High Throughput Phenotyping for Essential Crop Traits

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Abstract

We report promising results for high-throughput estimation of several key phenotypic traits through the use of small mobile robots and machine-learning based machine-vision algorithms. Our autonomous robotic data collection system, data association pipeline, and analytics algorithms can provide accurate estimation of Stem Width, Stand Count, Ear Height, and Plant Height traits for corn, as well as the Pod Count trait for soybeans. Collecting data for these phenotypes is manually extremely labor intensive, and has been difficult to automate. Our results are significant because they show that autonomous robots equipped with multiple relatively low-cost RGB-vision, RGB-Depth, LiDAR, inertial, and GPS sensors can significantly increase throughput in phenotyping tasks across corn and soybean at a variety of growth stages.

Introduction

A significant challenge in modern crop breeding research is the lack of real-world data on traits that are considered useful for optimizing yield, achieving pesticide resistance, and more. Difficulties include a lack of automated methods to gather data and an insufficient amount of data to make informed breeding decisions (Fasoula, Ioannides, and Omirou 2020; Furbank and Tester 2011). Traditional methods of gathering trait data involve many hours of inefficient manual measurement in crop fields. Estimating these traits has proven to be a key bottleneck in crop breeding pipelines in general. In recent years much research and development has gone into efficient and automated approaches to both collecting crop data and computing these traits (Shamshiri et al. 2018). Here we report the results for estimation of these traits from in-field imagery using "TerraSentia"–a robotic, high-throughput field phenotyping system that does not utilize any destructive sampling. We summarize successful results that we have achieved on rapid autonomous collection of crop data as well as results on accurately estimating five traits from data from multiple robots and across multiple fields at a high throughput. Our results demonstrate the potential for direct trait estimation in breeding as well as production fields, and suggest that low-cost high-throughput phenotyping with robots could be a strong solution to the phenotyping bottleneck (Fasoula, Ioannides, and Omirou 2020; Furbank and Tester 2011). The five traits we discuss in this paper are are

1. Corn Stem Width
2. Corn Stand Count
3. Corn Ear Height
4. Corn Plant Height
5. Soybean Pod Count and Yield

These traits are difficult to measure manually. Furthermore, over-canopy systems such as drones, do not provide information relating to all of these traits (except corn plant height, which has been previously estimated using over-canopy data from drones), since they require a view of the plant from under-the-canopy. We note here that high-throughput plant phenotyping using machine vision is an active and exciting area of research (Singh et al. 2016, 2018). We describe our results, and provide a brief overview of the algorithms we have devised, but do not go into exceeding details of the algorithm due to lack of space. Our intent for this paper is to not claim novelty in the specifics of the algorithmic design, but rather in the fact that high-throughput phenotyping with robots is now a reality. As such, we expect that our results will provide a baseline for researchers to compete against and we fully expect following methods to exceed the benchmarks set here. Accordingly, a dataset will be released publicly following the workshop for this.

TerraSentia Field Phenotyping System

TerraSentia robot and automated under-canopy data collection:

The backbone of the TerraSentia high-throughput phenotyping system is the TerraSentia robot that autonomously collects field data with multiple sensors. See Figure 1. The TerraSentia robot is capable of fully autonomous under-canopy row-following in a farm setting with very low intervention rate (average distance between interventions well exceeds the length of an average row). The robot traverses using a combination of GPS, LiDAR (Higuti et al. 2018), or vision-based autonomy (Sivakumar et al. 2021). Field data is collected with several onboard sensors, including 3 cameras on front and two sides, one upward facing camera, a RGB-D sensor, and two LiDARs (front and rear). Through a simple user-interface, the angles, resolution, field-of-view, and

Figure 1: EarthSense TerraSentia robot is a compact robot designed to collect under-canopy traits in an autonomous manner. We built over 100 such robots in 2021. In this paper we describe results for high-throughput phenotype estimation in corn and soybean using data from these robots.

frame rates of the cameras can be programmatic customized for specific traits. On-board software transfers the data to a remote computer on the cloud using Ethernet where the data is processed.

Data pre-processing:

The data transmission pipelines have been optimized to work with low-bandwidth rural connections. The data collected and metadata input by the user is used to automatically split the data into Experimental Units (plots). This process uses GPS geotags, visual data from the side camera, and the LiDAR data using a deep learning model (not described here). Next per-plot data is processed using machine-vision algorithms to calculate the desired traits. These results are then associated back with the appropriate EUs in the database and presented to the user using an intuitive web-based interface (Wei and Molin 2020).

In 2021 season EarthSense collected data over 100,000 EUs (plots) with multiple robots deployed in the field. A reasonable subset of these data were annotated for the traits shown below. The toal number of annotations (not images) well exceeded 3.5 M. All results shown below are on validation sets that were not used in training.

The algorithms discussed in this paper for computing the desired five under-canopy traits all take advantage of some combination of GPS, any of the multiple cameras present on the robot, and LiDAR. Unless explicitly mentioned otherwise, all algorithms are run on camera data recorded with a framerate of 30 frames per second.

Corn Stem Width

Corn Stem Width is defined as the real-world width of the lowest segment of a corn stem, measured along the corn stem diameter parallel to the orientation of the plot. High-

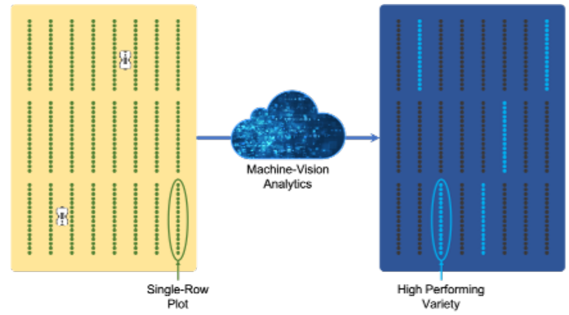

Figure 2: A visualization of the high-throughput phenotyping pipeline, shown here with single-row plots. Robots collect data in an autonomous manner through breeding diversity panels, split into plots or experimental units. The data is transmitted to the cloud (or a remote computer at the Edge) where it is processed, yield estimates are computed, and reported back to the breeder with a user-friendly interface.

Figure 3: A visualization of the corn stem width algorithm on a 2021 corn field. Masks are annotated with estimated width in millimeters at several points.

throughput corn stem width in cluttered under-canopy environments with machine vision data has been a challenging open problem (Choudhuri and Chowdhary 2018; Sahiner et al. 2019; Vit and Shani 2018). Breeding researchers are interested in knowing the average Corn Stem Width as well as the distribution of widths per-plot. Our Stem Width algorithm showed high correlation ($r^2 = 0.86$) on data we collected and measured. The algorithm is run on data collected from the side cameras on the TerraSentia robot, at an angle of -5 degrees from the horizontal. Our algorithm uses an object detection network trained from a Mask-RCNN Inception ResNet v2 Atrous coco checkpoint to detect corn stems. The depth to corn plants is estimated from LiDAR data from the front LiDAR or the rear LiDAR depending on data quality. The camera angle is accounted for combining the inertial angle estimate and the measured angle of the camera from camera encoders. See Figure 3 for a correlation graph that shows strong correlation with our automated measurements against manual measurements. The manual measurements were collected by measuring each corn stem at 1 location for the plots against which our algorithm is verified.

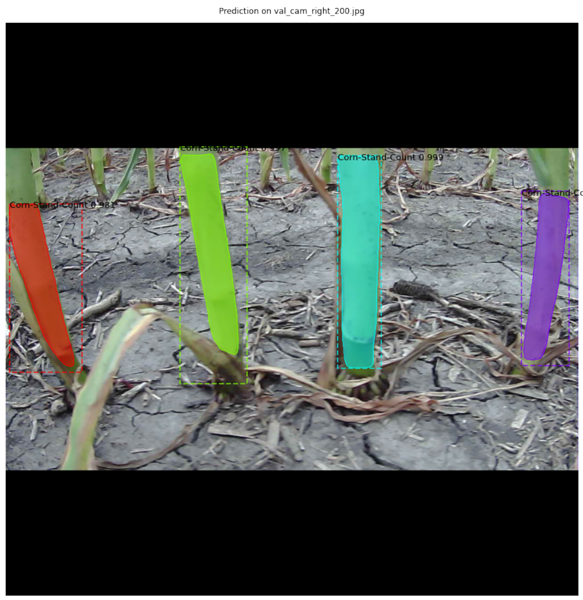

Figure 4: A visualization of the corn stand count detector fed into the stand count algorithm. Masks are annotated with confidence.

Corn Stand Count

Corn Stand Count is defined as the number of corn plants within a distance range, typically aggregated per-plot. Early season stand-counts can often be accomplished using drone data (Khaki et al. 2020; García-Martínez et al. 2020; Pearson 2018; Ghosal et al. 2019), however, later in the season, when the canopy closes, robotic under-canopy data is necessary for accurate stand-counting. The challenge in corn stand count is avoiding double counting (Kayacan, Zhang, and Chowdhary 2018; Zhang et al. 2020). Our Corn Stand Count algorithm showed high correlation ($r^2 = 0.88$) on a dataset we collected and measured. The algorithm is run on data collected from the side cameras on the TerraSentia robot, at an angle of -30 degrees from the horizontal. Our algorithm uses an object detection network trained from a FPN and Mask-RCNN ResNet-101 coco checkpoint to detect individual corn stems. To avoid double counting, two approaches are possible, first is to use an object tracker similar to work in (Zhang et al. 2020), however this can be computationally intensive and needs image-to-image tracking labels. The other approach, which we have devised, uses a a heuristic based estimator of where the corn plant is going to be seen using the robot velocity estimate. This enables our algorithm to distinguish and isolate different real-world corn plants across the course of a video. Finally we aggregate the count of distinct corn plants across a unit of distance. Figure 4 that our algorithm has strong correlation with manual counts of stems visible in the video from the robot.

Corn Ear Height

Corn Ear Height is defined as the real-world distance between the ground and the base of the corn ear, or the location at which the corn ear is attached to the corn stem. This is an extremely difficult trait to measure manually, and to automate because often the corn ears look quite like the leaves around them, and the view to the ears are often occluded due to leaves (Wong et al. 2020). Breeding researchers are interested in knowing the average Corn Ear Height per plot. We utilize a RGB-D sensor to ensure accurate height predictions. We show here subset of our results on dataset collected and measured on a corn field maintained by the CROPPS project at the University of Illinois. See Figure 5 which shows that our algorithm from robot collected data shows strong correlation with manual measurements ($r^2 = 0.74$). The algorithm is run on data collected from a forward-facing camera mounted to the top of the robot angled at a pitch of 25 degrees. The camera records both RGB images as well as aligned depth images. Our algorithm uses an object detection network trained from a Mask-RCNN Resnet 101 Atrous checkpoint to detect corn ear masks and uses camera pose to estimate the real-world height of a detected corn ear mask

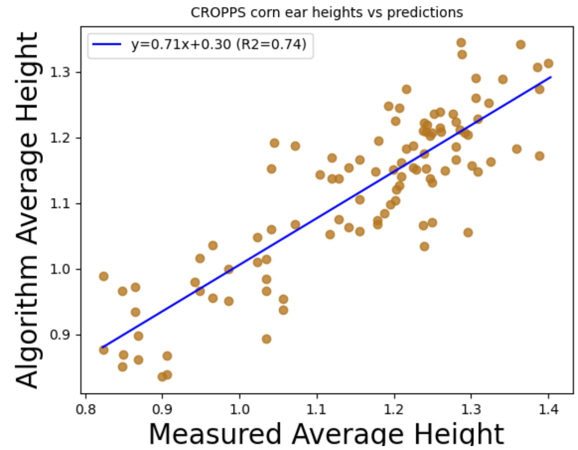

Figure 5: Performance of our automated Corn Ear Height prediction algorithm on data from multiple corn plots shows strong correlation with manual measurements.

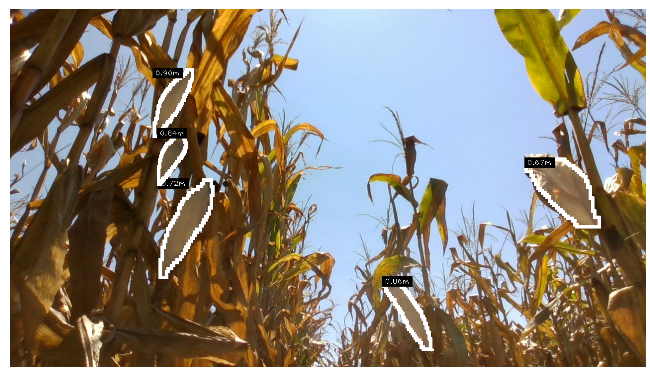

Figure 6: Visualizations of our Corn Ear detector on data collected from the TerraSentia robot. Detections are annotated with algorithm height estimates.

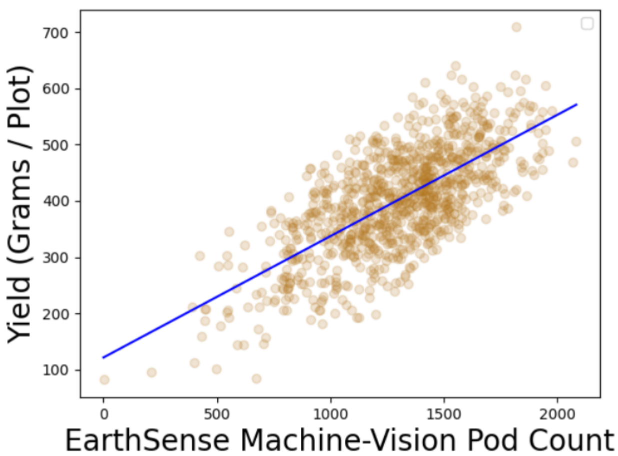

Figure 7: Performance of our Soybean Pod Count prediction algorithm on a 2020 soybean field. $r = 0.70$.

based on depth and angle information from the RGB-D sensor. We provide a visualization of our Ear Height algorithm superimposed on an image sampled from the color and depth camera mounted to the top of the robot. This image was sampled from a field on which we achieved high correlation. See Figure 6.

Corn Plant Height

Corn Plant Height is defined as the real-world distance between the ground and the base of the highest leaf, or the location at which the highest leaf is attached to the corn stem (Waliman and Zakhor 2019). Breeding researchers are interested in knowing the average Corn Plant Height per plot. Our Corn Plant Height algorithm showed strong correlation ($r^2 = 0.91$) on a customer dataset we collected and measured on. Our algorithm explicitly computes the height of the top of the plant stem rather than the height of the base of the highest leaf due to ease of algorithm computation, but our high correlation shows that this is a sufficient proxy measurement. Our algorithm runs on vertical LiDAR data and averages the top k-the percentile of the LiDAR returns for estimating the height from the LiDAR, after correcting the scan for robot pitch, roll, and yaw. The ground plane is also detected to compute height directly above the ground. The LiDAR scan sees a 270 degree arc to the left, right, and top of the robot, in a plane perpandicular to the robot's direction of movement at a rate of 40 Hz.

Soybean Pod Count and Yield

Soybean Pod Count is defined as the number of soybean pods in a plot of soybean plants. There have been several attempts at measuring soybean podcounts from camera data (Riera et al. 2021). Our pipeline is fully automated in the sense that it can go through the plots, collect data, and associate the data back to individual plots. Sometimes per-plant pod count is also desired. Soybean yield, similarly, is the aggregate of soybean pod weight per plot or per plant. In our previously published research we demonstrated our algorithm for accurate estimation of soybean yield per plot (McGuire et al. 2021). Additionally, we demonstrated that an algorithm directly computing pod count is sufficient to achieve correlation on soybean yield, which is consistent with other research showing that soybean pod count and yield are strongly correlated across many global experiments (Wei and Molin 2020). Our Soybean Pod Count algorithm showed strong correlation ($r = 0.7$,$r^2 = 0.49$) on data collected and measured from a collaborating group at the University of Illinois. See Figure 7. The algorithm is run on data collected from a side-facing camera pointing at 5 degrees from the horizontal. The camera has a fisheye lens to provide a wider field of view and ensure that the entire soybean plant from bottom to top is covered. We automate a simple preprocessing step of cropping out the left and right extremities of the image to focus on the vertical center of the field of view. Our algorithm uses a detection network trained from a Faster-RCNN Resnet-101 checkpoint to detect soybean pod bounding boxes and adds up the number of soybean pods in an image, or in all images within a plot if we are aggregating per-plot.

Discussion

We have demonstrated successful methods of applying artificial intelligence algorithms to improving the efficiency, scale, and accuracy of crucial plant phenotypes for crop breeding research. Working with our partners and customers, data were collected with multiple robots over more than 100,000 Experimental Units (plots) across multiple locations in the US. Only a very small subset of total data collected and analyzed by the EarthSense field robotic field-phenotyping system is shown here due to reasons surrounding data privacy. We are in the process of working around these issues to pool data from multiple sources in 2021 for a more exhaustive analysis that will be submitted to a peer reviewed venue. The main hypothesis that is being verified by our activities is that high-throughput phenotyping can be enabled at far lower cost, and at higher efficiency than manual measurements using compact autonomous robots. Our results presented here clearly provide evidence towards this hypothesis. Our work shows that under-canopy data can provide access to a number of phenotypes that are difficult to measure from over-the canopy with drones or satellites. The TerraSentia robotic system will provide a strong data source to a large amount of ongoing work in high-throughput phenotyping, not all of which could be covered here due to space limitation. As such, we strongly believe that with the robotic phenotyping tools presented here, researchers will be able to significantly advance algorithms for analytics as they bring new innovations to bear to overtake the baseline results presented here. We will help enable such research in high-throughput phenotyping by releasing a subset of our dataset openly.

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