \mathbb{R}^k$ with the k-means algorithm into clusters $C_1, \ldots, C_k$.
Retrieve the clusters $A_1 \ldots A_k$ with $A_i = \{j | y_j \in C_i\}$.

Spectral clustering is time and memory consuming process in above Algorithm 1. The number of points in the 3D cloud presented as matrix size N, which has significant impact to its following matrix operation including the eigenvalue decomposition and k-means algorithm. In our cases, the 3D point cloud may contain hundreds of thousands points, sometimes it is impossible to directly apply such huge amount data with SC algorithms by general PC hardware setup. For instant, a 3D plant model has $400K$ points requires more than 6GB memory just for storing the double-precision floating-point matrices $\mathbf{W}, \mathbf{L}, \mathbf{D}$, not even mention the later matrix operation. Lu [20] proposed to down-sampling the original point cloud to $3\% \sim 10\%$, however, such process may lost the small detail and effect the following operation on the point cloud. For example in Fig.3a and 3b, the feature of Ixora's corolla is too weak to see and the leaves missing some of the parts. It is always possible using higher memory and more powerful PC to segment the dense 3D point cloud, however, it is not always the case in most applications.

Generally, directly apply SC on 3D plant model maybe fail in segmentation due to the complex phenotype of plant. For example, as shown in Fig.4. It is possible to clustering the unorganized point cloud model P into small parts so that the overall processing time is significantly reduced and apply spectral clustering on the subparts. Radu [36]



(a) Original (b) Down sample to 10%

Fig. 3: Ixora point cloud from [35]

Algorithm 2 Euclidean clustering using nearest neighbors

Require: Point cloud $P = \{p_i \in \mathbb{R}^3, 1 \leq i \leq n\}$.

create Kd-tree for P, let C is the list of clusters, and Q is points to be checked
for $p_i \in P$ **do**
  add p_i to Q
  for $p_i \in Q$ **do**
    search for the set P_i^k of point neighbors of p_i in sphere with radius $r < d_{th}$
    check every neighbor $p_i^k \in p_i^k$ if already processed, if not, add to Q
  end for
  if all the points in Q has been processed, add Q to the list C, reset Q to empty.
end forthe algorithm terminates when all points $p_i \in P$ have been processed and are now part of the list of point clusters C.

proposed approximate nearest neighbors queries via kd-tree representations clustering described in Algorithm 2. It has well performance on structured object like man-made targets, but it has difficulty to deal with complex natural scene. However, we may using it to segment the point cloud into reasonable parts before SC algorithm. We proposed the iterative clustering process to deal with high dense 3D plant cloud segmentation as described in 3.

In our proposed algorithm in 3, Step.2 using euclidean clustering method to have initial cluster list Q for point cloud P and then we perform SC for each cluster. Such process can be iterative until the current cluster can be recognized as complete organ of the plant, such as single leaf, branch or corolla. Fig.5 demonstrate the process of our proposed method on ixora.

IV. EXPERIMENTAL RESULTS

We used both our scanning images and the public data sets from [37] to built up various 3D plant point clouds.

Our scanning used Nikon D3300 with 18-135mm variable focus lens and a rotational table to capture tens of thousands of images of the plants (up to 6000×4000 high-resolution)

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Fig. 4: Directly applied SC on Ixora, point cloud number is 0.5 million ,desired number of clusters $k = 35$

Algorithm 3 Proposed iterative based spectral clustering

Require: Point cloud $P = \{p_i \in \mathbb{R}^3, 1 \leq i \leq n\}$, θ is the points threshold, k is the desired number of clusters for P.

1: perform outliers and noise removal on point cloud P
2: perform euclidean clustering on P, then we have the initial list of clusters $C = \{c_i \in C, 1 \leq i \leq k\}$, n_i is the number of points for each c_i.
3: **for** each $c_j \in C$ **do**
4:     perform SC for each cluster c_i, then we have list of clusters $Q = \{q_i \in c_j, 1 \leq i \leq k\}$
5:     **for** each $q_i \in Q$ **do**
6:         Mark the clustered organs, such as the leyaves and branches
7:     **end for**
8: **end for**
9: Repeat the steps 2 to 8 until we have k desired clusters.

without prior knowledge of the camera calibration to generate the data sets of 3D plant point clouds. We used an Intel E3 1230v3 3.3GHz PC with 16GB RAM. The most time-consuming process is distance and similarity matrix construction in spectral clustering, which depend on the number of 3D points. The point cloud size has heavy impact on the spectral clustering, typically thirty thousand points almost consume 7G RAM space in our machine. The proposed method using iterative process and parallel computing that successfully perform the segmentation on large point cloud in a reasonable time. Comparatively, the clustering time is almost negligible in some cases. We compared the proposed method with Euclidean clustering and Spectral clustering. Sometimes it is difficult to evaluate the segmentation quality because the effectiveness of segmentation depends on the application purpose. Fig.6 and Table I show the experimental result on various 3D plant clouds. From the result, we found that: (1) The proposed achieve better segmentation result and robust to noisy points and only using raw data. (2) The proposed method directly apply on the dense point cloud without heavy down-sampling and remain much more information and detail for the later processing. It is clearly that the 4th column in Fig.6 has much denser point cloud that SC in 3rd column and most of small detail are remained and well segmented. (3) 3D point cloud segmentation on different shape plants is really a hard assignment.

It is not always possible to have the meaningful and accurate segmentation, especially the curved surfaces of leaves and junctions of branch. As Fig.6c shows, it is still remain great challenge to segment the leaves of Wheat since some the them are overlap each other.

(a) Side view

(b) Top view

Fig. 5: Iterative segmentation process on Ixora

TABLE I: 3D plants segmentation and processing time. EC: Euclidean clustering, SC:Spectral clustering(with down-sampling point clouds)

Plant	Point number	Process time		
		EC	SC	Proposed
Ixora	307,757	2.26s	2m10s	3m30s
Brassica	1,614,842	7.78s	1m02s	1m12s
Wheat	314,904	1.6s	3m43s	5m3s
Basil	156,798	1.8s	4m18s	5m52s

V. Conclusion

This paper introduces a 3D point cloud segmentation method based on extending the Euclidean distance and spectral clustering for diverse plants and present the experimental result on various 3D point clouds reconstructed from multi-view images. Compare to the original spectral clustering, our proposed method do have couple of advantages: (1) we can

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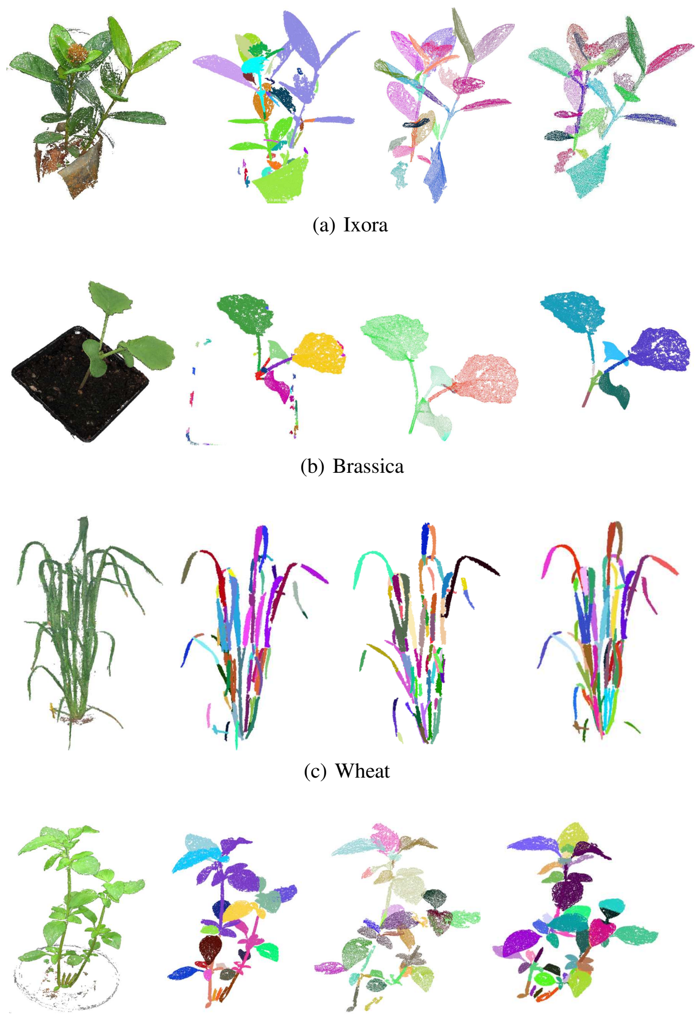

(a) Ixora

(b) Brassica

(c) Wheat

(d) Basil

Fig. 6: 3D segmentation of plants. 1st column: 3D point clouds. 2nd column: Euclidean clustering using manually selected K-means value. 3rd column: Spectral clustering. 4th column: Proposed method. Plants have downed sample up to 3% for spectral clustering method; Colors on columns 2 to 4 represent different clusters.

perform 3D plant segmentation on large scale of point cloud with over $500K$ points; (2) using iterative based segmentation process we can separate the raw 3D point cloud to elementary shape units that could represent the plant organs (stems, branches, leaves, etc.) without loosing details.

The main limitation of proposed segmentation method is that the components recognition could be further refined and not all the segmented parted are meaningful. Fully automated 3D segmentation methods suitable for wide range of different shaped 3D point cloud plant is still a rather challenging task, even for the same kind of plant. An efficient segmentation method that incorporates biologically accurate feature recognition may require a combination of machine learning, artificial intelligence, prior knowledge or user intervention.

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