Hyperspectral 3D Reconstruction: towards Non-destructive Plant Nutrient Estimation

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Background

Motivation	Farmers want **feedback** to track crop health Researchers want **data** to develop plant growth models
Existing Methods	Cut down plant and send to lab for analysis Measuring nutrient content is **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 **nutrient content** using hyperspectral imaging

Prior Works

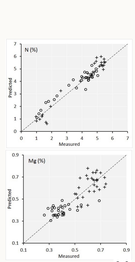
Hyperspectral (HS) Imaging

HS for plant nutrient estimation

- Remote Sensing (e.g. satellite):
  - Nutrients at the field-level
- High-throughput Phenotyping:
  - Nutrients at the single-plant level
- IR/thermal imaging:
  - Stress & Growth at sub-plant level

Limitations

- Nutrient tracking at the sub-plant level
- Sensitivity to calibration & SNR



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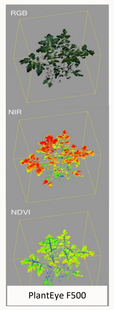


PlantEye F500

HS Camera Limitations

(long exposure time)
(aka low-throughput)
Temporal Resolution

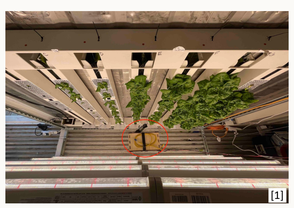
Spatial Resolution — Spectral Resolution

HS Super-Resolution

- Low-res HS -> high-res HS
- High-res MS -> high-res HS

3D Reconstruction

Robotic systems for Plant Phenotyping


[1]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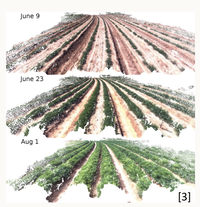

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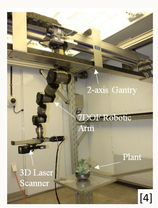

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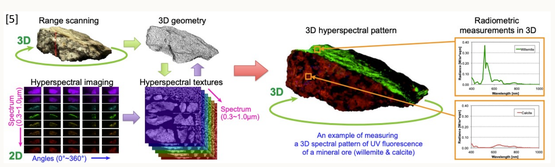
Hyperspectral 3D Reconstruction

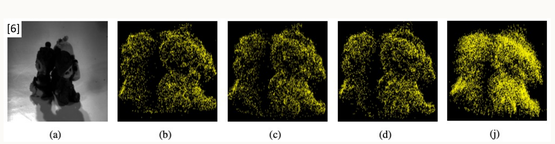
Baseline 1

Project HS images onto 3D pointcloud



Baseline 2

Create 3D pointcloud for each wavelength
Merge using ICP



Objectives

1. Identify important considerations for hyperspectral camera
2. Collect a small hyperspectral image dataset
3. Validate Hyperspectral 3D reconstruction approaches
4. Qualitatively assess potential for nutrient estimation

Methodology

1. Collect a Dataset

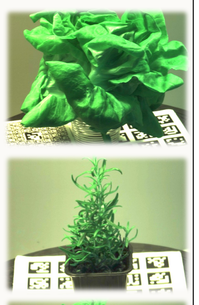
- Dataset:
  - 4-6 distinct plants
  - ~50 images / plant (2 elevations, 24 images/elevation)
  - Measure volume (using water displacement)
- Camera:
  - SOC710-VP Hyperspectral Camera
  - 128 spectral bands (371-1044nm)
  - 696x520 resolution
  - 12bit depth

2. Create Hyperspectral (HS) 3D Reconstructions

- Pseudo-RGB SfM to validate image/feature quality
- Implement 2 baselines
  - Project HS images onto 3D point clouds
  - Merge single-wavelength SfM results using ICP
- Implement Proposed HS-NeRF approach

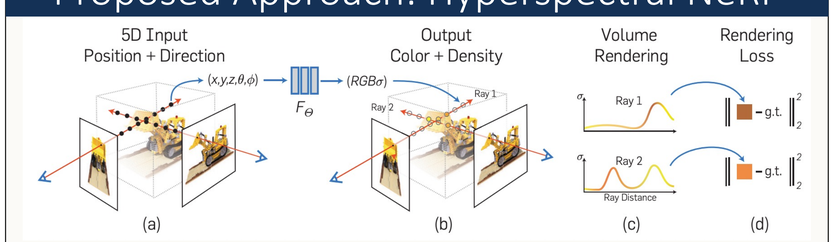
3. Evaluate

- Qualitative: spectral reflectance vs plant, organ, tissue
- Quantitative: compare reconstructed volume to GT
- Quantitative: compare spectral reflectances to literature



Pseudo-RGB Images from dataset

Proposed Approach: Hyperspectral NeRF



Original NeRF estimates:

$$MLP(x, y, z, \theta, \phi) = (R, G, B, \sigma)$$

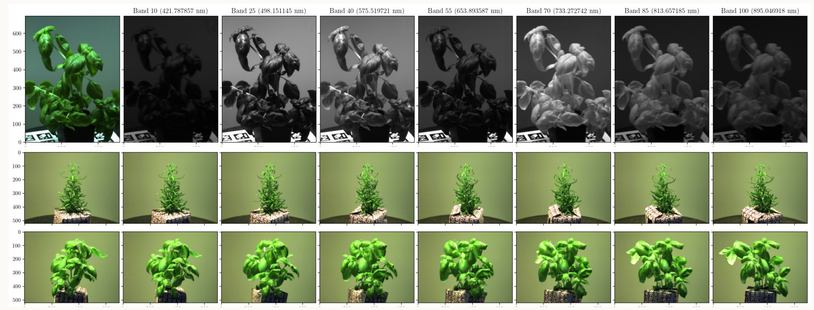
We propose estimating:

$$MLP(x, y, z, \theta, \phi) = (\lambda_1, \lambda_2, \ldots, \lambda_{128}, \sigma)$$

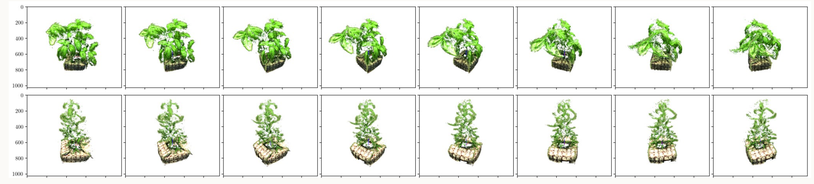
where λ_i is the i^{th} wavelength band at the image pixel

Preliminary Results

Dataset Collection: Collected 2 datasets of hyperspectral images:



RGB 3D Reconstruction: Perform SfM on pseudo-RGB images



Expected Results

Implementing Baselines

- Baseline 1 (projection) will be more difficult than Baseline 2 (ICP)
- Baseline 1 (projection) will be more accurate than Baseline 2 (ICP)
- Hyperspectral NeRF will be most accurate, but have more noise

Evaluation

- Spectral reflectance will differ by plant, but spatial resolution may be insufficient to detect per-organ or per-tissue differences.
- Volume estimation will be within 25% of ground-truth volume.

Future Work

Robotics: Mount a hyperspectral (HS) camera to a robotic imaging system.
Dataset: Collect a larger dataset with ground-truth nutrient measurements.
Phenotyping: Nondestructively estimate nutrient content using HS imaging

Selected References

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