SKELETONIZATION OF 3D PLANT POINT CLOUD USING A VOXEL BASED THINNING ALGORITHM

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ABSTRACT

Understanding the point clouds of plants is crucial for the plant phenotyping. However, it is challenging due to a number of factors such as complicated structures and imaging noise. The primary objective of this project is to simplify the complicated 3D structure of the plant point cloud data into 1D curved skeleton. The simplified skeleton will be helpful for the structural analysis and understanding of plants of interest and the measurements of their traits such as the areas, perimeters of leaves, curvatures, and the lengths between different nodes. To this end, we propose a novel method to voxelize the given plant point cloud, extract the skeleton voxels, and find the nearest neighbors to connect the skeleton points as a connected representation. A number of different plant point clouds are used to validate and compare the proposed voxelization thinning method with a state-of-the-art one. Better results have been obtained.

***Index Terms*—** Plant phenotyping, point cloud, skeleton, voxelization, thinning

1. INTRODUCTION

More and more researchers tend to believe that phenotyping may play a crucial role in finding the functions of genes and developing varieties of plants that can resist such stresses as flooding, cold weather, drought, and windy weather and produce more yield. Such plants and crops are becoming even more important when the population on the earth is increasing and the arable land is decreasing. In [1], the fast feature persistent histogram [2] was extracted and used to distinguish the wheat ears from the wheat stems and the grapevine leaves from the grapevine stems through the support vector machines (SVM). It was found that the volumes of the wheat ears are highly correlated to the wheat yield. This method requires training data available and concludes that the points in the transition areas between different organs are challenging for classification. It is reviewed in [3] how the genotypes interact with the environment and the genetic variation may need to be changed with different soil types, nutrient inputs, and environmental stresses. To this end different experimental platforms and the field phenotyping systems need to be developed for such investigation.

The point clouds of plants can be built using various techniques such as laser scanning [1] and structure from motion [4]. How to interpret the reconstructed point clouds is then crucial for the plant phenotyping. However, it is challenging due to a number of factors such as complicated structures, self-occlusion, volumetric nature, the state of different organs being close together and imaging noise. In this paper, we propose to extract the skeletons of plants, so that the understanding of the whole point cloud can be advanced a step further for plant phenotyping.

Skeleton is a fundamental one dimensional shape and become more prevalent due to its simplicity in topology. A skeleton can be easily manipulated and processed with minimal computational cost in the area of researches for 3D pattern matching, 3D recognition, 3D surface reconstruction and structural analysis of objects of interest. The skeleton structure has been used in a wide range of applications like surface reconstruction [5], shape matching [6], animation [7] and mesh segmentation [8, 9] as well.

Different techniques can be used to extract the skeletons of 3D shapes. Based on what data they operate, these techniques can be classified into three main categories or a combination of these: (i) Volumetric data operation: This class of methods operates the volumetric data usually produced from the voxelization of the given 3D data in the form of either point clouds or meshes. A voxelization and thinning approach was proposed in [10]. This is a topology preserving process which carves a voxelized object layer by layer until medial or centerline skeleton voxel is found. Each layer of 3D voxelized object is mapped to a binary image and each voxel in 3D space is assigned 1 for point presence and 0 for otherwise. The thinning operation is performed to remove the object points until the mid-point is reached. This can be done in parallel and this approach is also called medial axis transform (MAT) or fire front propagation; (ii) Mesh operation: This class of methods operates 3D meshes and thus 3D surfaces. The method proposed in [9] is based on Laplacian smoothing by shrinking the boundary of the 3D object inwards until 1D skeleton is obtained. But this method could be applicable only to clean and well defined meshes without being corrupted by noise; and (iii) 3D point cloud operation: This class of methods operate the points themselves directly. In [11], it is proposed to

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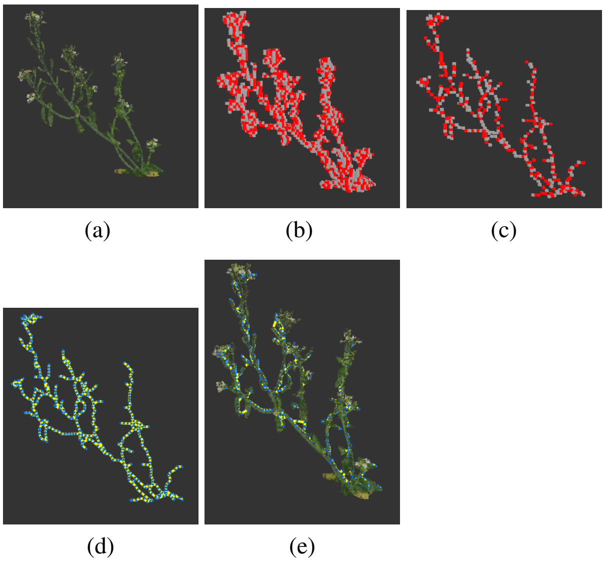


Fig. 1. The main steps in the process of plant point cloud skeletonization. The red and grey colors used were nothing more than to represent some good visibility of voxels in the scene. (a) Input points with texture colors; (b) Voxelization of input points; (c) Skeletonized voxels after thinning; (d) Final connected skeleton; (e) Final skeleton + input point cloud.

obtain a set of projected points through minimizing an objective function between these points and the input points regularized by the constraints that these points are collinear. In order to find more accurate branch points, the support radius would be gradually increased. The branch points are finally connected. If there are gaps, then bridge points may need to be found satisfying three constraints: collinear to the existing branch, closest to the branch points with their distances being small enough.

In this paper, we propose and adapt the voxelization and thinning (VT) approach for the skeletonization of given plant point clouds. While it satisfies our specific requirement for plant structure analysis, it also has the promising features like topology preservation, keeping the skeleton in the middle of the plant structure, producing one voxel width skeleton and on top of all with less processing time.

2. A NOVEL METHOD

There are four main processing steps in our proposed method for the skeletonization of a given point cloud data: voxelization of point cloud, voxel classification, voxel thinning and voxel connection using the approximated nearest neighbor (ANN) search. These are detailed in the following sections.

2.1. Voxelization of point cloud

Our voxelization process depends on only the points in the input point cloud. A bounding box is first found that contains the whole point cloud data. The size of this bounding box is calculated from subtracting maximum and minimum value of points from X, Y and Z co-ordinates respectively. This bounding box will be divided into an equal number of small boxes in X, Y and Z directions. These equally divided small boxes are called as voxels. This is a similar technique like rasterization of 3D object. We set the size V_s of the voxels to $V_s = 0.04$ in this paper, unless otherwise stated.

2.2. Voxel classification

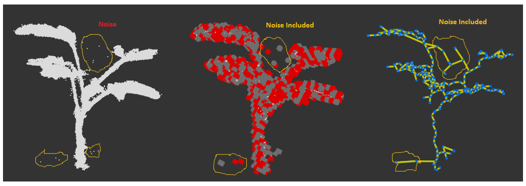
Once the bounding box has been divided into voxels, we need to separate the voxels with and without point cloud samples or points within their volumes. This has been done by processing each point sample to find the right voxel it belongs to. The voxels which contain samples will be voted as 1 and retained for further processing and remaining voxels will be ignored from further processing. In this paper, we used a threshold N_s of samples inside a voxel to control when it should be retained. This threshold can be determined by the noise corrupting and density of points in the given point cloud. The heavier the noise and the denser the points, the larger the value this threshold has. Unless otherwise stated, we set $N_s = 1$ in this paper. The retained voxels are used to represent voxelized structure of the input 3D plant point cloud with regularly sampled surfaces.

2.3. Voxels thinning

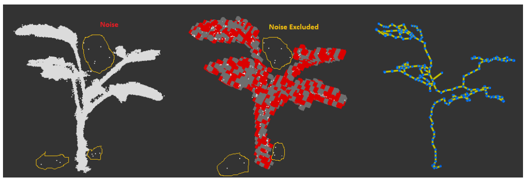
The next step is to apply a thinning process to find the medial axis of the 3D voxels for the topological and geometrical representation of the plants of interest. There are two types of approaches for 3D skeletonization: line skeletonization and surface skeletonization. Both approaches are to carve the voxels layer by layer until the minimum size is reached. The thinning approach always removes the voxels to find the skeleton without introducing a new one. In this paper, we adapted the method in [10] for line skeletonization. This method designs six masks along each of six directions: up, down, north, south, east and west for the determination whether a voxel should be deleted, retained, or do not care. Such masks are applied to each voxel and delete all redundant neighboring voxels iteratively until no more voxels can be deleted. The adaption lies in that instead of seeking the points on the median lines, we calculate the averages of points along different directions, so that consensus points can be found to resist imaging noise or even fill in holes in the original point cloud.

2.4. Voxel connection

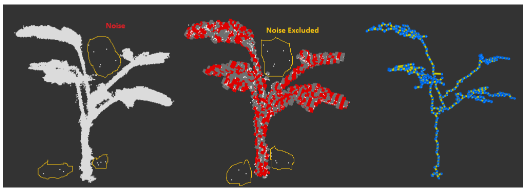
The thinned voxels found by the above thinning algorithm need to be connected as a continuous and topological representation of the structure of the plant of interest. To this end, we used the ANN approach [12] to find a number of two nearest neighbours of any thinned voxel of interest. The two



(a) Voxel size=0.05; N_s=0.



(b) Voxel size=0.05; N_s=1.



(c) Voxel size=0.035; N_s=2.

Fig. 2. Results of plant point cloud skeletonization with different voxel sizes and thresholds for denoising. From left to right in each row: Input points, voxelized points, and finally extracted skeleton.

neighbours are sorted according to their distances. Ideally if the thinned vixels are evenly distributed, the two neighbours lie on the two sides of the voxel of interest and one is already on the skeleton and the other can be connected to the thinned voxel of interest. If not, then three neighbours are found and see whether there is a neighbour appearing on the other side with a distance smaller than the diagonal size of the voxel. If so, then it is connected to the thinned voxel of interest. Otherwise, this thinned voxel of interest is treated as an end point of the skeleton. This ANN approach uses a space partitioning method to accelerate the search of the neighbouring voxels and has a computational complexity of $O(\log m)$, where m is the total number of voxels built.

The different steps in our proposed method are illustrated in Figure 1. Figure 1(a) shows the loaded point cloud of an Arobidopsis plant with textures for better visualization. Figure 1(b) shows the voxelized point cloud. Figure 1(c) shows skeletonized voxels after thinning. Figure 1(d) shows the finally connected skeletons of the Arobidopsis plant. Figure 1(e) shows the superimposition of the extracted skeletons onto the the original point cloud so that the quality of the extracted skeletons can be better appreciated.

The proposed method has a computational complexity of $O(n)$ for the point cloud voxelization, $O(m)$ for voxel classification, $O(km)$ for voxel thinning and $O(m \log m)$ for voxel connection where n is the number of points in the given point cloud and k is the number of iterations for voxel thinning. Thus, the overall computational complexity of the proposed method is $O(n + m \log m)$.

3. EXPERIMENTAL RESULTS

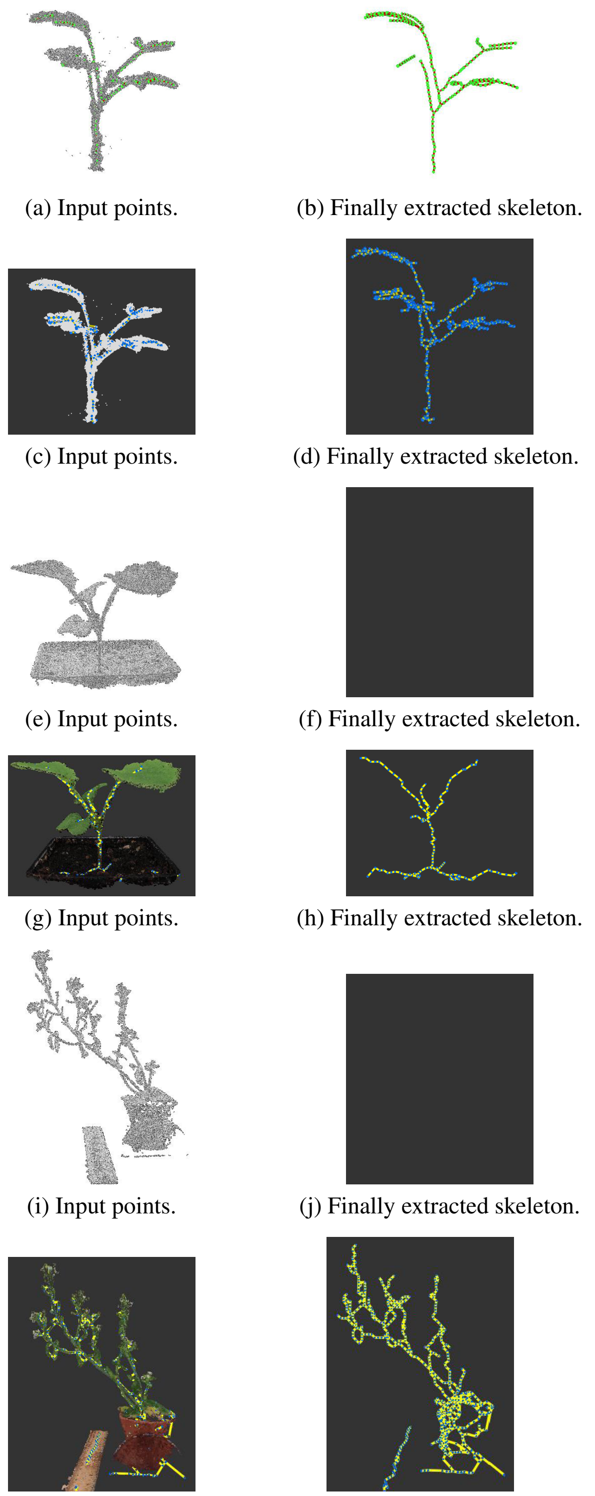
In this section, we validate our proposed method using the point clouds constructed using the method proposed in [4]. While the point clouds include rich information about the plant structures, some points are noisy introduced by the point cloud reconstruction process. Note that such noisy points could hardly be avoided, since the plant images always include areas without much textures for accurate feature extraction and matching.

3.1. Voxel size and samples for denoising

Most of the reconstructed point clouds are contaminated with noise and contain outliers [4]. This is one of the major problems to be handled effectively and it is important to clear or ignore the noisy points and outliers from our skeletonization process. In our voxel based thinning approach we handled the noise by ignoring the voxels which have fewer samples than a threshold N_s such as one or two samples. This threshold can be configured between 0 and 10 by changing N_s according to the input point cloud noise levels. By default this parameter was set to 1, in this case our voxelization algorithm considered the voxels with only one sample as noisy ones and thus will be ignored based on the observation that noisy points usually sparsely distribute. If this threshold is set to 0, then our algorithm does not eliminate any voxels with points. Low level noise makes our algorithm to produce better skeletons.

Another important parameter is voxel size V_s. In our voxel based thinning approach before applying the thinning algorithm the input point cloud is voxelized. In order to produce better output skeleton the voxel structure has to be created without any holes in it. The voxel size V_s has to be changed based on the density of the points: if the input point density is high then the voxel size should be decreased to produce better skeleton. Whereas if the input point density is low then the voxel size should be increased to reduce holes in the voxelized structure. In our application the default voxel size was $V_s = 0.04$, but it can be configured by the user based on the input point density.

Some experimental results are presented in Figure 2, illustrating the impact of the threshold N_s and voxel size V_s on the output skeletons. Handling the noise is quite challenging while voxelizing the point cloud. When the input point density is high, the noisy points can be detected and ignored easily because most of the voxels contain more samples than the threshold N_s. This observation has been clearly demonstrated by Figure 2. With the increase of the parameter N_s and decrease of the parameter V_s, the noisy points at the bottom left hand side and top middle were removed and thus produced more accurate skeletons. Whereas in the case of low density



(a) Input points. (b) Finally extracted skeleton.

(c) Input points. (d) Finally extracted skeleton.

(e) Input points. (f) Finally extracted skeleton.

(g) Input points. (h) Finally extracted skeleton.

(i) Input points. (j) Finally extracted skeleton.

(k) Input points. (l) Finally extracted skeleton.

Fig. 3. Input plant point clouds (left) and their skeletons (right) extracted using different methods. Odd rows: L1 medial method; Even rows: our VT method.

point clouds, finding the noise is highly complicated because ignoring the noisy voxels may eliminate the valid voxels as well. This may lead to the existence of holes or hollow blocks in the voxelized structure. Eventually the thinning algorithm may produce some inaccurate output skeletons with disconnections.

3.2. Comparative study

Here our voxelization and thinning (VT) approach has been tested and compared with L1-Medial skeletonization method [11] on the extracted skeletons, memory usage and computational time. Since the L1-Medial method claimed as best compared with other existing ones, by comparing our VT method with the L1-Medial method can clearly bring out the advantages and disadvantages of our algorithm. Although our primary goal is to skeletonize the 3D plant point cloud data with narrow cylindrical structure and multiple branches, here our algorithm is tested and compared with different point clouds of plants with different structures and shapes. The following test cases with output images will clearly illustrate different performances between the two approaches.

The experimental results are presented in Figure 3 and Table 1. Figure 3 shows that L1-Medial skeletons extracted from the Mimosa plant resemble our skeletons along with some minor topological discrepancy in the left lower branch. For the Brassica and Arobidopsis input point clouds, the L1-Medial algorithm failed to produce any result due to its limitation of handling a huge number of input points (Brassica-1614842 and Arobidopsis-538066). This could be a major flaw or limitation of the L1-Medial algorithm which cannot be used for the extraction of highly complex plant structure skeletons. Yet our voxel based thinning approach produced some excellent results without any preprocessing. Although our algorithm preserved excellent topology and connectivity in the area of stems, branches and leaves, it still produced some inaccurate result at the pot area, which is actually the clutter introduced in the point cloud reconstruction process. Such clutter could be removed in advance for better results.

The complexity, variation, and growth of the plants always render it difficult to collect ground truth. Even though manual approaches may be used instead, they have to destroy the plants and introduce errors during the process of measurements due to the necessity of flattening the units of plants. In this case, it is always difficult to quantify the performance of different techniques. The reconstructed point clouds may be used with careful operation in the future to collect the ground truth.

The computational time of our method includes voxelization and skeletonization processing time and that of the L1 medial method includes regularization, iterative contraction and re-centering processing time. But here we compare only the total time taken to produce output skeleton. Table 1 shows that on the whole, our method is more computationally effi-

Plant	n	Technique	Time	Memory	CPU
Mimosa	40551	VT	1.14	128M	13%
		L1	88.9	263M	24%
Brassica	1614842	VT	4.54	487M	28%
		L1	N/A	N/A	N/A
Arobidopsis	538066	VT	2.24	224M	23%
		L1	N/A	N/A	N/A

Table 1. The computational time in seconds, memory usage in MB, and CPU usage in percentage of different techniques for the skeletonization of different plants represented in different numbers n of points.

cient than the L1-medial algorithm in the sense of both computational time and CPU usage.

4. CONCLUSION

In this paper, we proposed a voxelization and thinning (VT) method for the extraction of the skeletons of plants from their point clouds reconstructed using typical structure from motion methods [4]. While the reconstructed point clouds are of high quality and include rich information about the plants of interest, it is challenging to extract measurements of plants from these point clouds due to various issues like imaging noise and complicated structure. This paper advanced the analysis of the point clouds a step further through extracting the skeletons of the plants. While these skeletons themselves provide guidance for the classification of the points into different categories of organs (stems, branches, leaves, flowers, for example), some measurements of traits of the plants can be performed directly on the skeletons for example, the inter-node distances and the including angles between different branches and the main stem. A comparative study based on several point clouds of different plants with different structures and shapes shows that the proposed method outperforms an existing one for the efficient and effective extraction of high quality skeletons. Further research will be to incorporate thinned voxel re-centering and hollow block filling technique into our VT approach for more reliable and robust skeleton extraction.

Acknowledgments

J.D. and J.H. acknowledge funding from the European Union FP7 Capacities Programme (Grant Agreement No. 284443: European Plant Phenotyping Network, an Integrating Activity Research Infrastructure project) and BBSRC NCG Grant (Ref: BB/J004464/1).

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