Automated extraction of corn leaf points from unorganized terrestrial LiDAR point clouds

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Abstract: Terrestrial LiDAR data can be used to extract accurate structure parameters of corn plant and canopy, such as leaf area, leaf distribution, and 3D model. The first step of these applications is to extract corn leaf points from unorganized LiDAR point clouds. This paper focused on an automated extraction algorithm for identifying the points returning on corn leaf from massive, unorganized LiDAR point clouds. In order to mine the distinct geometry of corn leaves and stalk, the Difference of Normal (DoN) method was proposed to extract corn leaf points. Firstly, the normals of corn leaf surface for all points were estimated on multiple scales. Secondly, the directional ambiguity of the normals was eliminated to obtain the same normal direction for the same leaf distribution. Finally, the DoN was computed and the computed DoN results on the optimal scale were used to extract leave points. The quantitative accuracy assessment showed that the overall accuracy was 94.10%, commission error was 5.89%, and omission error was 18.65%. The results indicate that the proposed method is effective and the corn leaf points can be extracted automatically from massive, unorganized terrestrial LiDAR point clouds using the proposed DoN method.

Keywords: corn leaves, terrestrial LiDAR, cloud points, automatic extraction, crop growth monitoring, phenotyping, difference of normal (DoN), directional ambiguity of the normals

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1 Introduction

Crop leaves play a significant role for crop plants[1], for example, they determines light interception and plant productivity[2]. Therefore, the estimation of leaf structural and biophysical parameters such as leaf area[3], leaf morphology, leaf structure, leaf chlorophyll content etc., is very important for crop growth monitoring[4]. Corn (*Zea mays*) is one of the most widely planted crops[5]. And the estimation of these structural and biophysical parameters for corn leaf is very important for crop growth monitoring. Unfortunately, the existence of corn stalk affects the estimation accuracy of these parameters[6]. Therefore, the identification of corn leaves is known as one of the important factors for leaf parameters estimation[7,8]. Remote sensing technique can obtain these parameters in a large imaging area in a short time[9], which is vital in agricultural application[10-12]. Terrestrial LiDAR is an active remote sensing technique[13], which provides highly accurate point clouds (vertical precision and horizontal precision ≤2 mm) of corn canopy[14]. Therefore, the LiDAR point clouds can be used to extract accurate leaf structure parameters non-destructively[15]. The primary work for this application is to extract leaf points[16].

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The raw terrestrial LiDAR points are massive, unorganized[17,18]. Therefore, the extraction of corn leaf points from terrestrial LiDAR points is a difficult but crucial work in agricultural application[19]. The difficulties also arise from the inherent complexity of point clouds within the corn canopy[20]. The existing extraction approaches can be basically classified as three groups: edge-based[21,22], region-based[23,24], and hybrid[25,26] algorithms. The edge-based algorithms detect the difference between leaves and stalk using the features such as the normal vector, gradients, and principal curvatures in a cross-section. The points are usually classified according to the differences of features between adjacent points. The region-based methods classify the data by detecting continuous surfaces that have homogeneity or similar geometrical properties[14]. Region-based methods are more robust (less sensitive to noise) than edge-based methods. However, there are over- or under-segmentation results and the border ambiguous[27]. The hybrid methods use a combination of edge- and region-based analysis techniques, which analyzes points using several kinds of geometrical, image-metrical, or even texture-metrical features.

In view of the massive, unorganized characteristic of terrestrial LiDAR point clouds, this paper proposes a multi-scale DoN operator for the extraction of corn leaf points[19]. The main contribution of this study is to propose the DoN method to extract corn leaf points automatically, whose geometrical surface is thin, irregular, and curly.

This study is aiming at extracting the corn leaves LiDAR points from massive corn plants points. The estimated multi-scale DoNs are used to identify leaves points based on the obvious difference of normals for corn leaves points and corn stalk points. The experimental results indicate that the proposed DoN method is effective and the corn leaf points can be extracted automatically from massive, unorganized terrestrial LiDAR point clouds with the high overall accuracy and low commission error and omission error.

2 Data source and pre-processing

2.1 Data source

The study area is located in a greenhouse of China Agricultural University, Beijing, China. Several corn plants were scanned in this greenhouse on December 4th, 2011, using a FARO Focus3D laser scanner (http://www.faro.com/products/3d-surveying/laser-scanner-faro-focus-3d/overview). The corn was in the jointing stage, and the corn plant was around 1.9 m tall. There were 11 corn plants in scanned area. We selected two plants to extract corn leaf points in this study. Table 1 shows the laser scanning parameters. The attributes of LiDAR points include x, y, and z coordinates, the intensity etc. There were two laser scanning stations for acquiring complete points of corn plants. One station is in the northwest of greenhouse and the other is in the southwest of greenhouse, and the distance between them are 12 m. Figure 1 shows the sketch of laser scanning for corn plant, and the laser lights illuminated from two stations and reached on corn leaves (red dots) and corn stalk (green triangles), then the returned laser lights are received by laser receiver. Every point pi (i = 1,2,…,n) is represented by $(Xi, Yi, Zi)^T$ in the local coordinate system (*LCS*). Therefore, they have different local coordinate system for the points returned from these two stations. These two different local coordinate systems were uniformed in the following data pre-processing stage.

Table 1 3D laser scanning parameters of FARO Focus3D (maize scene) scanners for corn plant scene

Parameters	Values
Scanning speed	48.8 mrad/s
Scanning angle	360° (horizontal), 305° (vertical)
Precision (systemic range error)	≤2 mm (within 25 m)
Distance accuracy	8 mm (within 50 me, single point scanning)
Angular resolution	1.8 arcsec (horizontal), 1.8 arcsec (vertical)
Vertical scanning step	0.009° (360°)
Horizontal scanning step	0.009° (360°)
Wavelength	905 nm

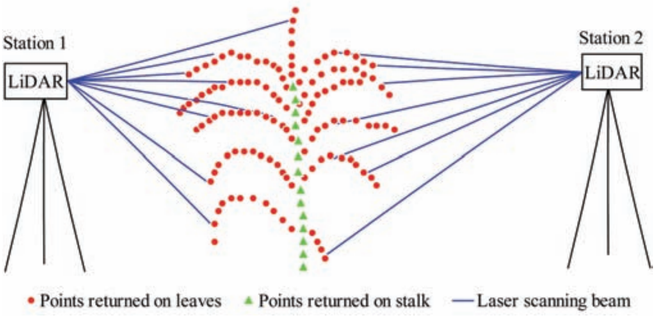


Figure 1 Sketch of laser scanning for corn plant

2.2 Data pre-processing

There were some isolated, invalid points returned on the wall, the roof and the lamp of greenhouse. Therefore, the first step was removing these invalid points from the corn plant points. An enveloped cuboid was used to identify the points returned on corn plants, thus the points returned on the wall, the roof and the lamp of greenhouse have been removed. Figure 2a shows the raw corn plant points from two scanning stations, we can see that there was obvious geometric shift between the points of two stations. Therefore, the points were registered using tie-points. The algorithm for LiDAR points registration were was developed using the C++ programming language in this study. The principle of LiDAR points registration is to rotate the coordinates and make the rigid transformation for the LiDAR points scanned from two stations. And the transformation matrix was built for registration. For the LiDAR points p_{i} and q_{i} from two stations, the optimal rotation matrix $\boldsymbol{R}$ and translation matrix T are built for LiDAR points registration and the value of function $\mathrm{f(R,T)}=\sum_{1}^{n}\left\|p_i-(Rq_i+T)\right\|^2$ is minimized. The coordinate transformation matrix $\boldsymbol{T}$ is defined as follows:

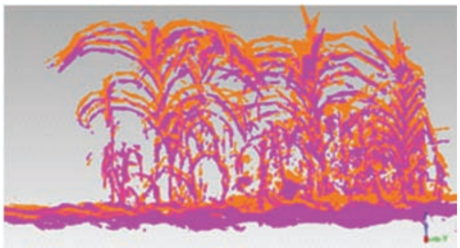
$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \mu R(\alpha,\beta,\gamma)\begin{bmatrix} x \\ y \\ z \end{bmatrix} + T$$

where, μ is a coefficient that counting the scale difference between these two coordinate systems; α, β, γ are rotation coefficients; $\boldsymbol{T}$ is translation matrix:

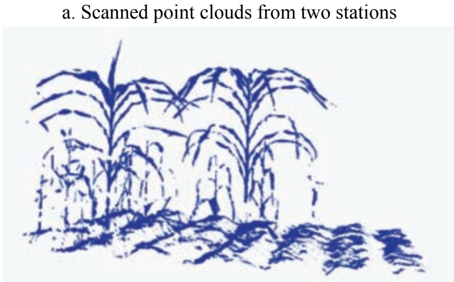
$$T=\begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix}$$

These seven conversion coefficients are needed to work out for registering the LiDAR points from two stations.

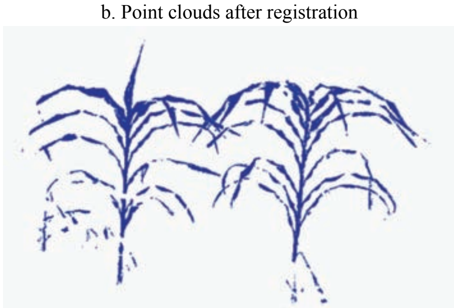
Using our registration code, we unify the positive plane and the reference plane to match the LiDAR points from two stations. The matched points are used to extract corn leaf points. There are 89 940 points after registration (Figure 2b), including the points returned on corn plants and ground. Finally, we classified the points into ground points and corn plants points based on the height. Figure 2c shows the classified points returned on two corn plants.



a. Scanned point clouds from two stations



b. Point clouds after registration



c. Point clouds after removing ground points

Figure 2 LiDAR points for (a) corn plants obtained from two scanning positions, (b) the same points after registration, and (c) the points after removing ground points

3 Method

The proposed method aims to extract corn leaf points from massive LiDAR points using the difference of the normal vectors calculated at two scales. The flowchart is as Figure 3. As shown in Figure 3, there are three vital steps for this extraction: 1) estimating the normals of corn plants using the principal components of neighborhood; 2) eliminating the directional ambiguity of normals using undirected graph traversal method; 3) computing the difference of normal. The DoN is used to extract corn leaf points.

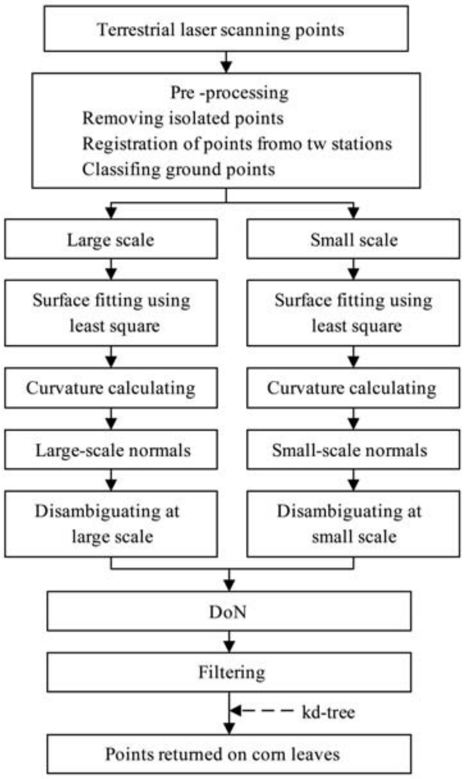


Figure 3 Flowchart of extracting corn leaf points with DoN method

3.1 Estimating the normals of corn leaf points

The massive unorganized LiDAR points are stored in kd-tree format. For each point, a least squares local plane is fitted with its k nearest neighbors[17]. Tangent plane S is a discrete point set in k-nearest neighbor, which is computed as:

$$S(n,d) = \arg\ \min \sum_{i=1}^{k} (np_i - d)^2 \tag{1}$$

where, n is the normal vector; p_i is point cloud; d is the distance between point p_i and the origin of coordinates.

The centroid of tangent plane S is $\overline{p}_i$, which is computed as:

$$\overline{p}_i = \frac{1}{k}\sum_{j=0}^{k-1} p_{i,j} \tag{2}$$

The normal vectors was estimated by finding the tangent plane (M) using the principal components of a local neighborhood for each point. The solution for estimating the surface normal is the eigenvectors and eigenvalues using principal-components analysis (PCA) of a covariance matrix created from the nearest neighbors of the studied point. The covariance matrix (M) is computed as:

$$M = \frac{1}{k}\sum_{i=1}^{k} (p_i - \overline{p})(p_i - \overline{p})^T \tag{3}$$

where, $(p_i - \overline{p})$ is a column vector; $(p_i - \overline{p})^T$ is transposed column vector; $\overline{p}$ is the centroid of neighboring points.

3.2 Eliminating the directional ambiguity of normals

The directional ambiguity is within the surface normals: there are two equal but opposite (negative and positive) normals for any object surface, both of them are mathematically valid. In many applications, this ambiguity can be resolved using the view point because the correct normal is always the one in the hemisphere that points towards the view point. Disambiguation of the normals is done by negating one of the normals if $n(p, r_1) - n(p, r_2) > \pi/2$, i. e. the angle between the two normals with different searching radius is greater than 90°. This assumes that the correct normals must be within an angle of $\pi/2$ for corn leaves points.

3.3 Computing DoN

Normals estimated with a specific support radius share some similarities with a scale-space operator[19]. If the structure of the larger neighborhood differs significantly from that of a smaller neighborhood, the directions of the two estimated normals are likely to be different obviously. Thus the difference of normals between these two radii for corn leaves points and corn stalk points is significant, which can be used to identify corn leaf points. The DoN (Δ) for a point cloud is defined as follows:

$$\Delta n(p, r_1, r_2) = [n(p, r_1) - n(p, r_2)] / 2 \tag{4}$$

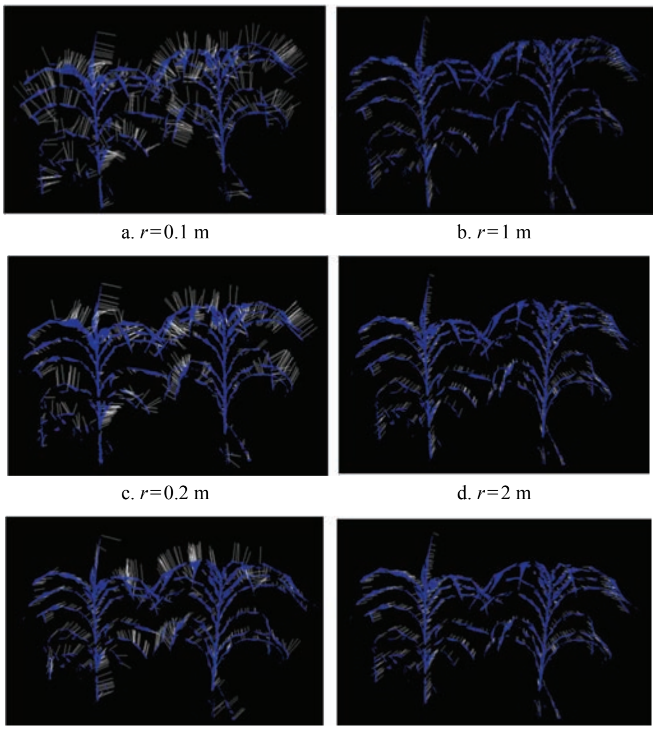
where, $r_1<r_2$, r_1 and r_2 are two searching radii. $\Delta n(p, r_1, r_2)$ is the difference of normals in two scales, the attributes of which include the x, y, and z coordinates, normals and normals' curvature.

4 Results and analysis

4.1 Estimated normals and DoN features for corn plants

The selection of optimum scale for normal estimation is vital for corn leaves points identification, the principle of which is maximizing the magnitude of the DoN for the points set within leaves points and minimizing the DoN value between leaves points and stalk points. Ioannou et al.[19] found that they got the best extraction result when the $\Delta n(p)$ vectors is computed on two scales whose ratio (r_2/r_1) is 10, for an example, r_2=2 m and r_1=0.2 m. Therefore, we computed the normal on three groups of scales for corn leaf points extraction, (0.1 m, 1 m), (0.2 m, 2 m), (0.4 m, 4 m), which is as Figure 4. The black points are LiDAR points and the white lines are normals of points in Figure 4. And Figure 4a and Figure 4b, Figure 4c and Figure 4d, Figure 4e and Figure 4f are the calculated normals using searching radius of (0.1 m, 1 m), (0.2 m, 2 m), and (0.4 m, 4 m) respectively. We can see that there is different vector direction, vector magnitude for the three pairs of normal results. Especially for Figure 4a and Figure 4b, there are obvious different normal vector using different scales.

The DoN values for every LiDAR points, $\Delta n(p, r_1, r_2)$, are computed using (0.1 m, 1 m), (0.2 m, 2 m), and (0.4 m, 4 m). Figure 5 is the resulted DoN vectors ($|\Delta n(p)|$) at scales of 0.1 and 1 m, 0.2 and 2 m, 0.4 and 4 m respectively. Figure 5a is the pre-processed LiDAR points returned on two corn plants, and Figure 5b, Figure 5(c), Figure 5d are the resulted DoN vectors at such three scales as (0.1 m, 1 m), (0.2 m, 2 m), (0.4 m, 4 m) respectively. From these three groups of DoN vector results, we can see that the DoN result at (0.1 m, 1 m) showed the strongest difference between corn leaves points and corn stalk points. Therefore, the (0.1 m, 1 m) is the optimal scale for corn leaf points extraction in our analysis.

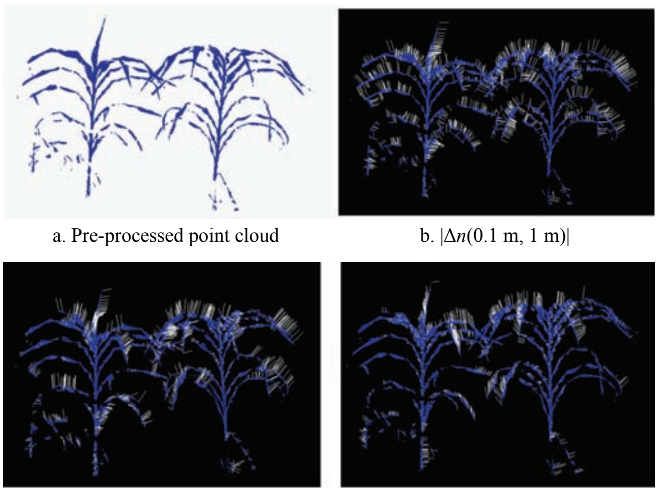


a. r=0.1 m b. r=1 m

c. r=0.2 m d. r=2 m

e. r=0.4 m f. r=4 m

Figure 4 Different normals of corn plant points using



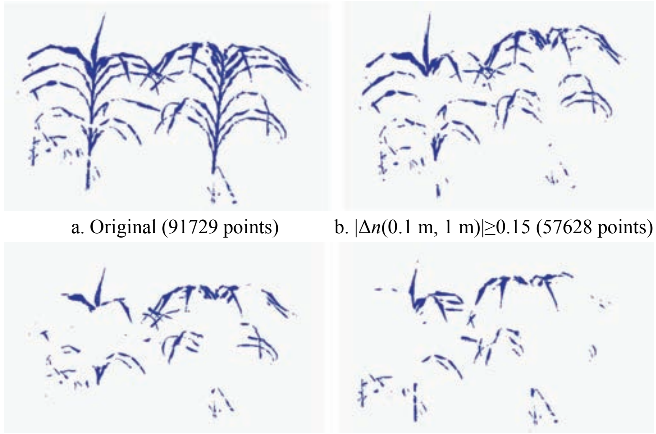
a. Pre-processed point cloud b. $|\Delta n(0.1\text{ m}, 1\text{ m})|$

c. $|\Delta n(0.2\text{ m}, 2\text{ m})|$ d. $|\Delta n(0.4\text{ m}, 4\text{ m})|$

Figure 5 Computed DoN for corn plants using scales

4.2 Filtered DoN results at multi-scales

The multi-scale DoN operators are used to identify corn leaves points and corn stalk points. Figure 6 shows the DoN filtered results for the corn plants. At the smallest scale of (0.1 m, 1.0 m), shown in Figure 6b, the leaves and stalks of the corn are filtered obviously, and the details of corn leaves are complete. Using larger scales of (0.2 m, 2 m) and (0.4 m, 4 m), as shown in Figures 6c and Figures 6d, many leave points are missed because these points are classified as stalk using the normal vectors computed on these two scales. On the larger scales, only large objects are preserved, and smaller objects are increasingly removed. Figure 7 is the sketch of incorrect extracted points when the DoN of leave points is the same to the DoN of stalk points. We can see that there are some points returned on top erect leaves (labeled “leave points” in the top of Figure 7) and the lower hanging down leaves (labeled “leave points” in the bottom of Figure 7) are classified as stalk because their normal vector is similar to the normal of corn stalk.



a. Original (91729 points) b. $|\Delta n(0.1\text{ m}, 1\text{ m})|\geq 0.15$ (57628 points)

c. $|\Delta n(0.2\text{ m}, 2\text{ m})|\geq 0.15$ (45373 points) d. $|\Delta n(0.4\text{ m}, 4\text{ m})|\geq 0.15$ (32157 points)

Figure 6 Extracted corn leaves points with three scales

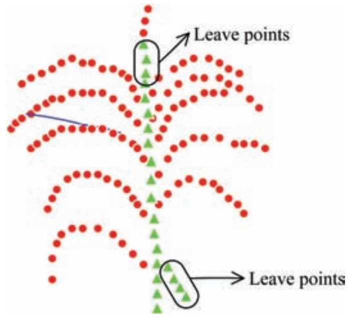
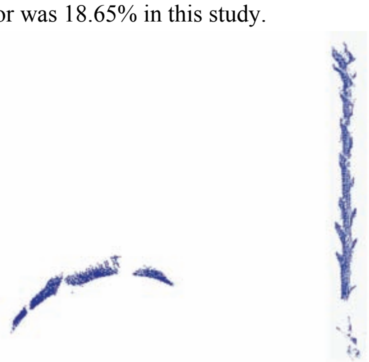


Figure 7 Sketch of incorrect extracted points when the normal of leave points is the same to the normal of corn stalk.

4.3 Extracted corn leaf points

After the comparison of extracted corn leaves points on three scales, the scale (0.1 m, 1 m) was used to identify corn leaves points. And a clustering algorithm of a simple Euclidean distance threshold[28] was used to extract corn leaves points and corn stalk points respectively. The parameters of clustering are as follow: distance tolerance is r3, the minimum distance is 100 cluster points, and the maximum distance is 100 000 cluster points. Figure 8a and Figure 8b show the details of corn leaf cluster and corn stalk cluster. It can be seen that the corn leave points can be extracted correctly from corn stalk points.

The accuracy was assessed quantitatively to validate the DoN algorithm for extracting corn leaf points. The leaves points were classified manually from the stalk points, which were the reference points for accuracy assessment. Overall accuracy, commission error, omission error, were used in accuracy assessment. There were 89 940 points totally returned on two corn plants. And the overall accuracy was 94.10%, commission error was 5.89%, and omission error was 18.65% in this study.



a. Corn leaf cluster b. Corn stalk cluster

Figure 8 Extracted results of corn leaves points and stalk points

5 Discussion

The DoN operator was used to extract the corn leaves points from unorganized corn plants LiDAR points automatically in this study. The extracted results and accuracy assessment indicated that the extraction was effective. In order to mine the distinct geometry of corn leaves and stalk, the difference of surface normal at different scales was used to identify corn leave points. One important issue for this extraction is finding the optimal search radius, i. e. these two scales ("large scale" and "small scale"). Referencing to the conclusion of Ioannou et al.[19], the ratio of large scale to small scale should be 10, thus such 3 groups of search radius as (0.1 m, 1 m), (0.2 m, 2 m), and (0.4 m, 4 m) were chosen for corn leaves points extraction. The computed DoN results (Figure 5) indicated that the (0.1, 1m) was the optimum one for corn leaf points extraction in our analysis. Thus the (0.1 m, 1 m) search radius was used in the study. The accuracy assessment results showed that the extraction was successful, and the overall accuracy was 94.10%. The disadvantage of this method is that the points returned on top erect leaves and lower drooping leaves cannot be extracted successfully (Figure 7). For this reason, the omission error is relatively high, which reached 18.65% in this study.

6 Conclusions

Compared with the extraction of points returned on buildings, man-made models etc., the corn leaf points extraction is difficult because the corn leaves are thin and curled. This study is aiming at extracting corn leaf points from unorganized LiDAR point clouds automatically. The extracted results indicate that the corn leaf points can be extracted effectively using the DoN method. This study on corn leaf points extraction from massive, unorganized data, is meaningful for agriculture application, especially in phenotyping of corn plants and corn canopy. Further research needs to be done through putting field phenotyping of corn canopy in the future, such as estimating leaf area index, leaf distribution function, biomass, the relationship between these phenotypic parameters and yield estimation etc.

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