Automated Phenotyping System for Energy Crops

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Structured Abstract

Background. Biofuels and biopower are a significant source of renewable energy. Our team has built a high-throughput (HTP) robotic phenotyping system in field environments which takes pictures of plants everyday and a software will take these pictures and output 3D point clouds of plants. We would like to use these 3D point clouds from the field to estimate the phenotypes.

Aim. Building an automated system that takes a noisy 3D point cloud of a plant as input and output its phenotypes which include leaf area, leaf length, leaf width, angle between leaf stem, etc.

Data. The data we will use has a small amount (~ 50) 3D point clouds of plants with measured phenotypes and a large amount of simulated plants ($\sim 10,000$) to help us train the prediction model.

Methods. We use geometric and learning based methods to simulate plants and use 3D Deep Convolutional Neural Network for phenotype estimation.

Results. The generated plants are similar to the real plants. The estimation algorithm achieves significant better result than the naive method ($\sim 25\%$ relative root mean squared error).

Conclusions. We validate the effectiveness of 3D convolutional neural network that only trained on simulated data for plant phenotyping.

Intellectual merit. Our proposed methods combined geometric knowledge of the target objects and modern day deep statistical models. This idea may be applied to other vision problems.

Broader impacts. This automated phenotyping system can be directly used by biologists to extract useful phenotypes from photos of plants. It will also draw computer scientists' attention to the problem of extracting useful information from noisy field data.

Keywords: Phenotyping, Deep Learning, Simulation

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1 Introduction and Background

Biofuels and biopower are a significant source of renewable energy. However, only limited amounts of biofuels are produced from non-grain feedstocks because production costs are not competitive. Increased yield of bioenergy crops would mitigate this barrier to utilization. While crop breeding and improved management practices have increased productivity, the rate of yield gain in most crops is 1-2% per year with very significant investment. The ability to correlate phenotypic traits with their genotypes plays a crucial role in improving plant breeding techniques. Phenotyping is the bottleneck in the plant breeding pipeline and high throughput automated methods are crucial to improved production (Araus and Cairns, 2014; Fahlgren et al., 2015).

Plant phenotyping is the quantitative assessment of plant traits like physiology, yield, etc. The traditional plant phenotyping procedure is a manually intensive and slow process which involves humans making measurements in the field or greenhouse. In most cases, the phenotyped data is analyzed post-season. Recently, our team has built a highthroughput system to collect the data much faster (c.f. Section A and Vijayarangan et al. (2017)). Unlike some manual methods, our system is non-instrusive, i.e., we can scan the plant multiple times during its life cycle and not affect its development. In this project, we use energy sorghum because it is a highly productive, annual, drought tolerant C4 grass with an excellent genetic (diploid, inbreeding) and genomics platform (Mullet, 2014; Vermerris, 2011).

Although this system is able to take pictures of sorghums in a non-instrutive way, the pictures of plants are highly noisy due the whether, occlusion and other reasons. See Figure 1 for some examples. These noise make phenotyping a challenging task because a typical phenotyping method requires (1) recognizing the target plant from the picture, (2) segmenting the target plant out from the background and other plants, and (3) measuring the phenotypes. The first two steps are more or less easy for human but are difficult even for the state-of-the-art computer vision algorithms. Further, the third step has inherit bias because the plant is three dimensional object but we can only measure them from two dimensional images.

To resolve these issues, instead of directly using these two dimensional images, our team use Structure from Motion (Wu, 2013; Fuhrmann et al., 2014) and Stereo (Besl et al., 1992) to build three dimensional point clouds. Structure from Motion algorithm often produces more detailed 3D point clouds but its computational complexity is large. On the other hand, Stereo is usually produces less accurate 3D point clouds but it has much shorter computational time. Figure 2 shows the exemplar 3D point clouds generated by Structure from Motion and Stereo. Note these 3D point clouds removes not only the inherit bias for phenotyping but also the majority of noise. Due to the computation constraints, we mainly use the 3D point clouds generated by the Stereo algorithm.

Another problem is most learning-based algorithms require a large amount of *labeled* data. As we mentioned in the first paragraph, collecting labels is labor-intensive and destructive and so we can obtain a small amount of labeled data (around 50). Therefore, these data are only used for testing

Figure 1: Sample images taken from our system. They are highly noisy due to occlusion and weather condition.

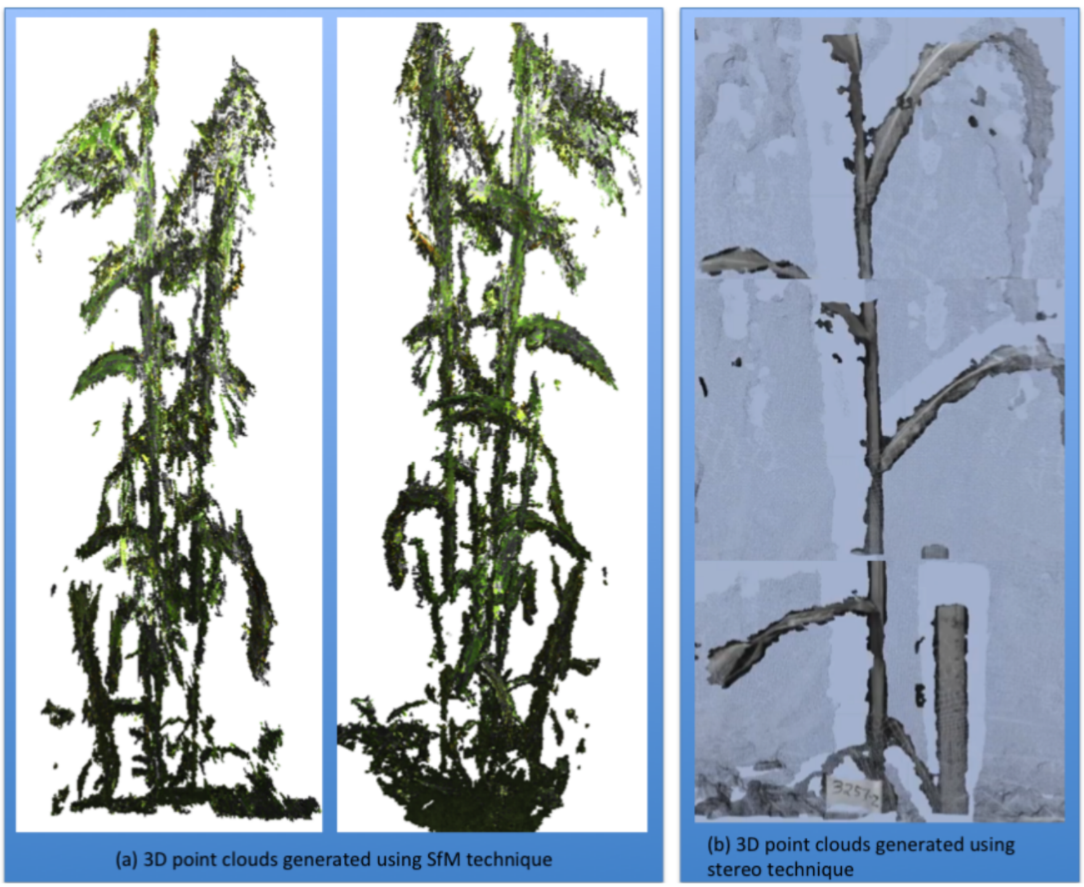

Figure 2: Some well generated 3D point clouds. (a): generated by Structure of Motion algorithm, (b): generated by Stereo algorithm.

instead of training and we need to find a way to provide training data for learning based algorithms.

The main purpose of this project is to explore the learning-based algorithms for automated phenotyping. Our contributions are summarized below:

- We use geometric and probabilistic methods to simulate plants to facilitate the learning-based algorithms for phenotyping. The simulation serves as two roles.
  - First, since we can control the generation process (especially for geometric methods), we know the labels of each plant. Therefore, we can use these generated data as training samples of users' favorite machine learning algorithms.
  - Second, because gathering real data with labels is costly and different machine learning algorithms often have require different kinds of data, we can use the simulated data as a testbed for comparing algorithms before collecting real data.
- We try 3D convolutional neural network for phenotyping and have achieved promising results.

1.1 Related Works

Field phenotyping platforms include ground-based and aerial-based methods (Li et al., 2014). Aerial-based platforms enable greater coverage and rapid characterization of field plots, but are limited in spatial resolution and payload capacity. They are more suitable for estimating macro-phenotypic traits like plant location and densities. Ground-based platforms can yield more detailed phenotypic information at the cost of relatively lower coverage rates. Lemnatec is one of the leaders in automated phenotyping with in-field platforms like Bonirob (Bangert et al., 2013) and Scanalyzer (Virlet et al., 2017). In contrast to previous systems, we used mobile tractor-based phenotyping platform capable of collecting plant images at multiple vertical and horizontal viewpoints inside the closed plant canopy.

High-throughput phenotyping platforms deploy a variety of imaging modalities like 2D visible imaging, 3D imaging, multispectral imaging, thermal infrared imaging and fluorescence imaging (Li et al., 2014). Given its low cost and ease of operation, 2D/3D visible imaging has been commonly used for applications like plant mapping and detection (Weiss and Biber, 2011), weed control (Slaughter et al., 2008), fruit counting and yield estimation (Dey et al., 2012). For the purpose of phenotyping, the use of 3D visible imaging is important in order to be able to make ground truth metric measurements purely from imaging. However, most of the current state-of-the-art in 3D plant reconstruction, segmentation and phenotyping is in controlled greenhouse environments (Mccormick et al., 2016; Lehnert et al., 2017; Chaivivatrakul et al., 2014). Our project uses Structure from Motion (SfM) and Stereo methods for in-field 3D reconstruction from imaging data collected by the phenotyping platform. The details are provided in our published paper (Vijayarangan et al., 2017).

Recently, there is an increasing interest in developing systems for automated phenotyping. A majority of works have focused on using sensored to obtain spectral information from the plants (Aparicio et al., 2000; Omasa et al., 2007). However these methods cannot estimate the geometric properties of crops like stem length and leaf area. Another line of works use computer vision techniques to estimate these phenotypes based on images. For example, Alenyà et al. (2011) proposed to use color and ToF data to reconstruct 3D leaves. Moore et al. (2013) used geometric methods to estimate length of the root of crops. However, all these works used images from highly controlled environment, i.e., there is no noise or occlusion. In this setting, simple geometric methods often works well. However, in our setting, the images are taken from the field which makes these geometric methods unreliable.

For phenotyping, unlike corn, wheat or grapes, sorghum is a fairly new crop of interest for developing automated segmentation and phenotyping methods. To the best of our knowledge, literature on sorghum phenotyping is sparse and fairly recent (Mccormick et al., 2016). Mccormick et al. (2016) generate 3D reconstructions of greenhouse grown sorghum and correlate phenotypes like leaf angle to underlying plant genetics. As detailed later, greenhouse data collected by Mccormick et al. (2016) has been used for analysis and comparison to field data in this paper. The focus of their work, however, is correlation of phenotypes to their underlying genotypes, rather than developing automated methods of phenotyping.

2 Data

In this section I describe in detail about the data. Our data come from three sources, namely, from the field, from the green house and by simulation.

2.1 Data from the Field

The raw 2D image data are photos of plants taken from farms located in Texas and Puerto Rico collected by the hardware built by Robotic Institute. Figure 1 shows some sample images from the field. Based on these 2D image data, our team member use SfM and Stereo methods to reconstruct the 3D point clouds (Vijayarangan et al., 2017; Sodhi et al., 2017). See Figure 2 for the good reconstruction samples and Figure 3 shows some low quality reconstruction. Our primary goal is to do phenotyping on these data.

Since supervised learning algorithms require labeled data, we have another team who cut off some plants and measure the phenotypes. However, as we mentioned at the beginning, human-labor measurement is costly and therefore we only have a small amount of labeled data. All data is currently stored in a server and we will make it public soon.

2.2 Data from Green House

The greenhouse 3D data used in the paper is the one collected by (Mccormick et al., 2016). Ideally, to obtain a geometrically consistent representation of a plant we would like to leverage 360 degree views of the plant. This is possible to setup for a controlled greenhouse environment. Mccormick et al. (2016) place sorghum plants on a turntable and capture 360 degree view depth images at

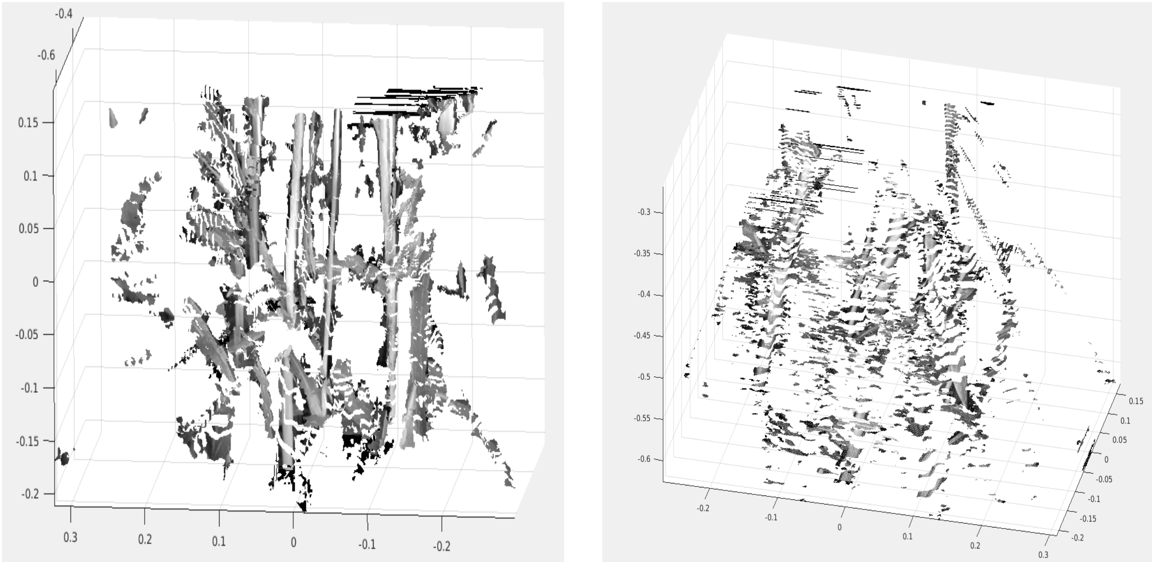

Figure 3: Low quality generated 3D point clouds.

30 degree increments using a Kinect camera. The multiple depth images obtained are then fused together into a single 3D point cloud using the iterative closest point (ICP) algorithm. See Figure 4 for some examples. Compared with field data, the green house data is much cleaner.

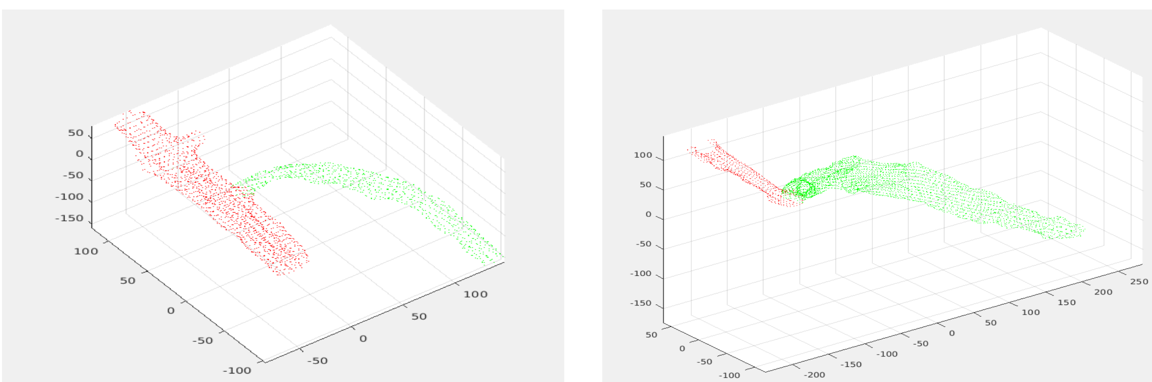

Figure 4: 3D point clouds from green house.

2.3 Data by Simulation

To facilitate the training of machine learning algorithms, we also generate data on our own. Some sample 3D point clouds and 2D images are shown in Figure 5 and 6, respectively. The detailed simulation process is in Section 3.1 and analysis is in Section 4.1.

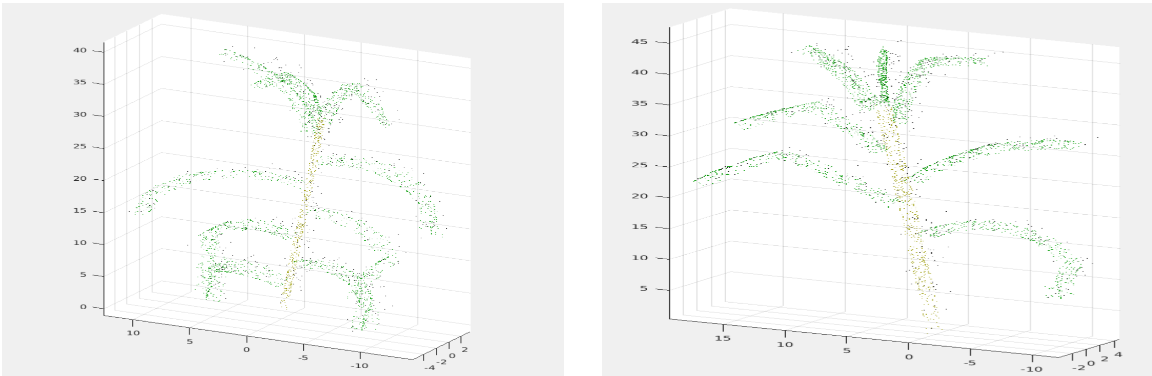

Figure 5: Simulated 3D point clouds using prior geometric knowledge of plants.

3 Methods

In this section I demonstrate the methods we used in this project. I will first provide the details of our simulation technique then I will illustrate the estimation algorithms for phenotyping.

3.1 Simulation Method

We used two approaches for data simulation, a pure geometric method and a learning method based on Generative Adversarial Networks.

Geometric Based Method The most straight forward way to simulate plant data is to compose a plant by simple geometric objects. Here, we model the stem as a cylinder with certain radius and height, which we can control. To generate a leaf, we first randomly choose position from the stem. Second, we either randomly generate or fix the angle between the stem and the leaf. Lastly, we use a polynomial surface to model the leaf. This idea has been adopted and further improved in our published paper (Vijayarangan et al., 2017). Notice that in this simulation algorithm, we are free to choose stem height, stem radius, leaf position, leaf angle and leaf shape (represented by the polynomial surface). These parameters can be viewed as the labels that can be feed into any supervised machine learning algorithms.

Learning Based Method Geometric based methods used our prior knowledge about the objects to generate the 2D image and 3D point clouds. Nevertheless, the prior knowledge may be inaccurate, lack of details or hard to be mathematically modeled. In this section, we explore a learning based method for simulation.

Recently, there is a significant breakthrough in generative modeling in which the goal is to learn the generative model from the data. In this project, we explore Generative Adversarial Networks (GAN) model (Goodfellow et al., 2014). Specifically, we use Deep Convolutional Gnerative Adversarial

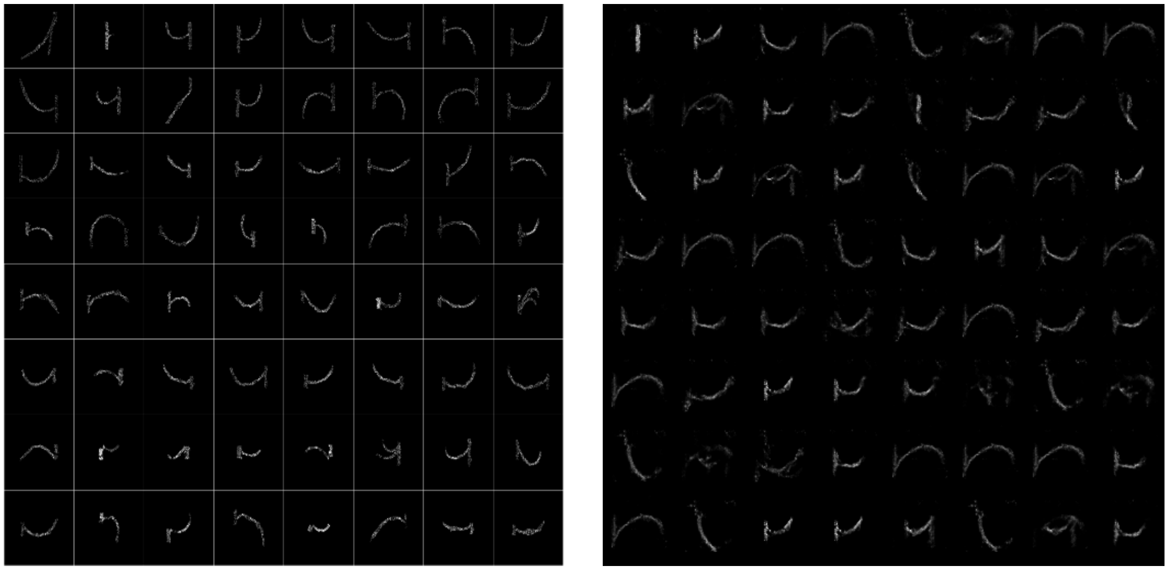

Figure 6: **Left**: real 2D phytomers from the green house. **Right**: generated phytomers using GAN.

Networks (DCGAN) proposed by Radford et al. (2015). GAN models try to solve the following min-max program:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}\left[\log(D(x))\right] + \mathbb{E}_{z \sim p_z(z)}\left[\log(1 - D(G(z)))\right]$$

where $p_z(z)$ is a prior on input noise variables, $G(z, \theta_g)$ is a function with parameters θ_g that maps the noise to data space and $D(x, \theta_d)$ is a function with parameter θ_d that represents the probability that x came from the data rather than from the true generating function. In DCGAN, both G and D are represented by deep convolutional neural networks and implementation details are in (Radford et al., 2015).[1] The main disadvantage of this simulation technique is that we cannot know the labels, or phenotypes of the generated plants because we just use the unlabeled training data to train the generator. Nevertheless, we expect recently proposed Conditional GAN (Mirza and Osindero, 2014) may be used to control the phenotypes when generating samples.

3.2 Estimation Method

We use deep learning methods which can be directly applied on the point clouds to estimate the traits of plants. Specifically, we use 3D Deep Convolutional Neural Network with Alexnet architecture Krizhevsky et al. (2012), which performs particularly well on computer vision tasks. The architecture consists of five convolutional layers and three fully connected layers. Note that since we use 3D point clouds, we replace the original 2D convolutional layers in (Krizhevsky et al., 2012) by 3D convolutional layers. Due to limited labeled data, we only use simulated data ($10,000$)

[1] The codes are available at https://github.com/carpedm20/DCGAN-tensorflow.

Phenotype	Relative Root mean squared error (%)
Leaf Area	26.15
Leaf Length	26.67
Leaf Width	25.15

Table 1: Relative root mean squared error on plant phenotypes.

for training. For the network hyper-parameters, we set dropout probability to be 0.8 and learning rate be 0.0001. The algorithm is implemented in Tensorflow (Abadi et al., 2016).

4 Results and Analyses

4.1 Qualitative Simulation Results

The simulated 3D point cloud based on geometric methods are in Figure 5. Note that they do have the ideal plant structures, similar to the green house data in Figure 4. Nevertheless, comparing to the point clouds from the field (c.f. Figure 3), the simulated point cloud is too clean, which may make the models trained on these clean cloud points not robust enough against noise from the field. An important future direction is to study the noise from the field and do simulation on the noise distribution to make the models more robust.

The exploratory 2D sample images generated by GAN is in Figure 6. Note that the generated images do have similar structures as the original input phytomers, thus validating the potential of GAN for the plant simulations. The next step is investigate whether 3D point clouds can be generated using 3D GAN, like the models proposed by Wu et al. (2016) and whether we can control the phenotypes during the simulation process (Mirza and Osindero, 2014).

4.2 Estimation Results

We trained our 3D convolutional neural network on synthesized data and test on 54 real plants to predict phenotypes values. The phenotypes of interest are leaf area, leaf length and leaf width. Table 1 shows the estimation results where we use the relative root mean squared error (our estimation error divided by the standard deviation in the test sets). Note all numbers are significantly smaller than 100%, which represents the results of using the mean of all plants' phenotypes to predict every plant's phenotypes. These estimation validates effectiveness of 1) the use of simulated data for training and 2) 3D convolutional neural network is useful for phenotyping. The next step is tune the network structure and use better simulation to further improve the accuracy.

5 Conclusion and Future Works

In this data analysis project we have made progress on building a practical automated phenotyping system. We explored both geometric and learning based methods to simulate plants that fit the real plant point clouds from the green house and the field. We also trained neural networks on *simulated* data tested on *real* data to predict the phenotypes and the results are promising. Two future directions are listed below.

- **Improved Simulation.** Simulation is a crucial step in this project. Because lack of real labeled data, models are usually trained on the simulated data. The current technique can simulate green house data quite well. However, the field data contains many kinds of noise, so we need better technique to simulate point clouds that are similar to the ones generated using the field data. Studying the noise distribution from the field or using conditional GAN are both promising approaches.

- **Improved Estimation.** 3D convolutional neural network is shown to be effective in this task. Nevertheless, in this project, we only tried the network structure from Krizhevsky et al. (2012). An interesting direction to explore is to exploit the prior knowledge of the structure of plants to further improve the estimation accuracy.

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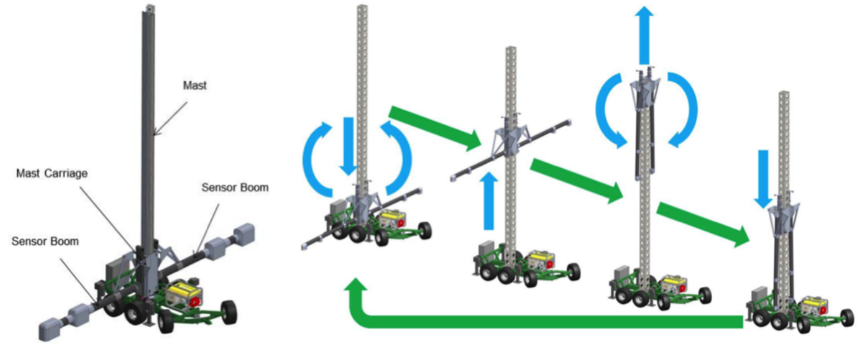

Figure 7: High Throughput Robot.

A Apparatus and Instrumentation

We use High-throughput Phentotyping (HTP) robots to collect data. The HTP robot resides on a trailer system that provides an inexpensive support and transport system for the sensor boom and mast. The trailer will move in the alley ways between sub plots and once in position, drop leveling legs to stabilize the mast so that the sensor boom can be deployed reliably. The trailer is a six-wheeled vehicle with "rocker-bogie" suspension. This type of suspension provides for a certain amount of terrain averaging without requiring a spring/damper-type suspension system. The trailer frame is a simple welded tube structure. Hubs, axles, tires and wheels, trailer coupler and stabilizing jack (auto leveling) system are all commercial off-the-shelf items. The total weight of the system is ∼1000 kilograms including the mast and sensor boom. The overall footprint of the trailer is 6 wide by 116 long. The solid front axle pivots for steering, providing an approximately 8-foot turning radius. This vehicle requires an alley way of 70. The system consists of a vertical column carrying opposing sensor booms as shown in Figure 7. Sensor pods are arranged along each of the sensor booms. The booms are mounted to a moveable carriage which is carried up the column by a linear actuator. The booms are extended and retracted by a linear actuator at the base of the sensor boom. Motion of this actuator, combined with motion of the carriage linear actuator, permits the booms to deploy while maintaining constant boom tip-to-ground distance. This substantially horizontal motion of the boom tip permits the sensor booms to enter the plant rows without damage to the plants. Once fully deployed the carriage linear actuator moves the booms upwards along the column to effect scanning of the plants. After reaching the top of the scan the booms are retracted in a reverse of the deployment motion and the system is moved to the next plant row to be scanned.

A.1 Sensor Pod

The sensorpod (Figure 8) has 10 cameras with 8 (low resolution) cameras placed in two rows and remaining 2 (high resolution) cameras to the sides at a verged angle of 30 degrees. The cameras are hardware synchronized and triggered every 10 cms when the boom moves up the canopy. The top centre pair cameras are designated for stereo reconstruction. The other low-resolution cameras

Figure 8: Sensorpod.

carry narrow bandpass filters to capture images in multiple wavelengths. The high-resolution verged cameras are used for Structure-from-Motion reconstructions. There is a bright LED strip below the camera array, with diffusers, to provide a uniform illumination of the plants. An ambient light sensor is attached to the bottom of the sensorpod, looking at the plant to help set the exposure values of the cameras. A PAR sensor is mounted on top of the sensorpod to make photosynthetic light measurements when the system moves along the canopy. All the cameras and sensors are connected to a embedded computer specs running Ubuntu 14.04. In addition to the internal storage (512GB) which holds the operating system and application software, a 1TB SSD is connected to the computer (via the hard-drive bay) exclusively for logging data. An identical setup, with the cameras and computer is mounted on the other side of the sensorpod so that we can scan two plants simultaneously.