A Hybrid Cable-Driven Robot for Non-Destructive Leafy Plant Monitoring and Mass Estimation using Structure from Motion

Gerry Chen[1], Harsh Muriki[1], Andrew Sharkey[2], Cédric Pradalier[3], Yongsheng Chen[2], Frank Dellaert[1]

[1]Institute for Robotics and Intelligent Machines, College of Computing, Georgia Institute of Technology
[2]N.E.W. Center for Agricultural Technology, Civil and Environmental Engineering, Georgia Institute of Technology
[3]School of Interactive Computing, CNRS IRL 2958, Georgia Tech Lorraine

ICRA London 2023

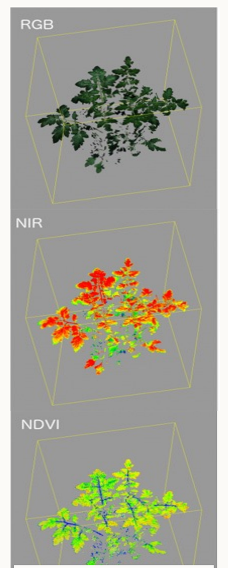
Georgia Tech Institute for Robotics and Intelligent Machines

Georgia Tech Nutrients, Energy, and Water Center for Agriculture Technology

Background

Motivation	Farmers want **feedback** to understand how their plants are growing Researchers want **data** to develop plant growth models
Existing Methods	Cut down plant and send to lab for analysis Measuring biomass and nutrient content are **destructive** and **expensive**
Current Limitations	Researchers need *very* large sample sizes to compensate for **destructive loss** and **statistical variation** Cannot track a single plant over time since the first measurement is destructive
Proposed Solution	**Non-destructively** estimate **useful metrics** using robotics and computer vision

Prior Works: Non-Destructive Phenotyping



PlantEye F500

Imaging Sensors

RGB Camera(s)
- Single Camera
- Stereo Camera
- Multi-camera rig

Depth Camera(s)
- IR-based depth (e.g. Kinect)
- Structured Light (non-IR)
- Time-of-flight (ToF)
- Light field (Plenoptic)

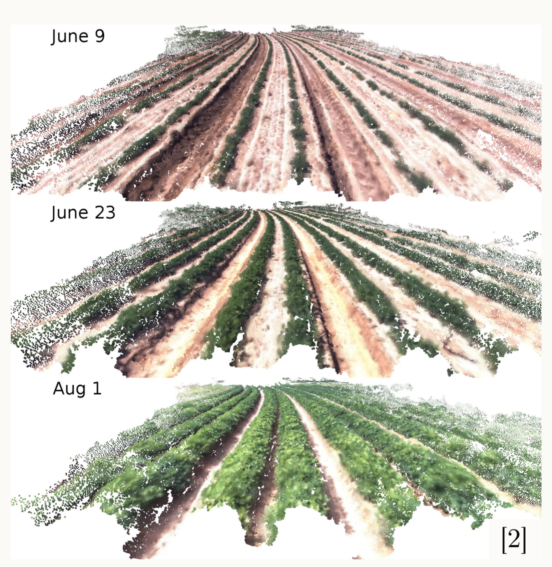
Multi-spectral Imaging
- IR (Thermal, NIR, VNIR)
  - ➢ Water, N, P, etc.
- UV
  - ➢ Disease, salt-stress
- Chlorophyll-Fluorescence
- Tomographic (MRI, CT)
  - ➢ Hidden morphology

Limitations

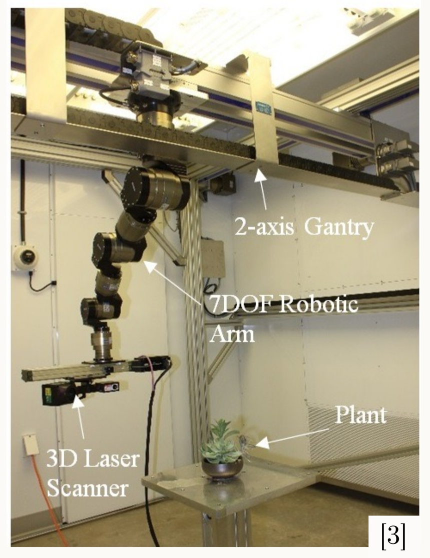
Current approaches exhibit a **<u>tradeoff between high-throughput phenotyping vs. high quality/resolution data</u>**. For example, [1] uses a push cart to achieve high-throughput, but doesn't image entire plants. Similarly, [2] uses a tractor for high-throughput, but produces coarse 3D reconstructions of entire plants insufficient to analyze plant morphology. Conversely, full-plant dense reconstruction approaches have not been shown in scalable, high-throughput settings (e.g. [3]).

Current approaches also struggle with leafy plants (e.g. lettuce)


[1]



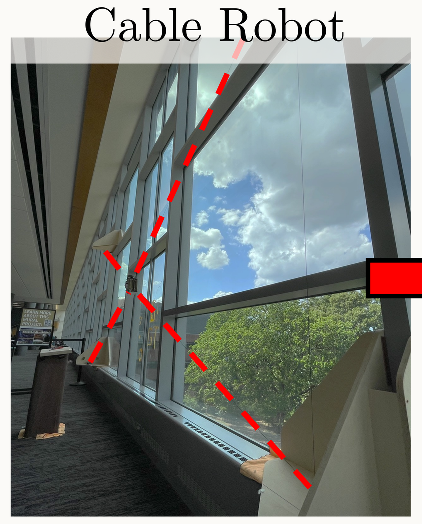
[2]



[3]

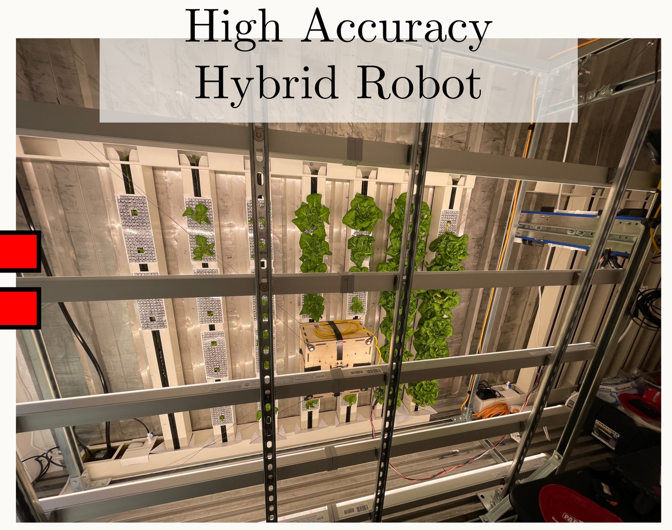
System Overview

Large Workspace Cable Robot



Dextrous Robot Arm

Medium Throughput, High Accuracy Hybrid Robot



64 Raw Images

⇨ 3D Reconstruction

⇨ Estimate Plant State
- Wet Mass
- Dry Mass
- % Nitrogen
- % Phosphorous
- …

Data Collection
- 71 plants, 64 photos per plant, every day for 6 weeks
- Harvest 6 plants, 2 times per week
  - Measure Wet Mass, Dry Mass, and USDA Nutrition Assay

Throughput
Ours: 2500 photos/hour, 64 photos/plant, 100% autonomous 24/7
56 plants @ 350 cm^2/plant (infinitely scalable in theory)
Baseline 3: 300 photos/hour with 2 skilled human operators

Future Work

Temporal Association: track plant growth over time by aligning 3D models across growth cycle
Plant Organ Segmentation: identify instances of each plant organ (e.g. leaves)
Plant Modelling: create a predictive model of plant growth dynamics
Model Predictive Control: Compute optimal fertilizer and env. inputs to maximize crop yield
Multi-spectral Imaging: for improved nutrient content estimation

Selected References

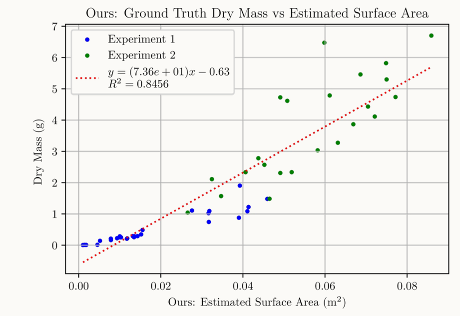
[1] Y. Song, C. A. Glasbey, G. Polder, and G. W. A. M. van der Heijden, "Non-destructive automatic leaf area measurements by combining stereo and time-of-flight images," *IET Computer Vision*, vol. 8, no. 5, pp. 391– 403, 2014.
[2] J. Dong, J. G. Burnham, B. Boots, G. Rains and F. Dellaert, "4D crop monitoring: Spatio-temporal reconstruction for agriculture," *2017 IEEE International Conference on Robotics and Automation (ICRA)*, 2017, pp. 3878-3885, doi: 10.1109/ICRA.2017.7989447.
[3] A. Chaudhury et al., "Computer Vision Based Autonomous Robotic System for 3D Plant Growth Measurement," 2015 12th Conference on Computer and Robot Vision, 2015, pp. 290-296, doi: 10.1109/CRV.2015.45.

Results

Methods
- Ours – Mesh to **Volume** to Mass
- Ours – Mesh to **Surface Area** to Mass
- Baseline 1: Top-down photo only, **Projected Area** to Mass
- Baseline 2: Simulated UAV Imagery, Mesh to **Vol/S.A.** to Mass
- Baseline 3: Arm-only, no cable robot, qualitative comparison

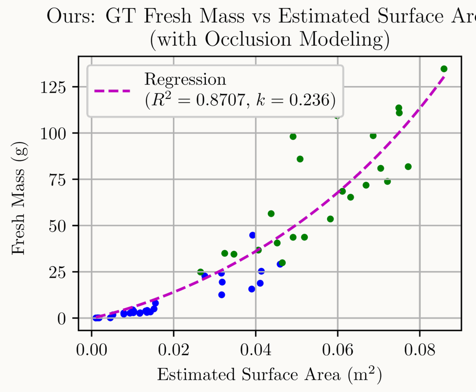
Linear Regression

Estimation Metric	GT: Fresh Mass $R^2\uparrow$	GT: Fresh Mass MAE (g) $\downarrow$	GT: Dry Mass $R^2\uparrow$	GT: Dry Mass MAE (g) $\downarrow$
Surface Area (ours)	**0.845**	**11.216**	**0.846**	**0.586**
Volume (ours)	0.833	11.671	0.832	0.617
Baseline 1: Projected Area	0.537	19.976	0.505	1.084
Baseline 2: Surface Area	0.292	26.049	0.285	1.401
Baseline 2: Volume	0.277	26.439	0.269	1.422



Point Cloud Occlusion

Estimation Method	Occlusion coefficient, k (g^{-1}) $\downarrow$ GT: Fresh Mass	GT: Dry Mass
Surface Area	**0.236**	**0.593**
Volume	0.261	0.659
Baseline 1: Projected Area	0.519	0.883
Baseline 2: Surface Area	0.333	0.680
Baseline 2: Volume	0.350	0.743



Statistical Significance

Metric	p-value ($\downarrow$) for Age Discrimination Exp. 1	Exp. 2	p-value ($\downarrow$) for Nutrient Schedule Discrimination
Fresh Mass (GT)	0.00156	0.00037	0.00284
Dry Mass (GT)	0.00137	0.00263	0.00288
Surface Area (ours)	0.00219	0.00352	**0.03134**
Volume (ours)	0.00204	**0.00338**	0.03766
Baseline 1: Projected Area	**0.00086**	0.02661	0.32745
Baseline 2: Surface Area	0.00287	0.31166	0.32066
Baseline 2: Volume	0.00265	0.26535	0.28106

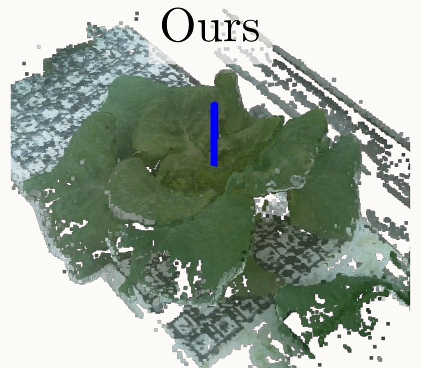
Is our data good enough for scientists to use in developing plant growth models?

Metric: For a given hypothesis, evaluate the statistical significance using GT value vs our estimate

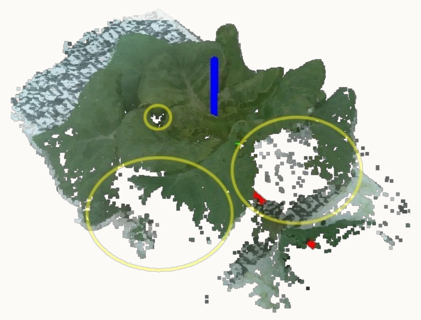
Qualitative Comparison

Occlusions

Ours



Baseline 2



Imaging Pose Consistency

Ours

Baseline 3

Example Point Clouds

Ours