Plant Trait Segmentation for Plant Growth Monitoring

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***Abstract*—3D point cloud segmentation is an important step for plant phenotyping applications. The segmentation should be able to separate the various plant components such as leaves and stem robustly to enable traits to be measured. Also, it is important for the segmentation method to work on range of plant architectures with good accuracy and computation time. In this paper, we propose a segmentation method using Euclidean distance to segment the point cloud generated using a structure-from-motion algorithm. The proposed algorithm requires no prior information about the point cloud. Experimental results illustrate that our proposed method can effectively segment the plant point cloud irrespective of its architecture and growth stage. The proposed method has outperformed the standard methods in terms of computation time and segmentation quality.**

***Index Terms*—Plant phenotyping, 3D reconstruction, Plant trait segmentation, Point cloud segmentation.**

I. Introduction

Plant growth monitoring is an important aspect of plant phenotyping which provides vital information about plants which is helpful to farmers for their decision making process. Plant phenotyping is a set of protocols and techniques used to calculate plant architecture/structure, composition, and growth with precision. Popular plant traits for growth monitoring include stem height, stem diameter, leaf area, leaf length, leaf width, and number of leaves or fruits on the plant [1]–[4]. This study is aimed at segmenting the plants at various stages of architecture complexity.

Conventionally all these plant traits have been evaluated by experts in this field depending on a visual score. This was responsible for creating disparity between expert judgements. In addition, this process is destructive, tedious, prone to errors, and labour intensive [5] which makes this method impractical for analysing large numbers of plants. To solve this problem, 3D imaging methods have been used widely in the literature. In recent studies [6]–[8], various 3D imaging methods have been used to achieve 3D models. These 3D models represent the plant traits fairly well in its leaves and stems. For further analysis, to measure plant traits accurately, there is a need of a robust segmentation algorithm to differentiate the plant components irrespective of the plant's growth stage and architecture.

The segmentation process focuses to cluster points in the point cloud with similar features into homogeneous regions. In a recent study [9], the segmentation methods are divided into two types: First, machine learning methods based on feature descriptors such as surface feature histograms (SFH), point feature histograms (PFH), and fast point feature histograms FPFH [10] to differentiate the various classes of the object and classify the data based on the resultant model. Second, methods based on geometrical interpretation and mathematical models such as model fitting [11], DBSCAN [12], K-means [13], region growing [14], and so on. Most of these methods perform exceptionally well on man-made objects which are completely uniform in terms of shape. However, plants have complex architectures because of self-occlusion and lack of texture for feature matching [15]. Also, reconstructing the branching region of a plant is an issue addressed by [16]. This complexity changes from species to species. These methods are time consuming and sometimes require prior knowledge for segmentation.

Paulus et al. [10] presented a method for plant segmentation based on a point feature histogram descriptor. This descriptor was selected into a surface feature histogram to give an efficient segmentation of leaves and stem. This new descriptor is then used as a feature for support vector machine (SVM) classification. However, SVM is a supervised approach for classification which needs labelled data. In this method, for training the classifier, a user has to label the point cloud and indicate what are leaves and stem, which is very tedious. Gelard et al. [17] also proposed a method in which the stem was detected first by fitting a geometric structure and then removing these points from the point cloud. It allowed them to then segment the leaves. Petioles were then inserted for every leaf. This process provided good segmentation results but still requires prior knowledge about the plant and user interaction for segmentation. However, this method struggles with plants with complex architecture and it is time consuming. Some methods use intensity data [18] or geometric distance data [19]. Luo et al. [20] used a spectral clustering approach on the graph between a 3D model's points. In another study, Yin [21] required to cut and scan the leaves individually to get the plant data. The aforementioned methods are not straightforward, particularly when the leaves are overlapping. These methods are time consuming and struggle on large point clouds or needs to cut the plant leaves which inevitably hampers the plant growth.

Another method uses the 3D mesh generated from the point

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cloud [22]. To achieve a mesh of the plant, they used commercial software named 3DSOM. The coarse segmentation is applied with a constrained region growing algorithm which helps to recognise the plant stem and leaves. Tubular shapes are fitted for accurate segmentation of the stem and for petiole detection. However, this process not only requires strong prior knowledge about the plants but also has a long computation time. Other approaches, such as Poisson reconstruction [23] and ball pivoting [24] also do not provide desired results, possibly because of the complex plant architecture.

In the literature, in the context of 3D plant phenotyping, only one deep-learning based technique [25] exists which results in the segmentation of plant's individual traits from a 3D point cloud. In general, the 3D point cloud segmentation into individual plant traits using deep-learning is a new field. Some general techniques exist, which can be divided into two classes. One class of techniques is point-based which directly works with unordered 3D point clouds. This consists techniques such as, SGPN [26], PointNet [27], PointNet++ [28], and 3DmFV [29]. These techniques process the 3D point cloud as input and provide class labels for each point as an output. However, these architectures have the drawback that they are limited to the number of points in the each model. If the size of the point cloud is large, there is no reliable solution for the network training and interface.

The other class of technique is based on multi-view geometry, which generates numerous 2D projections from the 3D point cloud and then uses deep-learning based segmentation techniques on the produced 2D images, later connecting the various projections into a 3D point cloud segmentation. For example, SnapNet [30] was applied for semantic segmentation of a 3D model by producing a number of virtual geometry-encoded RGB images of the 3D object, training these images on a network, and then back-projecting the predicted labels to the 3D model to provide each point a label. The important limiting factor to use neural networks in plant phenotyping applications is that it requires a large ground-truth training data which is time consuming and tedious.

Clearly, there is a need of a fast and robust segmentation method for various plant architectures. In this paper, our focus is on processing the 3D model of the plant reconstructed using a passive 3D imaging technique called structure-from-motion (SfM). Our contribution lies in proposing and investigating the practicality of a fast and robust point cloud segmentation of plants with different architectures. The rest of the paper is organized as follows: section II provides the brief description of materials and methods. Section III describes our proposed segmentation algorithm. The experimental results are discussed in section IV and finally the conclusion in section V.

II. Materials and Methods

In the last 15 years, with the advancement in technology, numerous 3D imaging methods have been developed such as, laser scanning [31], LiDAR [32], structured light [33], stereo vision [34], structure-from-motion [35], space carving [36],

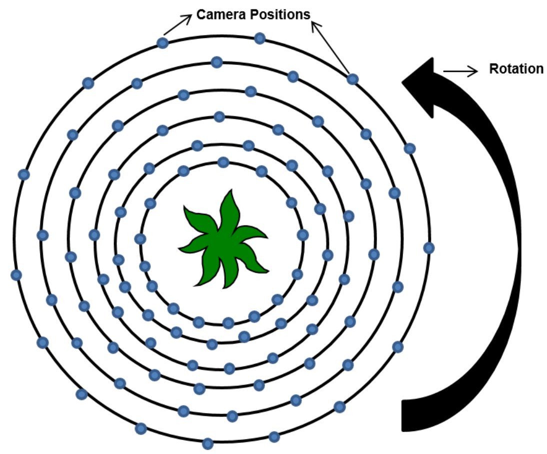

Fig. 1. Image acquisition process

and so on. Each imaging method has its own advantages and disadvantages and the user should select the method according to the application. As Paturkar et al. [6] demonstrated, SfM has performed well in the outdoor scenario. The important limiting factor was the computation time as SfM requires many of images to generate a 3D model. However, another detailed analytical study [37] showed how to select the appropriate number of images to generate an accurate 3D model of the plant.

In this study, we considered three different plant species namely: chilli, tomato, and maize. We conducted this experiment on a commercial farm in Palmerston North, New Zealand. We have captured images of the plants every week over a period of 2 months. We have 81 3D models at different growth stages to work with. We aimed at reconstructing a single plant in 3D; hence, the plants were planted in a row having a distance of approximately 90 cm between adjacent plants. Therefore, other plants did not interfere in the 3D model and only one plant is modelled in each reconstruction.

A. Image Acquisition

We acquired the images sequentially with the camera following roughly a circular path around the plant axis. Six rounds were captured at different heights, and distances, with at least 15 images acquired in every round at 10° to 15° intervals as shown in fig. 1. In this study, a mobile phone's rear camera is used to acquire the images (Apple iPhone 6s Plus with 12 MP main camera, f/2.2, and 29 mm focal length). The range of images provides enough view angles to reconstruct the plant in 3D. At every position, the camera was oriented in such a way that the whole plant is in the complete field of view. Here, structure-from-motion is used to generate the 3D model and SfM also provided the intrinsic and extrinsic camera parameters, so that the camera positions do not need calibration during image acquisition.

B. 3D Reconstruction of Plant

Structure-from-motion is the most widely used method for 3D reconstruction [6]. This process consists of achieving 3D

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structure of a scene from multi-view 2D images. SfM is used for calculation of 3D camera motion, structure, to get 3D information of the objects, calibrate a number of camera positions and the location of 3D points for every camera track [5]. For 3D reconstruction of the plant, it is necessary to find common keypoints and then match these between the different view images. For this process, we used the scale-invariant feature transform (SIFT) [37]. We converted an image into a large set of keypoint vectors, all of which are invariant to image rotation, translation and scaling.

Once we generated a dense 3D point cloud of the plant, it requires some preprocessing before segmentation. During the 3D reconstruction process, there can be various errors such as, noise and outliers. Also, the 3D model might contain some redundant points and therefore it is important to pre-process the 3D model without losing its quality. Before eliminating the outliers present in the 3D model, background should be removed to have robust segmentation result.

C. Background Removal

If the point cloud is achieved using passive techniques such as stereo vision or structure-from-motion, it also includes color information as the RGB camera is used for image acquisition. This color information is then used for background removal. The efforts taken in controlling lighting condition during image acquisition process will decide the reliability of simple color-based thresholding, classification or clustering approaches to differentiate between the background and plant. Jay et al. [38] proposed a clustering method based on both color and height above the ground to differentiate between background points in the point cloud generated from structure-from-motion and plant. In this study, we used the similar method for background removal.

D. Outlier Removal

The resultant 3D model might have some outliers produced by feature matching errors or registration errors. Such outlier may lead to inaccurate segmentation. However, they can be removed by performing statistical analysis on each point's neighborhood [39], [40]. In this study, we used statistical analysis to eliminate the outliers.

E. Down-sampling of Point Cloud

In general, the generated 3D model is detailed and dense, processing it is a memory and time consuming process. Lu et al. [41] suggested down-sampling the point cloud by merging close vertices with 0.5% to 10% of the diagonal length of the bounding box which consists of selected 3D points. Nonetheless, down-sampling the point cloud may lose important information about the plant such as parts of the leaf or stem. Therefore, depending on the plant species, architecture, and quality of 3D model, one should select the down-sampling rate. If it is not essential to down-sample the point cloud then one can simply skip this step. In this study, we have not down-sampled the point clouds as it is not necessary.

III. Plant Point Cloud Segmentation

The goal of a segmentation algorithm is to divide an unorganized point cloud *P* into various parts for further operations and also to reduce the computation time for processing *P*. The majority of the straightforward methods are based on spatial decomposition which find boundaries and subgroups to allow the points to be grouped closely based on a proximity measure. This measure is a Minkowski norm; important examples are Manhattan and Euclidean distance.

A basic segmentation technique in Euclidean space can be performed by using an octree structure (3D grid subgroup of a space based on fixed width boxes) An octree representation is important for cases where volumetric representation of the contained space is required and is also fast to build. This octree representation can be applied for specific applications which needs equal spatial sub-groups. In some scenarios where the cluster size changes, we need a robust method. In the context of 3D plants models, the cluster size changes from region to region. For instance, the leaf cluster may have different point cloud size than the stem cluster.

To solve this problem, the algorithm should understand that what is a leaf cluster and what makes it different from stem cluster. Mathematically, a cluster is defined as follows.

Let *P* be the set of points in the point cloud being segmented with a radius threshold r_{th}. Two points, $P_1, P_2 \epsilon P$ are adjacent if:

$$min \parallel p_i - p_t \parallel < r_{th} \tag{1}$$

Points $p_i\ and\ p_j$ are in the same cluster C_i if they are connected by a path of adjacent points. Consequently, points are in different clusters if there is not such a path, i.e. :

$$min \parallel p_i - p_j \parallel \geq r_{th}, \forall\ p_i \,\epsilon\, C_1,\ p_j \,\epsilon\, C_2 \tag{2}$$

However, from an implementation perspective, it is necessary to know how the minimum distance threshold between two clusters can be calculated.

Algorithm 1 Algorithm Plant Point Cloud Segmentation

Input: Point cloud ***P***
Output: Segmented point cloud
    Value of r_{th}

```
while P ≠ ∅
select one p_i ϵ P                    *Seed Point for new cluster
    move p_i from P to Q              *Q is points being processed
    create new cluster C_n
    while (Q ≠ ∅)                     *Growing region
    select one p_j ϵ Q
        move p_j to C_n from Q
        find all (p_k ϵ P)            *Adjacent points
                where || p_k − p_j || < r_th
                move p_k from P to Q
    end while
end while
```

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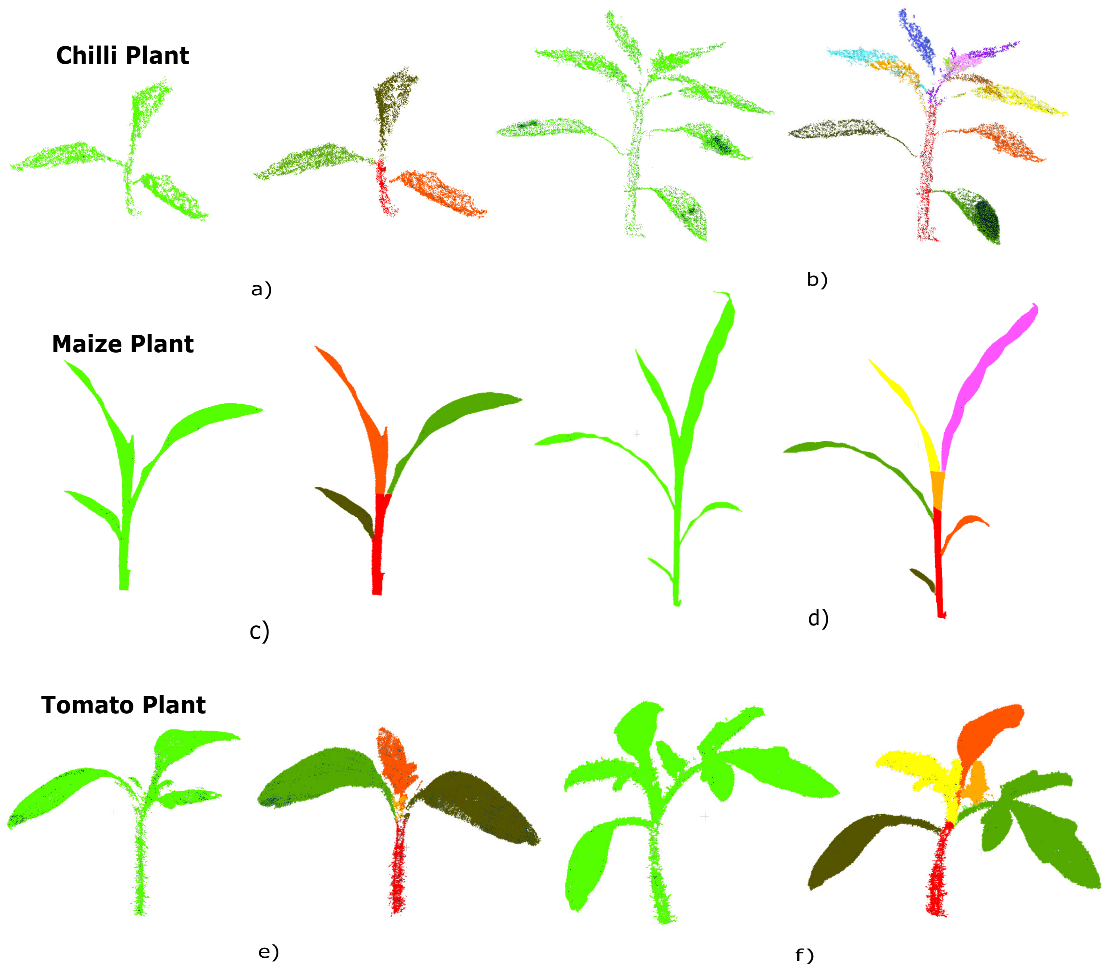

Fig. 2. Results of the proposed algorithm of different plants at various growth stages

However, the question to be asked here is, what is a correct value of r_{th} in order to get accurate segmentation? A very small value of r_{th} will give multiple clusters which may not be the desired result. In contrast, a very high value of r_{th}, will cluster the leaves and stem as a single cluster. So, the value of r_{th} has to be selected after a detailed analysis and to check what value gives a better result. The value of r_{th} will change according to the plant architecture and growth stage. This also limits this algorithm from being automatic. Algorithm 1 shows the pseudo code of the proposed radius search algorithm. To deal with the noise present in the point cloud and to prevent wrong segmentation, cluster with fewer than 10 points is considered as noise and it is discarded. Fig. 2 illustrates the results of our proposed algorithm of different plants at various growth stages.

IV. Experimental Results

We tested the proposed algorithm on 81 point clouds of 3 different species at various growth stages. This allowed us to assess our algorithm for accuracy, sensitivity, and reliability on the range of plant architectures from easy to complex. Fig. 2 shows a few segmentation results to examine the performance over the growth period. We used a personal computer (Intel Core i5-4570 CPU at 3.20 GHz and 8GB RAM). In most cases, plants were successfully segmented into leaves and stem, only 7 point clouds were not well segmented. 5 out of these 7 point clouds belonged to maize plants. The reason for the unsuccessful segmentation of maize plant was the architecture. In some cases, the maize leaves were sticking to each other which made them very difficult to separate. In addition, the difficult point clouds are from a more advanced growth stage. As shown in Fig. 2c, when the maize plant is at an early growth stage, the segmentation was better than the advanced growth stage segmentation Fig. 2d. The remaining two unsuccessful cases belong to one chilli plant and one tomato plant. The reason was the crown of small leaves at the top which made the segmentation difficult.

Apart from these cases, as shown in Fig. 2a and 2b the proposed algorithm provided successful segmentation of leaves and stem at different growth stages. Fig. 2a shows an early growth stage of the chilli plant and Fig. 2b shows a month old chilli plant. Similarly, for tomato plant, the algorithm has shown good performance and provided successful segmenta-

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TABLE I
COMPARATIVE ANALYSIS OF STANDARD ALGORITHMS

Plant	Point Cloud Data	Computation Time			
		K-Means	DBSCAN	Proposed	ML(SVM)
Chilli	387,845	1m.3s	3m.1s	30s	43s
Maize	487,768	1m.46s	3m.57s	35s	1m.4s
Tomato	413,639	1m.30s	3m.34s	41s	56s

tion irrespective of growth stage.

Table I compares the run times for different algorithms on the plant point clouds. The computation time varies according to the size of the point cloud and size of the point cloud depends on the growth stage of the plant. Here we provided the computation time of plants with advanced growth stage. K-means is reasonably fast but it requires a exact number of clusters as an input to perform the operation. DBSCAN on the other hand takes the longest as it is dependant on the point cloud size. Machine learning methods once trained, take much less time to give the output. However, to train the model, we require a lot of labelled data which is a time consuming process. The proposed algorithm has outperformed other segmentation methods by taking less than a minute to execute the segmentation operation. The computation time as well as complexity of the proposed algorithm is less than other algorithms. However, immunity to the noise points is satisfactory. We compared our proposed algorithm with Machine learning methods, K-means, and DBSCAN. It is tricky to assess the quality of the segmentation algorithm as it may depend on the application's purpose.

A. Performance Evaluation

Hubert et al. [42] and Rand [43] have demonstrated methods and metrics for the evaluation of the similarity of results from two different segmentation methods. In this paper, we are using adjusted rand index (ARI) proposed by Hubert et al. [42] for quantitative analysis. In this study, the point cloud dataset is manually segmented using TerraScan software by TerraSolid Inc. to use as a reference for performance evaluation. The segmented point cloud from the algorithm is compared with the manually segmented point cloud by measuring the ARI. The highest value of ARI between the segmentation methods shows the best performing algorithm. Table II shows the performance of the algorithms based on ARI.

TABLE II
ALGORITHM PERFORMANCE BASED ON ARI

Algorithm	**ARI**
K-means	0.8890
DBSCAN	0.9181
Proposed	0.9342
ML(SVM)	0.9254

It is seen that the proposed algorithm has performed better than other algorithms on plant data with reference to ARI. The proposed method therefore can be a potentially beneficial algorithm for segmenting plant point clouds.

B. Determination of Best (r_{th}) Value

In order to get the best r_{th} value, the same ARI metric is used. Experiments are conducted on each plant in the dataset with various r_{th} values. The same process of manual segmentation is used to compare with the segmented point clouds using ARI. The similar approach is used to select best parameters for other baseline algorithms. The r_{th} value was varied from 0.003 to 0.08 throughout the experiments for various species. The highest ARI value achieved for each of the r_{th} values, provide us the best r_{th} value. This process is repeated for all species and growth stages.

We have three important findings from the result:

1) The proposed algorithm performed well and shown potential when compared to the standard algorithms in terms of computation time, performance, and complexity.
2) The proposed algorithm does not need down-sampling and can applied directly on the dense point cloud.
3) The proposed algorithm performed well on the various plant architectures irrespective of plant species when compared to reference point clouds using ARI.

However, it is very difficult to achieve precise and meaningful segmentation every time, especially in the heavily occluded area. As Fig. 2d illustrates, it is very difficult to segment the maize leaves as some of leaves might be sticking to each other. However, the algorithm still segments the point cloud but it is not accurate and meaningful.

V. CONCLUSION

This paper proposed a plant point cloud segmentation algorithm based on Euclidean distance for various plant species and demonstrates the results on different 3D point clouds generated using structure-from-motion. Compared to the other segmentation algorithms, the proposed algorithm has shown potential advantages:

1) Irrespective of point cloud size, plant growth stage, and architecture, the algorithm did not take more than 50 secs.
2) The proposed algorithm does not require any prior knowledge of the plant for segmentation like we need in k-means and machine learning methods.

The proposed algorithm could be further developed and the main limitation of the algorithm is that not in all the cases the segmentation is meaningful. One domain in which more progress can be expected for plant trait segmentation is deep neural networks. The fundamental obstacle to use neural networks in plant phenotyping applications is the requirement of large ground-truth training data.

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