Development of an Autonomous Ground Robot for Field High Throughput Phenotyping

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Abstract: High throughput phenotyping holds promise of accelerating crop breeding programs and has gained great attention in the past several years. Although many platforms for data collection, including ground and aerial vehicles, have been developed to adapt to different crops and field setups, fully autonomous ground robots have not been readily available and widely used so far. In this study, we developed a ground robot that is capable of autonomously navigating in the field. We designed a sensor mounting frame that can be modified to mount different sensors for different data collection tasks. The robot was tested in a cotton breeding field and color images of the plants were collected. We developed an algorithm to count the cotton bolls using the color images. The preliminary results demonstrated that the system was capable of collecting data autonomously without human intervention and the collected data were useful to extract phenotypic traits.

Keywords: ground robot, phenotyping, autonomous navigation, cotton, high throughput

1. INTRODUCTION

To meet the demands of the predicted global population of 9 billion by the year 2050, current crop production must double by that time (Tilman et al., 2011). This is a tall order, challenging plant breeders to find genotypes with high yield, as well as high-stress tolerance to adapt to the changing climate in the next 30 years. Recent technological advances in molecular biology have offered tools that can significantly accelerate the breeding process (Phillips, 2010). However, phenotyping has become the bottleneck to using these new technologies to their full potential. Screening genotypes—in order to select those with the most desirable traits—heavily relies on the ability to characterize and measure traits (Cabrera-Bosquet et al., 2012). Therefore, many plant breeders and engineers recognize the need for a high-throughput phenotyping (HTP) system capable of efficiently and accurately measuring phenotypical traits (Araus & Cairns, 2014; Cabrera-Bosquet et al., 2012).

The development of an HTP system is challenging in both the platform design and the associated data processing methods. Development of a field-based high-throughput phenotyping system (FHTPS) is even more challenging due to heterogeneous field conditions and uncontrolled environments, which can affect the data quality and make results difficult to interpret (Araus & Cairns, 2014). Early development of FHTPS utilizes ground vehicles equipped with sensors to acquire data. Some representative systems utilizing tractors has demonstrated the usefulness in breeding and genomic research (Andrade-Sanchez et al., 2014; Busemeyer et al., 2013; Sharma & Ritchie, 2015). With the advantage of large payload of tractors, such systems can easily carry multiple sensors at the same time and ensure the data quality by controlling data collection environment (such as light condition) with a well-designed enclosure. However, those platforms also have several disadvantages, for example, the data scan speed is low, frequent data collection can cause soil compaction, and the platform is hard to be used for wide range of crops.

To overcome the disadvantages of the ground platform, more and more researchers realize the need of developing small robots that are lightweight, autonomous, adjustable and scalable. There are also several commercial ground-based robotic platforms currently available for purchase, such as the Husky and Jackal developed by Clearpath Robotics. and Summit XL from Robotnik Automation. However, those commercial robots are usually expensive and difficult to modify to meet the specific requirement of different research projects. Therefore, many researchers developed customized robots for different crops, for example, the Robotanist developed for sorghum and Ladybird for row crops (Mueller-Sim et al., 2017; Underwood et al., 2017).

In order to assist the plant breeding, we aimed to develop autonomous ground robots that can be used to quickly scan thousands of individuals using an array of advanced sensor and data analytic tools. Specific requirements for the robot are low cost, autonomous navigation in the field, easy to modify to adapt to different plot layouts and crops. We will test the robot in a cotton field and demonstrate some preliminary results of the phenotypic traits collected by the robot.

2. SYSTEM OVERVIEW

2.1 Mechanical design

The robot system consists a four-wheel drive robot base and sensor frame. The robot base is an off-the-shelf product (MMP30, The Machine Lab, USA), which has a maximum payload of 20 Kg and maximum speed of 2 m/s. We modified the robot base to fit our need. Specifically, we added a robot controller (NI roboRIO, National Instrument, USA) to provide high level control for autonomous navigation. The robotRIO supports LabVIEW and provides rich interfaces to interface with different sensors and actuators.

The sensor frame was designed to mount different phenotyping sensors, such as color camera, thermal camera and LiDAR. The frame was made from aluminium extrusions, which can be reconfigured easily.

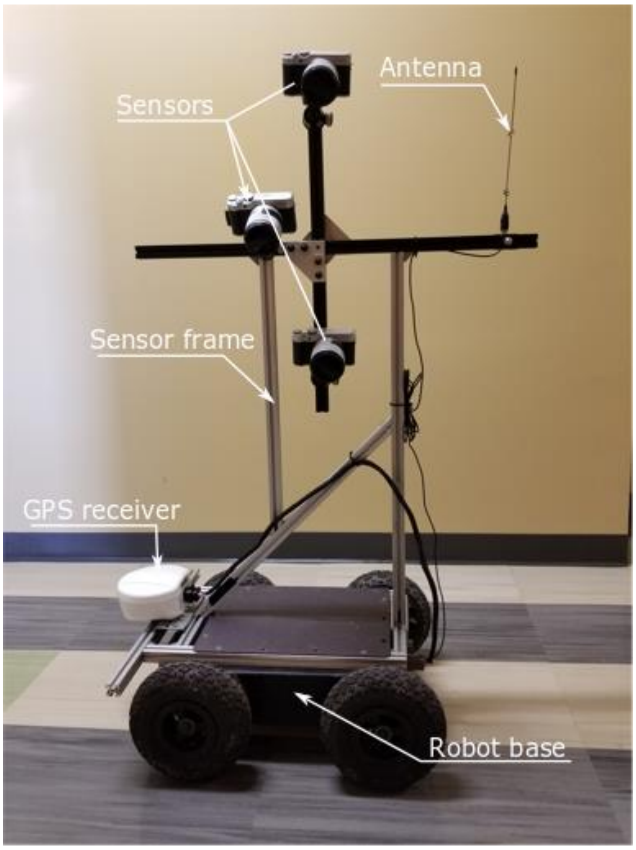

Fig. 1. Overall design of the robot. All other components are inside the robot base. The sensors are three color cameras.

2.2 Hardware design

The hardware of the robot consists of a RTK-GPS system, an inertial measurement unit (IMU), two motor drivers, four DC brushed motors, four optical encoders that are attached to the motors, a radio receiver and the RoboRIO (Fig. 1). The RTK-GPS system includes a GPS receiver (Smart 6L, Novatel Inc., USA) and a radio receiver (FGR2-C, FreeWave Technologies, USA) to provide RTK correction. The RTK-GPS system can provide centre-meter level global positioning, which is accurate enough for the robot to navigate between crop rows without damaging the plants. The IMU (VN-100, VectorNav Technologies, USA) is used to measure the true heading of the robot. The motor driver (Sabertooth 2X12, Dimension Engineering, USA) uses serial communication to accept users' commands to adjust the speed of the motors by changing the output voltages. The speed of each motor was measured by each encoder attached to it. The radio receiver that directly connected with the RoboRIO was used to receive manual operation from the remote control.

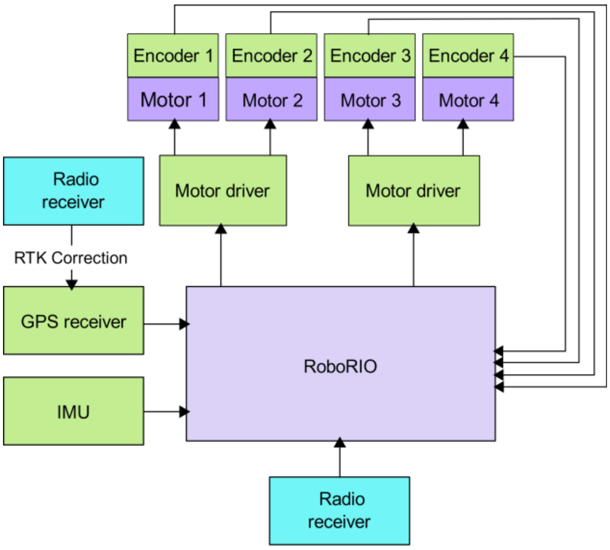

Fig. 2. Diagram of the hardware design

2.3 Autonomous Navigation System

We developed an autonomous navigation system that allow the robot to travel through waypoints without human intervention (Fig. 3). First, the user defines a list of waypoints using geographic coordinates (latitude and altitude). Then the robot will generate a list of reference trajectories (straight lines) that connects all the waypoints. We implemented the nonlinear controller proposed by Soetanto, Lapierre, and Pascoal (2003) to make the robot travel from one waypoint to another waypoint following the reference trajectory. The nonlinear controller calculates the desired forward speed and turning speed based on the robot's deviation from the reference trajectory at current location and heading reported by the RTK-GPS and IMU. The desired forward speed and turning speed of the robot is converted to the desired wheel speed and the speed of each wheel is regulated to the desired speed using a PID controller. The control variable of each wheel's PID controller is the wheel speed measured by the encoder. The output of the PID controller is the motor's speed value that ultimately changes the voltage of the motor by the motor driver. The robot was assumed to reach the waypoint if its distance to the waypoint is less than a threshold, which is 0.05 m in our implementation.

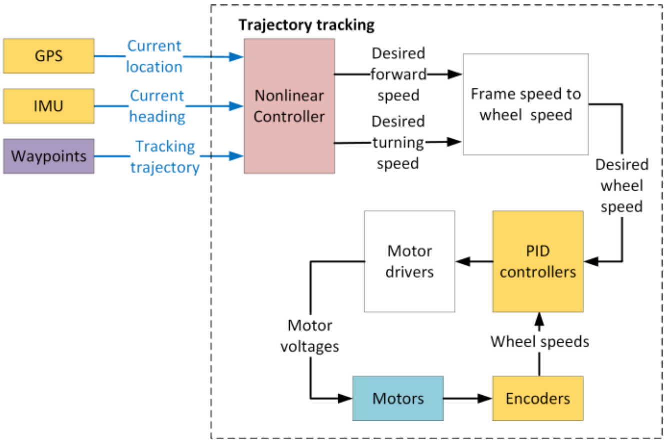

Fig. 3. Diagram of the autonomous navigation system

The autonomous navigation system was implemented in LabVIEW. We also developed a PC program in LabVIEW to help users monitor and visualize the robot's movement (Fig. 4). The real-time location, speed and heading of the robot was transferred to the PC through WiFi and displayed on the program. The waypoints and trajectory of the robot are displayed in the plot. Users can modify the waypoints by adding new waypoints or deleting existing waypoints. The waypoints can be saved to a file or loaded from a file. User can load waypoints to the robot using this program.

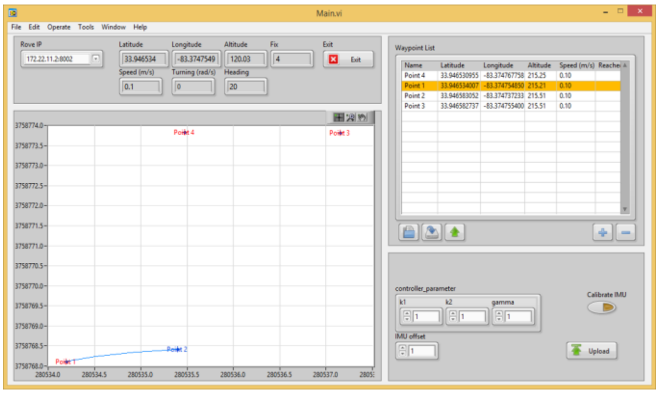

Fig. 4. Front panel of the PC program to monitor the robot.

2.4 Phenotyping Sensors

We used a separate data acquisition system to control the phenotyping sensors so that we can easily add sensors to the robot without modifying the robot controller. The robot can provide its location and pose to the data acquisition system so the sensors can use the data to correct the data. For example, the LiDAR sensor can use the data to correct the position of the scans. Although different sensors can be integrated into the system, we primarily used color cameras to acquire phenotypic data in the current tests.

3. DATA COLLECTION TEST

3.1 Data collection

We mounted four DSLR color cameras (X-A10, Fujifilm, Japan) on the sensor frame to acquire color images of a cotton field. The goal of the test was to test the data quality under autonomous navigation. The cotton field located in Watkinsville, GA, USA. The field was arranged in plots and each plot consisted of one plant. Plots were separated from each other with a distance of 1 m. The distance between plant rows was 1.6 m. The test was conducted on October 8th, 2017. We setup the waypoints shown in Figure 5 to make the robot to navigate between the plant rows and take images of both side of the row 1 and 3. Because of the low speed of camera trigger (1 Hz), the speed of the robot was set to 0.2 m/s to ensure the color images has enough overlap. The color images were retrieved from the cameras after data collection.

3.2 Data processing

The data processing consists of two major steps (Fig. 6). The first step was to construct 3D point cloud from raw images using PhotoScan (1.2.6, Agisoft, Russia). The second step was to count the number of cotton bolls from the point cloud. First, the cotton boll points were separated based on its white color. Second, the cotton boll points was divided into connected components using DBSCAN algorithm (Ester et al., 1996). Third, small components was removed based on the volume of the bounding box. Components on the ground level was also removed. Lastly, the remaining components were counted as cotton bolls.

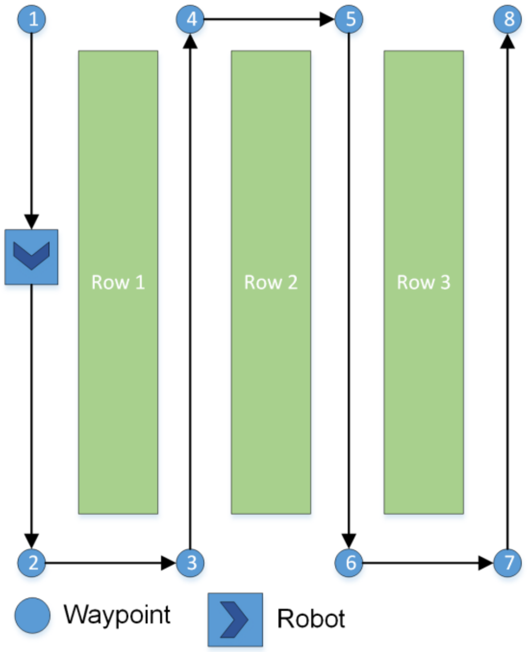

Fig. 5. Schematic of the setup of the data collection test.

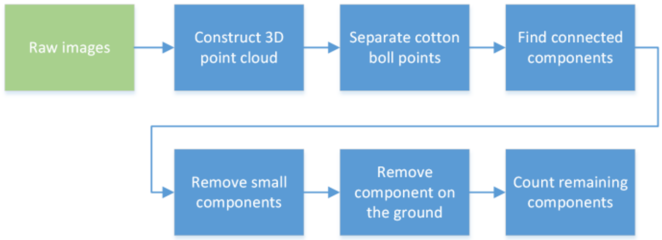

Fig. 6. Data processing flowchart.

4. RESULTS

Figure 7 showed the reconstructed 3D point cloud of three cotton plants. Due to the whether condition of year of 2017 in Georgia, the cotton plant did not yield many cotton bolls and most of the cotton bolls were not open. It is clearly seen that the opened cotton bolls have distinct color from other plant branches and ground, so it can be easily separated using color information. The point cloud also showed the details of the cotton branch so it is possible to measure the branch pattern and the position of the cotton boll on the branch, which is important to predict the yield and fiber quality.

Figure 8 showed the result of final counted cotton bolls. Most of the opened cotton bolls were all detected, except some bolls that are either not fully opened or too close to the ground. Since the plant are well separated from each other, there is litter overlap between plants. In regular plot based cotton field, due to the high crop density, detecting and counting all the cotton boll would be more difficult. Nevertheless, it is promising to use the point cloud to count cotton bolls.

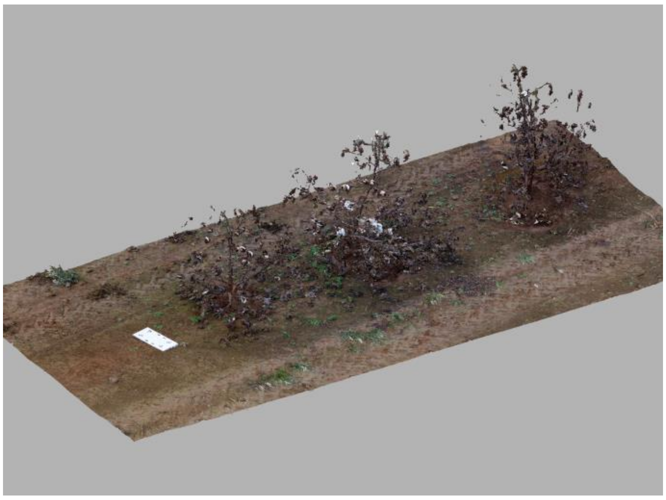

Fig. 7. Reconstructed 3D point clouds from color images. The white plate on the ground is scale bar.

Fig. 8. Cotton boll count result. The red box indicates the bounding box for each cotton boll.

5. CONCLUSIONS

In this study, we designed an autonomous ground robot for in field high-throughput phenotyping. We developed a navigation system that allows the robot to autonomously navigate through user defined waypoints. We tested the robot in a cotton field and showed the collected color images can construct a detailed 3D point cloud for cottons. The proposed data processing flowchart showed that the 3D point cloud can be used to detect and count opened cotton bolls, which indicates that the robot is capable of collecting qualified data for field phenotyping. Future work will include testing other imaging sensors such as thermal and multispectral cameras and LiDAR and further improve the robustness of the autonomous robot.

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