The Robotanist: A Ground-Based Agricultural Robot for High-Throughput Crop Phenotyping

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***Abstract*— The established processes for measuring physiological and morphological traits (phenotypes) of crops in outdoor test plots are labor intensive and error-prone. Low-cost, reliable, field-based robotic phenotyping will enable geneticists to more easily map genotypes to phenotypes, which in turn will improve crop yields. In this paper, we present a novel robotic ground-based platform capable of autonomously navigating below the canopy of row crops such as sorghum or corn. The robot is also capable of deploying a manipulator to measure plant stalk strength and gathering phenotypic data with a modular array of non-contact sensors. We present data obtained from deployments to *Sorghum bicolor* test plots at various sites in South Carolina, USA.**

I. INTRODUCTION

Plant phenotyping is a critical step in the process of breeding crops for higher yield, disease resistance, drought tolerance, and other desirable traits. Plant genome researchers must empirically confirm that new cross-breeds exhibit associated phenotypes, such as stalk width, leaf area, leaf angle, and color. Unfortunately, the rate at which these associations are measured and analyzed is slower than the rate of plant genome research.

This deficiency is well-recognized by the scientific community, which has deemed it the Phenotyping Bottleneck [1]. This bottleneck is caused by a variety of factors, including labor-intensive processes, their associated costs, and the necessity of replicated trials. The laborious process of plant phenotyping is currently performed by highly skilled plant scientists and breeders who must assess thousands of plants under field conditions. Unless the rate of plant phenotyping is accelerated, the agricultural promise of plant genomics will not be fully realized.

In this paper, we outline the design and testing of a novel ground robot capable of autonomously navigating within sorghum rows. The robot gathers phenotypic data using a custom manipulator and non-contact sensors such as a custom side-facing stereo camera, and offers significantly higher throughput than manual measurements performed on plant structure beneath the crop canopy. The robot was tested in fields located in Clemson, SC and Florence, SC in July and August of 2016. These tests demonstrate that the platform is capable of navigating fields exhibiting a variety of soil conditions and phenotyping a wide array of sorghum accessions.

The development and deployment of this novel mobile system has yielded the following contributions to the field of agricultural robotics:

Fig. 1. The Robotanist in sorghum breeding plots near Clemson, SC.

- A platform capable of navigating between row crops and deploying phenotyping sensors for sub-canopy data collection
- What we believe is the first-ever demonstration of outdoor contact-based automated phenotyping

The rest of this paper is organized as follows: Section 2 describes related work on this topic and the current state of the art. Section 3 provides an overview of the system and validation in the field. Future work and conclusions are presented in Sections 4 and 5.

II. RELATED WORK

A. High-Throughput Phenotyping

Lemnatec has developed an outdoor phenotyping platform, the Scanalyzer Field, which is an overhead gantry with a sensor payload consisting of multi-spectral cameras, fluorescence imaging, and LiDAR [2]. Two of these gantry systems are commercially deployed, each capable of measuring up to 0.6 hectares of crops. While gantry systems will yield very detailed information, they are expensive and constrained to a relatively small plot size.

Researchers associated with the University of Arizona and the United States Department of Agriculture (USDA) developed a tractor-based platform for phenotyping Pima cotton. The system consists of sonar proximity sensors, GPS, infrared radiometers, and NIR cameras to measure canopy height, temperature and reflectance [3]. However, the data collected by the system is restricted to overhead

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*This work was supported by the ARPA-E TERRA Program

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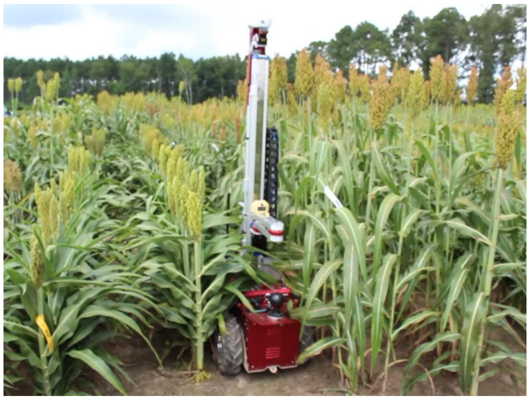

Fig. 2. The Robotanist enters a row of sorghum.

views, and the tractor's maximum boom height (1.93 m) limits the height at which plants could be phenotyped. Texas A&M University is also developing an overhead phenotyping platform [4]. Both of these systems require a trained operator.

Aerial-based research platforms are easy to deploy and can collect data over large distances in relatively short periods of time. However, they are limited by sensor resolution, payload, and flight time. Drone-based sensors are also unable to directly measure sub-canopy phenotypes such as stalk strength, stalk count, and leaf angle. Rotorcraft such as the DJI Inspire or Yamaha RMAX have flight times that range from 8–120 minutes, depending on payload, and maximum payloads range from 0.8–8.0 kg [5].

B. Plant Manipulation

Few intelligent agricultural manipulation systems have been deployed in field conditions. A team from the Netherlands describes a recently-developed system for autonomous harvesting of sweet peppers, but operation is constrained to the controlled conditions of a greenhouse [6]. A Belgian team developed an apple-picking robot that retrieves 80% of fruit at an average rate of one apple every 9 seconds, but the system requires a shade covering the entire tree when deployed outdoors [7]. Several commercial systems provide mobile platforms for harvesting, but laborers must still pick the fruit [8]. To the best of our knowledge, the only automated system that manipulates vegetation, rather than fruit, is a grapevine pruning system developed by Vision Robotics Corp [9]. However, this system also requires a shade positioned over the entire plant.

C. Unmanned Ground Vehicles

Ground-based research platforms have been developed for applications such as precision pesticide spraying, soil sampling [10] and weeding [11], for a wide variety of field conditions and crops [12]. Several commercial ground-based robotic platforms were also investigated for their viability.

Clearpath Robotics Inc. has developed a family of field tested all-terrain robots which have been used under a wide range of conditions, from mapping underground mines to navigating in dense forests [13]. Robotnik Automation S.L.L. has developed several robotic platforms that have been used to deploy sensors within an agricultural setting [14]. QinetiQ North America sells a small tracked robot primarily used by military and police organizations for explosive ordinance disposal and reconnaissance [15], and Omron Adept Technologies, Inc. offers a variety of wheeled platforms used primarily for robotics research [16]. Rowbot Systems has developed a platform [17] that is designed to travel between crop rows autonomously.

While a variety of ground-based robotic vehicles are currently available, none meet the specific functional, quality, performance, and modularity requirements of this project.

D. Perception, Localization, and Navigation

Image-based plant phenotyping using commodity sensors is a growing field within the computer vision and bioinformatics communities. Researchers associated with the University of Bonn developed a method of segmenting plant stalks from plant leaves using indoor laser scan data [18]. Another team reconstructed corn plants indoors using a time-of-flight camera, a turntable, and 3D holographic reconstruction techniques [19]. While a significant amount of research focuses on image-based plant segmentation indoors, very few of these methods have been applied in field conditions.

Localization and navigation within agricultural settings has been the focus of significant research. A group from Carnegie Mellon University (CMU) used a monocular camera [20] and data from a LiDAR sensor [21] to navigate between rows of an apple orchard, while a group from the University of Illinois investigated the use of a variable field-of-view camera to navigate within corn [22]. Most previous work was performed in monoculture fields, which do not contain the wide phenotypic variation inherent in sorghum breeding plots. This phenotypic variation, such as stalk height and leaf angle, causes significant visible clutter within rows (see Figure 2). Prior work does not address reliable navigation from early season through to late season growth stages.

III. SYSTEM OVERVIEW

The state-of-the-art systems outlined above exhibit limitations ranging from payload capacity to geometric limitations to weather rating to cost. For this reason, we have developed our own custom intra-row autonomous mobile sensor platform - the Robotanist.

The Robotanist is a wheeled skid-steer, electrically powered ground vehicle that is capable of autonomously navigating within sorghum rows. It can travel at speeds up to 2 m/s for more than 8 hours per charge. The robot is equipped with LiDAR, RTK GPS, RGB cameras, inertial measurement units, and the computing power necessary to run perception and localization algorithms in real time. The system houses a custom manipulator capable of taking contact measurements from sorghum stalks, and is capable of deploying a wide range of non-contact phenotyping sensors.

A. Robot Base

1) Requirements: System requirements were driven by the need to reliably traverse a typical breeding plot (1–2 hectares) within a few days in order to avoid significant plant growth throughout a single measurement period. Functional requirements include the ability to autonomously transport

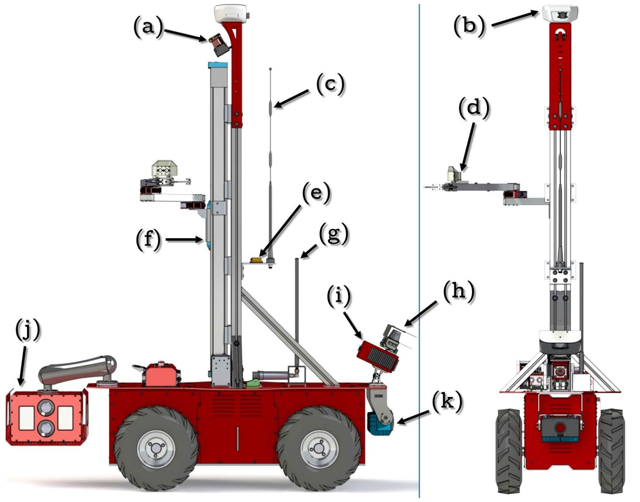

Fig. 3. Rendering of the Robotanist: (a) Hokuyo UTM-30LX; (b) Novatel SMART6-L GPS; (c) 900 MHz antenna; (d) robotic manipulator; (e) Xsens MTi-30 AHRS; (f) linear stage for mast sensor payload; (g) 2.4 GHz antenna; (h) SICK TiM561; (i) IDS UI-5240CP RGB camera; (j) custom stereo camera with active lighting; (k) SICK Visionary-T.

contact and non-contact sensor payloads between rows of biofuel sorghum crop, navigate from one row to another autonomously, transmit robot state, sensor and diagnostic data to a nearby base station, and be tele-operable. Performance requirements include the ability to maintain ground speeds of 1.5 m/s, operate from 5 °C to 45 °C, traverse 3 hectares per day, carry a sensor payload up to 50 kg, reliably traverse the minimum 0.61 m row space available prior to harvest, wirelessly communicate with a base station up to 500 m away, localize within the crop row with a nominal accuracy of <5 cm relative to a global coordinate frame, have a turning radius of <2 m, and be robust to dust and water ingress.

2) Hardware: The mobile platform is $1.34\times0.56\times1.83$ m (L×W×H), with a total mass of approximately 140 kg including the manipulator. The chassis of the robot is comprised of 5052-H32 aluminum sheet metal with riveted and bolted connections. A usable volume of 103 L for electrical hardware and wiring was obtained within the sealed frame of the robot. Structural members were strategically placed within the frame of the robot to not only minimize compliance under expected loading but to also provide convenient connections for hardware mounting plates. Louvers fitted with air filters were placed on the side, front, and rear panels to act as inlets and outlets for thermostat-controlled cooling fans placed inside the chassis. A cutaway of the interior of the base is shown in Fig. 4.

Each of the four pneumatic tires are driven by a 200 W brushless DC (BLDC) motor connected to a 50:1 hollow shaft gearhead, both sourced from Oriental Motor USA Corp. The motors are capable of outputting a combined torque of 108 Nm and driving at speeds up to 2.0 m/s. The BLDC motors are in turn controlled by custom–built HEBI Robotics motor drivers which expose position data from the Hall effect sensors and current draw through a C++ API. Motor velocity commands are sent via Ethernet to the HEBI motor controllers, which are then achieved through a PID controller on the motor driver.

Computing is handled by three Intel NUC Mini-PCs, each with a 3.4 GHz Intel i7 processor, 16 GB RAM, and a 1 TB SSD storage drive. Each computer is connected to a bank of unmanaged Gigabit network switches to provide a means of communication between themselves, sensors, and radios. Due to its reliability and robustness, communications within the system are provided primarily with Ethernet via shielded Cat5 cabling. Sensor selection opted for Ethernet variants where possible.

Four DC-DC converters provide regulated power to various subsystems. A Vicor VIPAC Array DC-DC converter with 500 W, 12V output provides the majority of regulated power, while subsystems which require 5V and 24V regulated voltage are powered by two CUI Inc. PQA50-T DC-DC converters. A 200 W, 12V DC-DC converter provides isolated power to the phenotyping sensor payload. All four DC-DC converters can be controlled via switches present on the bulkhead near the rear of the robot.

The energy requirements of the mobile platform were calculated using the sum of average predicted current draw of each subsystem. A conservative estimate of the rolling resistance was calculated as described in [23] to be roughly 51.8 N, which was used to calculate the average current draw of the drive motors on flat terrain. To allow for 8 hours of continuous operation a required energy capacity of 2125 Wh was calculated, therefore a 24V, 100 Ah $LiFePO_4$ battery pack was chosen for the power source. The battery chemistry offers a higher specific energy and volumetric energy density than a typical lead-acid battery while also offering a slower rate of capacity loss when compared to Lithium-ion battery chemistries.

3) Navigation Sensors: Reliably localizing, detecting obstacles, and navigating within the highly occluded and dynamic environment of a sorghum breeding plot is a difficult task, particularly as plant height begins to exceed the height of the GPS antenna. To attempt to resolve this issue, a suite of perception sensors was selected that would enable modularity and provide a broad range of sensor data.

Navigation sensors are shown in Fig. 3. The design of the base is such that all of the navigation sensors are configurable; there are multiple mounting points for various sensors and the pitch of the navigation cameras are configurable to 15° increments. A Novatel SMART6-L GPS antenna/receiver is mounted at the top of the mast of the robot to provide

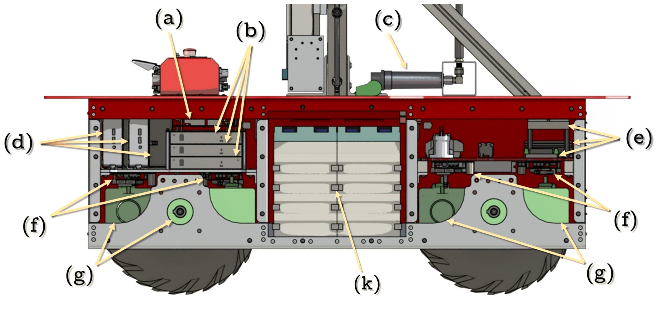

Fig. 4. Rendering of the interior of the Robotanist: (a) Freewave 900 MHz radio; (b) 3x 8 port Gigabit network switch; (c) Ubiquiti Networks BM2-Ti 2.4 GHz Radio; (d) 3x Intel NUC; (e) 4x DC-DC converters; (f) 4x Hebi BLDC motor drivers; (g) 4x Oriental Motors BLVM620K-GFS and GFS6G50FR BLDC gearmotors; (k) 24V, 100 Ah $LiFePO_4$ Battery

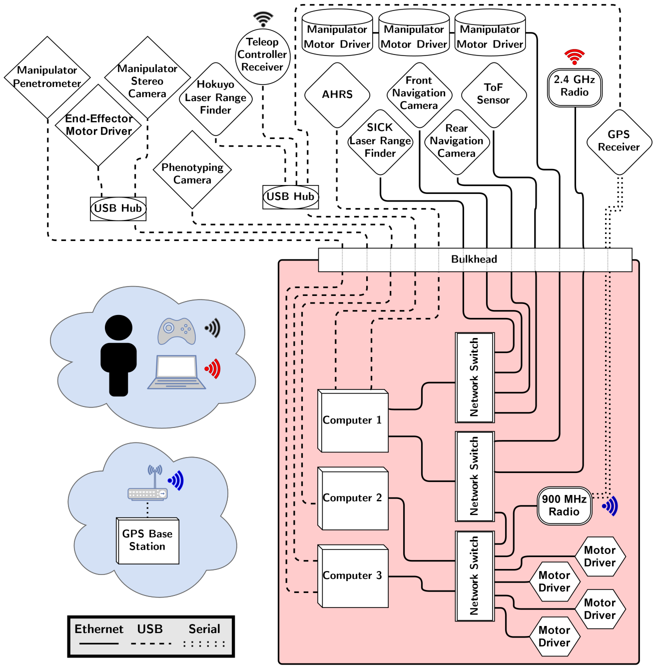

Fig. 5. A block diagram of the Robotanist.

a clear view of the GPS constellation. GPS carrier phase signals are broadcast to the Novatel receiver using a 900 MHz radio from a base station set up approximately 2.2 km away, allowing for a nominal horizontal accuracy of 0.010 m +1 parts-per-million (RMS) relative to the calculated position of the base station.

Two planar LiDARs, the Hokuyo UTM-30LX and the SICK TiM561, are both mounted in a pushbroom orientation in opposing directions of travel. A SICK Visionary-T time-of-flight sensor is mounted in the front of the robot and provides a means of detecting fallen stalks and other obstacles in the row beneath the canopy. Two IDS UI-5240CP-C-HQ cameras with Kowa LM5NCL fixed focal length (4.5mm) lenses are also mounted to the front and rear of the robot. This camera and lens configuration provides a field of view of 74°x62° at a pixel resolution of 1280x1024.

An Xsens MTi-30 Attitude and Heading Reference System (AHRS) is mounted midway up the mast and provides attitude information along with raw sensor data. The AHRS uses an Extended Kalman Filter (EKF) to fuse the inertial data from the tri-axial accelerometer and gyroscope and the tri-axial magnetometer data into an estimate of the 3D orientation of the sensor with respect to an Earth fixed coordinate frame.

4) Phenotyping Sensors: Two types of plant phenotyping cameras have been mounted to the robot base. A custom stereo camera described in [24] and shown in Figure 3 gathers high-quality side-facing stereo images. Point Grey Flea3 cameras outfitted with fish-eye lenses capture upward-facing images to measure canopy light penetration.

5) Software: Robot Operating System (ROS) and a variety of its open source packages are used for the software framework. Nodes were written or sourced to communicate with sensor hardware, to communicate with the base platform remotely to query data and send commands, to perform coordinate frame transform calculations for individual sensors, to fuse sensor data and perform state estimation, and to visualize sensor data.

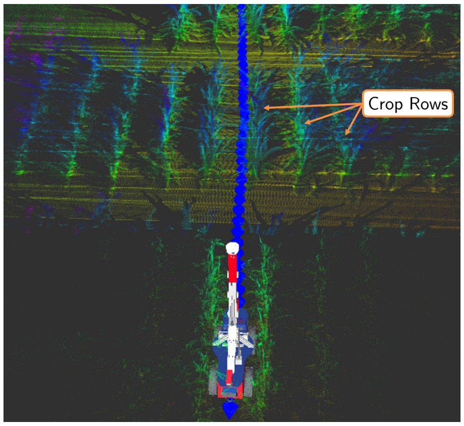

Fig. 6. Data from planar laser scanners in push-broom configurations collected in a *Sorghum bicolor* breeding plot is transformed to an Earth referenced fixed frame.

The GPS antenna is placed at the highest point on the robot, but in order to reliably navigate within the narrow corridors of a sorghum breeding plot pitching and rolling of the vehicle needs to be accounted for. A ROS node was written which uses the relative poses of the AHRS, GPS antenna, and base coordinate frame of the robot along with orientation data from the AHRS to calculate the corrected GPS coordinate of the vehicle at the base frame. Vehicle state estimation is performed using an Unscented Kalman Filter (UKF). This node takes data from the AHRS, Hall effect sensors, and orientation-corrected GPS data and fuses them to provide a current state estimate of the 3D pose and velocity of the robot in an Earth fixed coordinate frame.

When the sorghum crop is short enough that the GPS antenna has a clear view of the satellite constellation, navigation within the crop rows is designed to be handled through GPS way point following. GPS coordinates were collected at regular intervals along the desired path, and the Pure Pursuits algorithm [25] with a fixed look-ahead distance was used to perform path following of a line drawn between GPS way points. While this method of navigation is widely used in the field of robotics and agriculture, it does not account for any obstacle that may be present in the narrow corridor, and is not robust to signal dropout from either the GPS satellites or the base station. In an effort to reliably navigate under GPS-denied conditions, pose corrected data from a 2-second sliding window from the laser range finders is combined into a single point cloud. Current development is focused on utilizing this data to localize within the crop row and detect obstacles.

6) Field Validation: The vehicle and its subsystems were tested at two breeding sites operated by Clemson University in South Carolina over 13 days during July and August of 2016. Maximum daily outdoor temperatures during deployment were 31–38 °C, with occasional rain showers during testing. The vehicle was driven more than 44.7 km over the course of deployment with no major system failures. Vehicle mobility was more than sufficient under dry and wet

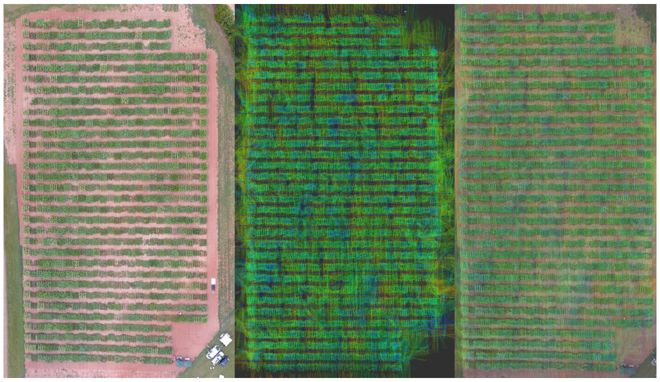

Fig. 7. (Left) An aerial view of sorghum test plots in Clemson, SC. (Center) Laser scan data of the same test plots corrected using calculated vehicle pose estimate. (Right) Overlay of two images, indicating accuracy of pose estimation.

conditions at both test sites. Sensor data was collected as the vehicle was driven through test plots, and a visualization of this data can be seen in Figs. 6 and 7. The coherence of the images is a testament to the accuracy of the UKF when calculating the vehicle pose estimate.

B. Robot Manipulator

1) Requirements: The manipulator design was motivated by a need to reliably servo to a sorghum stalk, apply a rind penetrometer, and log the output within 30 seconds. The manipulator architecture also needed to accommodate future applications such as core sampling and spectroscopy, and have a maximum reach of 0.53 m. The manipulator and end-effector must also be safe to operate, robust to dust and water ingress, and lightweight.

2) Hardware: Sorghum stalk geometry was the primary influence on hardware design. When fully grown, the stalks are roughly vertical, exhibiting a variation of approximately 15° from vertical. Given this structured environment, it was concluded that a 3 degree of freedom (DOF) manipulator would be sufficient to grasp the majority of stalks. A SCARA-style arm configuration was chosen, consisting of a vertical prismatic joint followed by two horizontal revolute joints. X5 motor modules developed by HEBI Robotics, Inc. were selected for their small package, light weight, and safety. The X5 motor modules feature a series-elastic gearbox, making them safer than traditional gearmotors. The prismatic joint, a Movopart M75 manufactured by Thomson Linear Motion, is belt-driven for fast operation and slide-guided for weather resistance.

A traditional rind penetrometer consists of a digital force gauge modified with a needle at the end of its probe. It is applied to a plant stalk using one hand to support the back of the stalk while the other hand pushes the needle and force gauge into the stalk. This process is automated on the Robotanist by deploying two aluminum fingers to support the back of the stalk while a motorized plunger drives a needle into the stalk. The mechanism is actuated using a single motor and ball screw: a Maxon Precision Motors Inc. EC-16 brushless DC motor and a GP16S ball screw. The plunger is constructed out of acetal plastic, and the mechanical fingers are positioned by a track in the plunger (see Figure 8). Data collection is performed using a Futek LLB215 miniature load cell, a LabJack LJTick-InAmp instrumentation amplifier, and a Teensy 3.2 USB development board.

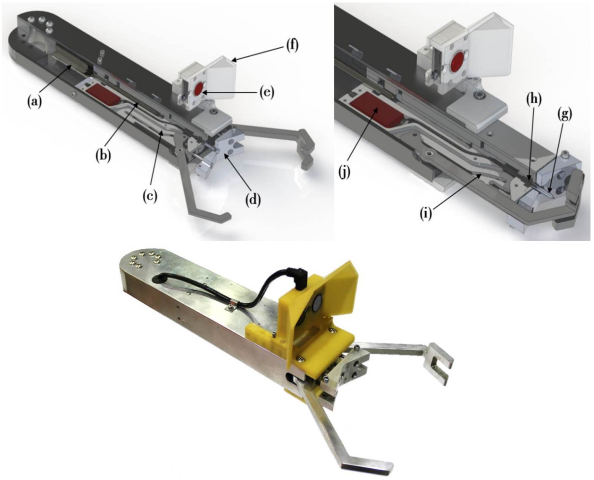

Fig. 8. The robotic manipulator for stalk strength measurements: (a) Maxon Motor EC16 brushless DC motor; (b) Maxon Motor GP16S ball screw; (c) acetal plunger block; (d) v-block for centering plants; (e) Code Laboratories DUO3d stereo camera; (f) sun shield; (g) needle for penetrating stalk walls; (h) Futek llb215 load cell; (i) track for actuating fingers; (j) instrumentation amplifier and A2D converter.

Stalk detection is performed with a DUO MLX stereo camera produced by Code Laboratories, Inc. The stereo camera has a minimum range of approximately 0.10 m which is critical for operation in sorghum fields where plants will be less than 0.60 m away from the camera at all times. The camera is designed for indoor operation, so linear polarizing lenses manufactured by Edmund Optics Inc. were installed to reduce the amount of incoming light.

3) Software: The stalk detection algorithm is based solely on geometry due to highly variable lighting and partial occlusion by leaves. RANSAC cylinder detection is applied to the stereo camera point cloud, and operates at 4-5 Hz. For added robustness, the manipulator maintains a stationary position and collects 50 point cloud frames. The location of each cylinder's centroid is recorded, and the centroid with the most neighbors is deemed the optimal stalk centroid. This data collection and processing framework takes approximately 10 seconds. The manipulator is then commanded to the location of the optimal centroid. The end-effector position is controlled using PID joint position control available through HEBI software.

4) Field Validation: The robotic manipulator was tested in Florence, SC on bio-energy sorghum (*Sorghum bicolor*) measuring approximately 3 m tall. A single pass was performed down 7.5 m of a crop row and the robot was stopped every 0.6 m. At each stop, the manipulator was deployed at a fixed height of 1 m to capture a single stalk on each side of the row. The stalk detection algorithm successfully identified 25 out of 26 stalks and successfully grasped all of the identified stalks.

IV. FUTURE WORK

One can envision an agricultural robot able to autonomously deploy itself from a docking station to breeding plots and begin traversing between rows. This robot

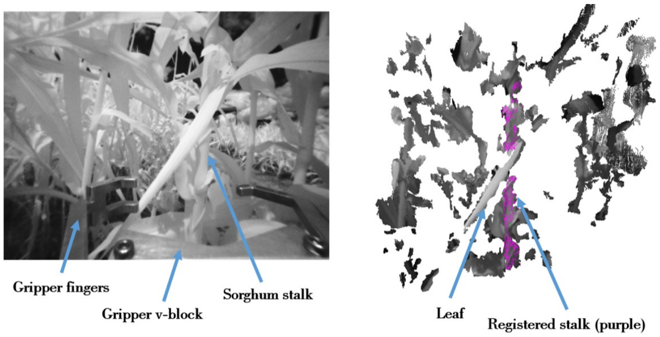

Fig. 9. Field data from the DUO3d stereo camera: (Left) 2D grayscale data from the left camera - the stalk is highly occluded and a vine is wrapped around it; (Right) the geometry-based stalk detection algorithm successfully registers the stalk.

could make data collection decisions in real-time, such as informing researchers which regions of a field require further inspection. The Robotanist does not yet exhibit these capabilities, but the current system architecture can accommodate this additional functionality.

Navigation within the sorghum plots is currently handled by path following between GPS way points. As the season progresses and the sorghum grows taller than the GPS antenna, that capability will be lost. Developing algorithms that make use of laser scan and navigation camera data will be required to autonomously traverse the field reliably throughout the entire growing season.

Future manipulation tasks include grasping leaves, which requires more sophisticated computer vision and 3D reconstruction from multiple viewpoints.

The phenotyping images have been processed but not validated. Currently, phenotypes extracted from 2D images include leaf erectness, leaf necrosis, and plant greenness using Green-Red Vegetation Index (GRVI) spectral indices. Future work will include validation of preliminary results and investigation of 3D stereo data for extractable phenotypes.

V. CONCLUSION

This paper presented a ground vehicle capable of autonomously navigating rows of sorghum while applying a suite of contact and non-contact sensors. It specifically outlined the hardware and software architecture of the ground platform as well as the architecture of the manipulator and end-effector. Field validation of the developed hardware is presented, including full 3D reconstruction of a sorghum breeding field and what we believe is the first-ever demonstration of contact-based automated phenotyping.

ACKNOWLEDGMENTS

This research was supported by the Advanced Research Projects Agency-Energy. The authors would like to thank the following people who provided assistance in the development and testing of this system: Stephen Nuske, Omeed Mirbod, David Kohanbash, Guoming Alex Long, Stephen Kresovich, Zach Brenton, Margaret Oates, Ressa Sarreal, and Michael Bailey.

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