VISION BASED AUTOMATED POINT-CLOUD PROCESSING PIPELINE FOR HIGH THROUGHPUT PHENOTYPING

Shreeshan S., Subhra S. Bhattacherjee, Priyanka Gattu, P. Rajalakshmi, Jana Kholova†, Sunita Choudhary †

Department of Electrical Engineering, Indian Institute of Technology Hyderabad, India
† International Crops Research Institute for the Semi-arid Tropics (ICRISAT), Hyderabad, India

ABSTRACT

High throughput phenotyping is rapidly gaining widespread popularity due to its non-destructive approach for plant traits extraction. In this study, we focus on developing a vision based automated 3D point cloud processing pipeline for accurate estimation of plant traits, namely - plant height, leaf area index (LAI), and leaf inclination. Furthermore, the obtained estimates are validated by comparing the results with LeasyScan data in terms of coefficient of determination ($R^2$), root mean squared error (RMSE), and correlation coefficient ($\rho$). These metrics are found to be around 0.90, 0.10, and 0.96, respectively, for each of the traits. Regression analysis has also been performed to gain some analytical insights on the data.

Index Terms— 3D point cloud, high throughput phenotyping, agriculture, computer vision

1. INTRODUCTION

The quality, quantity, and security of the food is a global challenge that needs to be addressed in the view of a growing population [1]. The agricultural industry must use the available resources to the maximum extent possible in order to cope with population growth. High throughput plant phenotyping includes measurement of LAI (Leaf Area Index, plant height, leaf inclination, etc.) [2]. It is one of the central areas of interest where both the developed and developing nations are increasingly focusing on developing different breeds of crops that are stress-tolerant, disease-resistant, and also provide high yields with optimized inputs. The traditional techniques used for plant phenotyping are the bottleneck as the methods used are manual, destructive, time-consuming, and hence require more workforce.

Remote sensing combined with imaging using various sensors (like RGB, Multispectral, Hyperspectral, Thermal) [3] can be used to address the challenges of plant phenotyping. These sensors can be mounted on a drone or on a platform to capture the images [4]. The traits like LAI, canopy coverage, flower detection are estimated using spectral indices (NDVI, NDRE, etc.) [5]. Also, Computer vision and Machine learning approaches are being used to estimate the phenotypic traits of plants. 3D imaging has gained popularity in recent times. The use of 3D imaging is that the plant structure, phenotypic traits (height, inclination, etc.) can be estimated in a better way and can further contribute to crop improvement programs. The 3D image known as point cloud can be obtained through LiDAR, stereo vision camera, laser scanners, Structure From Motion (sfm), time of flight (tof) cameras, etc [6]. 3D point clouds give the depth information, which gives the ability to view the plant from all view with more information as compared to 2D imaging [7].

Authors in [8] used a terrestrial laser scanner to obtain 3D point clouds for maize plants. They proposed an accurate skeleton extraction approach to estimate phenotyping traits of the maize plant. Point cloud clustering with color difference denoising is used to reduce the noise of the input point clouds. Laplacian contraction algorithm is applied to shrink the points. Neighbourhood points are combined to form the skeleton of plant, and traits of interest are estimated. A multi-view stereo (MVS) imaging system was developed [9], which captures data from 360 around a target strawberry fruit. The point cloud obtained is used to estimate height, length, width, using custom-developed software. In [10], the authors used a histogram-based classification algorithm to separate the organ leaf and stem from the barley plant. A Velodyne LiDAR is mounted on to a mobile robot in [11]. The robot moves inside and around the field to collect the data in 3D with a 360 view laser scanner. Point cloud merging and Iterative Closest Points algorithm was used to compute the morphological phenotyping parameters (row spacing and plant height) of maize plants using depth-band histograms and horizontal point density.

In this paper, we have proposed a computer vision-based automated point cloud processing pipeline for high throughput plant phenotyping. The point cloud is obtained using Planteye scanner, which moves on the LeasyScan platform at ICRISAT, Telangana, India [12]. We have estimated three basic plant parameters- plant height, leaf area index (LAI), and leaf inclination. The estimated parameters are statistically validated using correlation coefficient, $R^2$, and RMSE metric with ground truth obtained from the same LeasyScan platform at ICRISAT, India. Regression analysis has also been performed to get insights on the estimated data.
The rest of the paper is organized as follows: the proposed pipeline is explained in section 2, inferences on results are provided in section 3, and conclusions are drawn in section 4.

2. PROPOSED PIPELINE

The pipeline relies on four stages: data acquisition, interpretation, outlier removal, and trait estimation. The following subsections explain the four stages sequentially.

2.1. Data Acquisition

The first step is data acquisition. Raw data is generally provided in polygon file format ply or point cloud data format pcd. It may be generated from LiDAR devices or lasers scanning a field. The LiDAR may be mounted on a drone or any vehicle that sweeps the field spatially. The pipeline is invariant to the data source.

2.2. Interpretation

Context-based knowledge is used to semantically interpret the data based on the shape, size, smoothness, and continuity of each component. Sub-plot detection in a given field is the issue to be solved here. Geometrically the sub-plots are well-defined polygonal structures such as rectangles, circles of different sizes. To deal with this issue, we have used a pass-through filter. A pass-through filter is a regular cuboidal filter of dimension \(x \times y \times z\) mm that moves along the point cloud in a fixed direction and returns the number of points inside the filter.

Let the coordinates of the vertices of the cuboid are given by \(p_i(x_i, y_i, z_i) = i = 1, 2 \ldots 8\). The points are represented by the set \(P = \{p_1, p_2 \ldots p_8\}\). The three important directions from \(p_1\) to the three perpendicular edges are,

\[
\begin{align*}
    u &= p_1 - p_2 \\
    v &= p_1 - p_4 \\
    w &= p_1 - p_5
\end{align*}
\]

For a new point \(p_k\), for some \(k\), to lie inside the cuboid it has satisfy three constraints,

\[
\begin{align*}
    u.p_1 &\leq p_k \leq u.p_2 \\
    u.p_1 &\leq p_k \leq u.p_4 \\
    u.p_1 &\leq p_k \leq u.p_5
\end{align*}
\]

The resultant points are stored in a matrix. The maxima and minima of corresponding rows of the matrix are found. The transition between sub-plots is represented by a sparse point cloud, i.e., minima in the matrix. We detect the first minima after each maximum value encountered, thereby detecting the corresponding transitions. As shown in Figure (1), we can segment each sub-plot sequentially.

2.3. Outlier Removal

This step removes any outliers in data such as noise, ground plane, etc. Noise is generated mainly due to device properties and is sparse. Noisy data leads to erroneous estimation. The point cloud can be represented by the set \(P = \{p_1, p_2 \ldots p_n\}\). We can define a distance metric \(d(p, q)\) on the set \(P\) such that it follows these properties \(\forall p, q, r \in P\)

\[
\begin{align*}
    1. & \quad d(p, q) = 0 \iff p = q \\
    2. & \quad d(p, q) = d(q, p) \\
    3. & \quad d(p, q) \leq d(p, r) + d(r, q)
\end{align*}
\]

Thus, the set \(S = (P, d)\) becomes a metric space. In the given metric space \((P, d)\), \(N\) neighborhoods around a random point, \(p\) are selected, and statistical outlier removal is performed in that neighborhood. Given an open ball \(B_r(p)\) of radius \(r\), the set \(N\) is called a neighbourhood around a point \(p\) if,

\[
B_r(p) = \{p \in P \mid d(p, r) < r\}
\]

is contained in \(N\).

Outliers are detected among all the points in this neighbourhood by,

\[
\|x - \mu_N\| \geq \delta_N
\]

where \(\mu_N\) and \(\delta_N\) is the mean and standard deviation of the point cloud in the neighbourhood \(N\) respectively.

After noise removal, the RANSAC model is used to form ground clusters. The RANSAC algorithm is run on \(I\) iterations to form the maximum ground cluster. Let \(u\) be the probability that a randomly selected set does not contain an outlier, \(v\) be the probability that any selected data-point is an outlier, and \(m\) be the minimum number of points. The maximum number of iterations \(I\) is given by [13]

\[
I = \frac{\log(1 - u)}{\log(1 - (1 - v)^m)}
\]

The resultant clustered point cloud is subtracted from the original point cloud to separate the ground.

[Fig. 1: Sample raw data]
2.4. Trait Estimation

The final step is the phenotypic trait estimation. We have estimated the plant height, leaf area index (LAI), and leaf inclination. The methods are explained below.

2.4.1. Plant Height

The ground may be rough or uneven, which is practically the case in a field. So while removing the ground, the average value of the cluster is stored in an array. Averaging of the cluster values in the ground plane accounts for the uneven texture. Let this value be $G$.

$$G = \frac{\sum_{i=1}^{n} (p_i)}{n}$$  (11)

Where $\{p_1, p_2, \ldots p_n\}$ are the ground points in the cluster.

After ground removal, clustering is performed in $z$ direction, and the values are arranged in a set in descending order since we want to obtain the maximum height, which is from the top branch. Let this set be $F$.

$$F = (h_i, \geq) \forall i = \{1, 2 \ldots n\}$$  (12)

Here $i$ is the number of points. Interestingly this set $F$ is a partially ordered set as it exhibits the reflexivity, anti-symmetry and transitivity property. The top 10% values of the set are taken and averaged out. Let this be $H$.

Thus, the plant height is given by,

$$\text{Plant height} = |H_i - G_i|, \forall i = \{1, 2 \ldots n\}$$  (13)

Here $n$ is the number of plots with single plant.

2.4.2. Leaf Area Index

Leaf Area Index (LAI) is a characterization of the plant canopy. It is a dimensionless quantity defined as a one-sided leaf area per unit ground area [14]. In our pipeline, we have used voxelization on the point cloud. A voxel represents a value on a regular grid in three-dimensional space. Voxel grid of size $x \times y \times z$ is taken over the given point cloud.

The voxel grid filter downsamples the data by taking a spatial average of the points in the cloud confined by each voxel. It approximates the points by their centroid. The voxel can be represented as a three-valued real function $f(x, y, z)$ with binary output as,

$$f(x, y, z) = \begin{cases} 
0, & \text{point is not present in voxel} \\
1, & \text{point is present in voxel}
\end{cases}$$  (14)

After voxelization we get a one-sided surface area for both plant and ground segment. Total leaf area is calculated as,

$$\text{Total leaf area} = \text{Total number of voxels} \times x \times y \ mm^2$$  (15)

We calculate LAI as,

$$\text{LAI} = \frac{\text{Total leaf area}}{\text{Sector size}}$$  (16)

2.4.3. Leaf Inclination

Leaf inclination measures the average erectness of leaves in the plant. The primary step for the estimation of leaf inclination is the calculation of the projected leaf area. Again here voxelization has been used. The $z$ coordinate values are set to 0, and the whole point cloud is projected onto $xy$ plane. The projected area is calculated as,

$$\text{Projected leaf area} = \text{Total number of voxels} \times x \times y \ mm^2$$  (17)

Thus, from equation (5) and (7), we get,

$$\text{Leaf Inclination} = \frac{\text{Total leaf area}}{\text{Projected leaf area}}$$  (18)

As it is seen, leaf inclination is directly proportional to total leaf area. This means that, the more curved a leaf is the more its leaf inclination value will be.

3. RESULTS AND DISCUSSIONS

To test the robustness of our pipeline, we have taken real-world data from a 3D scanning platform called LeasyScan.
As stated in the original paper [12], LeasyScan is a novel 3D scanning technique to capture leaf area development and estimate various phenotypic traits. Parameters computed with plant eye are plant growth, digital biomass, plant height, 3D leaf area, projected leaf area, leaf inclination, leaf area index, leaf angle, light penetration depth.

<table>
<thead>
<tr>
<th>Trait, Parameters</th>
<th>RMSE</th>
<th>$R^2$</th>
<th>$\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plant height</td>
<td>1.26</td>
<td>0.84</td>
<td>0.92</td>
</tr>
<tr>
<td>Leaf area index</td>
<td>0.05</td>
<td>0.90</td>
<td>0.95</td>
</tr>
<tr>
<td>Leaf inclination</td>
<td>0.2</td>
<td>0.81</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Table 1: Statistical measures

We have estimated three phenotypic traits- plant height, leaf inclination, and leaf area index (LAI) for six days of data.

Point cloud data is collected in the form of .ply format, as shown in Figure 1. The .ply format used by PlantEye is different from standard .ply format. The obtained data has fields namely- $x$, $y$, $z$, intensity, $x_{pos}$ and profile. The data is converted into standard .pcd format by using ROS PCL library in Python 3.6. Further implementation of the pipeline is carried out in C++ with open-source PCL Library. The raw data is fed to the pipeline. The sub-plots containing the plants are detected accurately, as shown in Figure 2. From the resultant point cloud, the noise and ground points are removed, preserving the plant information. The extracted plant is shown in Figure 3. The accuracy of the plant extraction is justified by the high value of the considered statistical metrics.

We have done statistical analysis of the obtained data by plotting the regression lines between the observed and ground truth value as shown in Figure 4, 5 and 6 for each trait. As shown in Table 1 we have calculated the root mean square error (RMSE), coefficient of determination ($R^2$) and correlation coefficient ($\rho$) for all the parameters. The number of points was around 500, which is sufficient to prove the accuracy of our pipeline.

It can be inferred from the metrics that the estimation is comparable to the ground truth values. Thus, this proves that our pipeline is generic and robust.

4. CONCLUSION

In this paper, we have proposed a generic automated point cloud processing pipeline for high throughput phenotyping. We have estimated three crucial plant traits, namely, plant height, leaf area index (LAI) and leaf inclination. The estimates are compared with ground truth values in terms of correlation coefficient ($\rho$), $R^2$, and RMSE score. The metrics indicate that the proposed pipeline is robust and can estimate parameters precisely. Regression analysis has also been performed for all three traits.

5. REFERENCES

[1] W. Admin, “Cema - european agricultural machinery - agri-food chain coalition voices its priorities to the eu institutions,”.

[2] Pinaki Mondal and Manisha Basu, “Adoption of precision agriculture technologies in india and in some developing countries: Scope, present status and strategies,”


