# Dynamic phenotype acquisition of maize organ-scale growth based on time series point cloud

Anonymous ICCV submission

Paper ID 8

Traditional phenotypic measurements: time-consuming, labor-intensive, prone to errors, and can harm plants. Convergence of electronic engineering, computer image processing, agronomy led to high-throughput crop phenotyping tech. Drones, sensors, robots, remote control, image analysis used for crop monitoring [3]. However, complete, accurate non-destructive phenotypic data acquisition remains challenge.The primary task of phenotypic research based on point cloud data is to obtain organ-scale point cloud data from unordered point cloud data. Point cloud skeleton-based instance segmentation more accurately extracts structure, topology, object shape , which makes it have better performance and application potential in the instance segmentation task of processing point cloud data[1].

Experiment in 2022 at Songjiang Experimental Station (30°94'N, 121°13'E). Data collected after first maize planting week. Data gathered daily at 9:00 am, multi-view images, phenotypic data of 13 time points (July 19 - July 31) from V2 to V6. Collected time series data from 7 maize plants at 13 consecutive time points.

Used Laplacian contraction algorithm [2] for maize plant skeleton extraction. Results shown in Figure 1(b) for maize point cloud skeleton, node classification in Figure 1(c), segmentation in Figure 1(d). Avg. distance of adjacent nodes used as threshold, points within threshold grouped as same organ around skeleton node. Organ segmentation shown in Figure 1(e), remaining points after segmentation in Figure 1(g). Euclidean distance used to merge remaining points with closest skeleton point, final organ segmentation in Figure 1(h).

Phenotypic parameters are extracted based on segmented organ point clouds, as shown in Figure 2. Plant height (cm) is the difference between max and min Z coordinates of plant point cloud, as shown in Figure 2(d). Leaf length is obtained by projecting the leaf along x, y, and z axes to get max and min points in y-axis, x-axis, and z-axis. Euclidean distance of shortest path between extreme points of three projections is computed within undirected graph $G$. The longest path is leaf length, as shown in Figure 2(a). For leaf width, we find skeleton point at 1/2 leaf position,

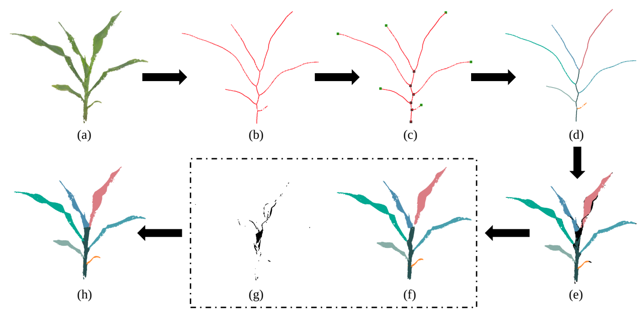


Figure 1. Point cloud instance segmentation diagram. (a) Maize plant point cloud (b) Maize plant skeleton (c) Maize plant skeleton node recognition result (stem node – brown point, leaf tip node – green point, connecting node – red point ) (d) Skeleton segmentation result (e) According to the skeleton coarse segmentation result (f) Rough segmentation of stem and leaves point cloud (g) Rough segmentation undivided points (h) Maize plant instance segmentation result

$Point[i]$. From $Point[i]$, we construct vectors $\vec{v_1}$ and $\vec{v_2}$ towards $Point[i-1]$ and $Point[i+1]$. Using vectors $\vec{v_1}$ and $\vec{v_2}$ as normal vectors and $Point[i]$ as a point on the cutting plane, we derive the equations $S_1$ and $S_2$ of the cutting planes. Point between $S_1$ and $S_2$ is leaf width position, longest path's Euclidean distance is leaf width. Due to sparse point cloud, move cutting planes upward along normal vectors by 0.5 cm to ensure intersection. Leaf width shown in Figure 2(b). Angle between z-axis and point at 1/4 leaf length is leaf inclination angle, shown in Figure 2(c). $Point\ O$ is intersection of leaf and stem skeleton, $Point\ M$ is z-axis point, $Point\ N$ is skeleton point on leaf skeleton at 1/4 length from $Point\ O$ intersection.

Linear regression analysis was used to evaluate the relationship between the artificial measured values of phenotypic parameters and the extracted values of this research method. The coefficient of determination ($R^2$) and root mean square error ($RMSE$) were used for quantitative evaluation. The calculation is shown in Equation 1 and

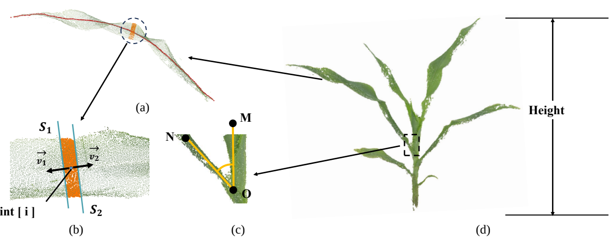


Figure 2. Point cloud instance segmentation diagram. (a) Maize plant point cloud (b) Maize plant skeleton (c) Maize plant skeleton node recognition result (stem node – brown point, leaf tip node – green point, connecting node – red point ) (d) Skeleton segmentation result (e) According to the skeleton coarse segmentation result (f) Rough segmentation of stem and leaves point cloud (g) Rough segmentation undivided points (h) Maize plant instance segmentation result

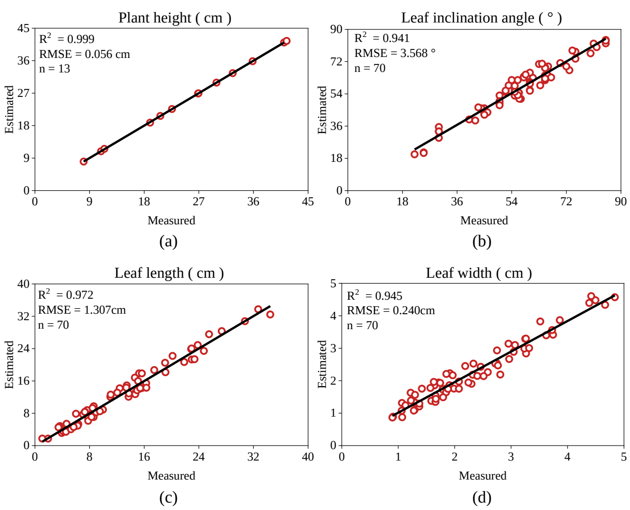


Figure 3. Fitting results of phenotypic prediction values and measured values of maize phenotypic parameters. (a) plant height (b) leaf inclination angle (c) leaf length (d) leaf width

Equation 2.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (2)$$

$y_i$ represents the $i$ sample value, $\hat{y}_i$ represents the model prediction value of the $i$ sample, $\bar{y}$ represents the sample average value, $n$ represents the total number of samples.

The phenotypic parameter extraction values of the same plant at 13 time nodes were compared with the manual measured values, and the fitting results are shown in Figure 3. The comparison results showed that there was a high degree of consistency between the plant height extraction value and the measured value.

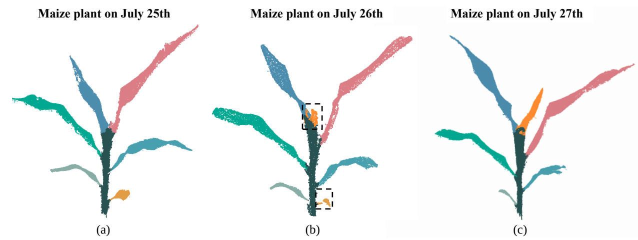


Figure 4. Time series point cloud blade matching results. (a) maize plant on July 25th (b) maize plant on July 26th ( The black box above is the newly sprouted leaves, and the black box below is the leaves that will fall off ) (c) maize plant on July 27th

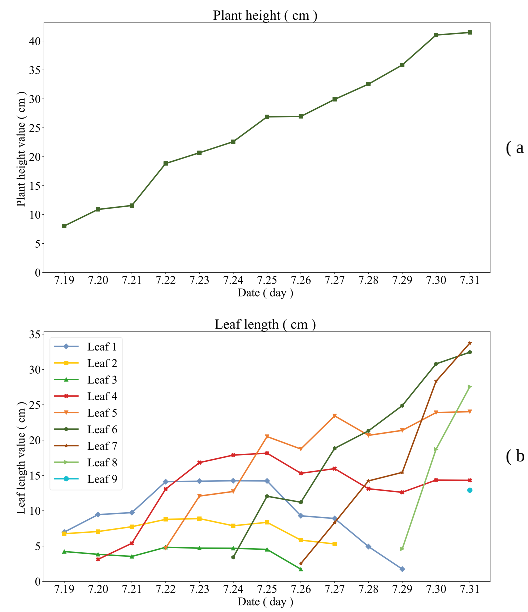


Figure 5. Dynamic phenotypic parameters of maize plants. (a) plant height (b) leaf length

By matching the skeleton nodes of adjacent time points, organ matching of point clouds at different time points can be achieved.To visualize temporal maize point cloud matching results, we selected point clouds of same maize plant over three days (July 25th-27th) for demo. Results shown in Figure 4, same color = same leaf. July 25th: 6 leaves, July 26th: 7 leaves, July 27th: 6 leaves. Figure 5 displays the dynamic changes of plant height and leaf number from July 19th to July 31st, consisting of 13 time points, leaves numbered by growth order.

In Figure 4, new leaf on July 26th, one shed. In Figure 5(b), leaf 3's data ends July 26th, leaf 7's starts July 26th, showing match with growth. Overall plant height rises, aligning with maize morphology. Observing leaf 1 in Figure 5(b), initial length increase stabilizes, then gradually decreases, matching maize leaf growth.

## References

[1] Nicu D Cornea, Deborah Silver, and Patrick Min. Curve-skeleton properties, applications, and algorithms. *IEEE Transactions on visualization and computer graphics*, 13(3):530, 2007. 1

[2] Lukas Meyer, Andreas Gilson, Oliver Scholz, and Marc Stamminger. Cherrypicker: Semantic skeletonization and topological reconstruction of cherry trees. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6243–6252, 2023. 1

[3] Manuel Vázquez-Arellano, Hans W Griepentrog, David Reiser, and Dimitris S Paraforos. 3-d imaging systems for agricultural applications—a review. *Sensors*, 16(5):618, 2016. 1