MOBILE ROBOT WEEDER AND HARVESTER PROTOTYPE FOR COTTON PRODUCTION

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Abstract

The U.S. cotton industry provided over 190,000 jobs and more than $28 billion total economic contributions to the United States in 2012. The U.S. is the third-largest cotton producing country in the world, following India and China. The U.S. cotton producers have been able to stay competitive with countries like India and China by adopting the latest technologies. Despite the success of technology adoption, there are still many challenges, e.g., increase pest resistance, mainly glyphosate resistance weeds, and early indications of bollworm resistance to Bt cotton (genetically modified cotton that contains genes for an insecticide), to name a few. The autonomous mobile platform used a Robot Operating System (ROS) version kinetic and runs in Ubuntu 16.04. A new weeder design based on the cultivator setup will be presented. The weeder module has the capability to easily change the cultivating equipment, e.g., harrow disk, finger tine, or the combination of both. The harvester design was based on a stripper mechanism and used a suction motor to move the harvested cotton bolls to the container. Preliminary results for the field test on the weeder and the new harvester design will be presented.

Introduction

The U.S is the third-largest cotton producing country in the world. Cotton producers must stay competitive by adopting the latest technologies. The cotton industry in the U.S. has a significant impact on the economy, with 190,000 jobs and more than $25B per year. This year's yield forecast at 386 kgs. Per harvested acre was slightly above the previous year (Meyer, 2020). The U.S. cotton industry has a long history of adopting distributive technologies, starting with the invention of the cotton gin in the 1790s, the adoption of mechanic harvesters in the 1950s, and the development of the module builder in the 1970s (Hughs et al., 2008). These technologies significantly decreased labor requirements and allowed the labor to produce a 218-kg bale of cotton fiber to reduce from 140 hours in 1940 to less than 3 hours today (Wanjura et al., 2015). Despite the success of technology adoption, there are still many challenges faced by the U.S. cotton producer. One major challenge is competition from polyester, where overproduction in China has resulted in polyester prices that are approximately 50% less than cotton and has resulted in suppressed cotton prices (Meyer, 2016). Thus, producers must continue to increase their production efficiency as increased cotton prices on the near horizon. Other challenges facing cotton producers are increased pest resistance, particularly glyphosate resistance weeds (Norsworthy et al., 2016), and early indications of bollworm resistance to Bt cotton (genetically modified cotton that contains genes for an insecticide).

Sistler (1987) provided a review of the different robotic applications and its future possibilities in agriculture. More robot-based technologies have been used in agriculture. They have been implemented through the use of automation and with ranges of form factors, e.g., ground-based (e.g., smart tractors, unmanned ground vehicle [UGV]), crane-based systems, aerial-based (e.g., unmanned aerial vehicles [UAV]). A rapidly adopted automation in agriculture, for example, is an automated system for milking cows. Salfer et al. (2019) estimated over 35,000 milking systems are currently used all over the world. For row crops, weed control with the rise of herbicide-resistant weeds and lack of new herbicide modes of action is a significant concern, and robotic systems are one of the proposed solutions (Westwood et al., 2018). Most of the major agricultural machinery companies have announced autonomous machinery plans, have prototype machines, and have filed patents on autonomous robotic systems for agriculture (e.g., Murray et al., 2018).

UGVs have been used for different purposes in agriculture. BoniRob is a four-wheeled-steering robot with adjustable track width and used as a crop scout (Bangert et al., 2013). Its sensor suite includes different cameras (3D time of flight, spectral) and laser distance sensors. It was at first design as a phenotyping robot, but additional functionality was added as a weeder as its development progressed. It used a hammer type of mechanism to destroy weeds. Unfortunately, BoniRob development was discontinued for an unknown reason. Vinobot is a phenotyping UGV implemented on a popular mobile platform from clearpathrobotics. Vinobot can measure phenotypic traits of plants and used different sensors (Shafiekhani et al., 2017). TERRA-MEPP (Transportation Energy Resource from Renewable Agriculture Mobile Energy-crop Phenotyping Platform) is another UGV that was used for high-throughput phenotyping of energy sorghum. It used imaging sensors to measures the plant from both sides as it traverses within rows, thereby overcoming the limitations of bigger UGV (Young et al., 2019).

Robots are becoming more integrated into the manufacturing industry. Though most of the manufacturing environment is not as complicated as the outdoors, recent advances in sensors and algorithms provide an interesting outlook on how robots will be working outdoors with humans. Commercial small Unmanned Ground Vehicle (UGV) or mobile ground robots with navigation sensing modality provides a platform to increase farm management efficiency. The platform, Husky (clearpathrobotics) can be retrofitted with different manifolds that perform specific tasks, e.g., spraying, scouting (having multiple sensors), phenotyping, weeding, harvesting, etc. Autonomous map-based robot navigation was developed, and a selective harvesting proof of concept was also designed and field-tested in 2018. The robot was retrofitted with a vacuum-type system with a small storage bin. Performance evaluation for the cotton harvesting was performed in terms of how effective the harvester suctions of the cotton bolls and the effective distance (Burce et al., 2019). Although, preliminary field test showed promising results, the first prototype, only used one suction cap. A new harvester module was designed in 2020 and will be presented in this paper. Using the same robotic platform, a new weeding module was tested in 2020.

This work is part of a bigger project sponsored by Cotton Incorporated to developed and designed different robotic platforms or automation for cotton field operation. The purpose of this research is to investigate the potential of UGV to be used for multiple operations.

Materials and Methods

Mobile Robot Platform

The robot used in this work is the Husky A200 (Figure 1) from Clearpath Robotics. The robot is suitable for field operations as its width of 68 cm fits common cotton row spacings. It is lightweight for field traffic, and thus soil compaction is not an issue as compared to huge farm machines. The robot is powerful enough to handle payloads of up to 75 kgs and can operate at speeds of 1 meter per second. It has a 24VDC Lead-acid battery, which can provide 2 hours of operation. Two new lithium polymer batteries with 6 Cells each and a 10Ah rating provide up to 3 hours of operation. Husky is equipped with IMU (CHR-UM7, CH Robotics, Australia), GPS (Novatel Smart6-L, Novatel, Canada), individual steering motors and encoders for each wheel for basic navigation, and a laser scanner (UST-10LX, Hokuyo, Japan) for obstacle detection. The robot can be programmed to perform specific tasks like mapping, navigation, and obstacle avoidance through its onboard P.C. (mini-ITX) running on Ubuntu 16.04 operating system and the Robot Operating System (ROS, Kinetic version) framework. A mini-LCD screen, keyboard and pointing device was connected to the onboard P.C. allowing the user to write and test code, view and perform operations quickly.

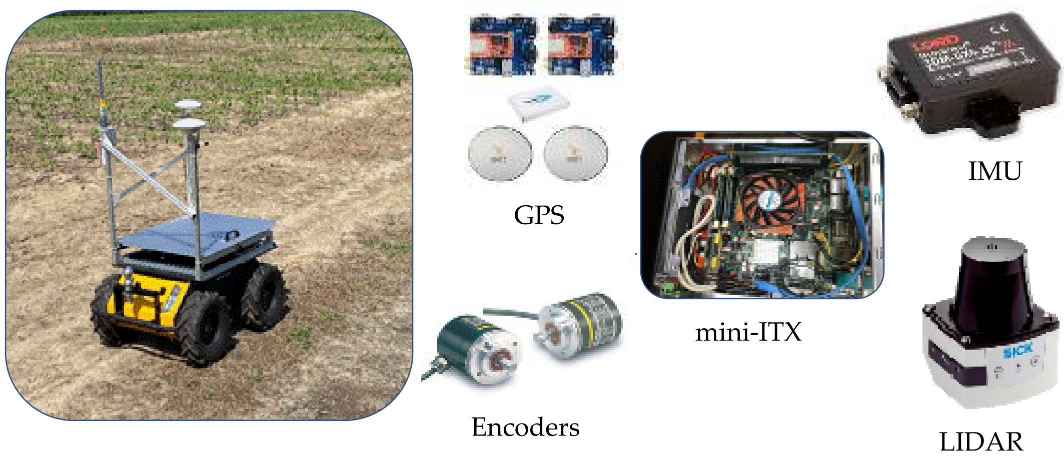


Figure 1. Mobile robot platform used in this project.

Field Navigation

Autonomous field navigation is achieved by having a digital map of the field and localizing the robot on that map. Localization involves integrating the coordinate frame of the robot with the coordinate frame of the digital map. The robot's coordinate frame, commonly referred to as its odometry, estimates the robot's position and orientation over time. The robot's odometry accuracy may be enhanced by integrating it with other positional readings from an IMU or a GPS device. The robot's position is first determined using the kinematic model in Figure 2. The kinematic model of the four-wheeled robot used in this study was treated as a two-wheeled differential robot with virtual wheels W.L. and W.R. to simplify calculations. The robot's current position is determined by a tuple (xc, yc, α) and its new position (xc, yc, α)' after time δt, given its right and left virtual wheel linear speeds, vR and vL, respectively. The linear speed of each virtual wheel is shown in Equation (1) and (2).

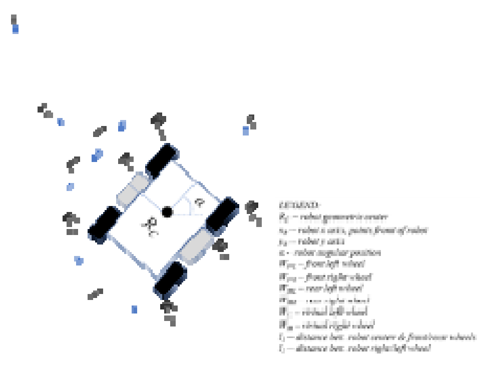


Figure 2. Robot's kinematics to determine its current position.

$$v_R = \omega_{W_R} \times r \quad (1)$$

$$v_L = \omega_{W_L} \times r \quad (2)$$

where ω is the angular speed and r is the wheel radius. The angular speeds ω and angular position φ of each virtual wheel is the average of its real counterparts as shown in Equations (3) to (6),

$$\varphi_{W_L} = (\varphi_{W_{FL}} + \varphi_{W_{RL}})/ 2 \quad (3)$$

$$\varphi_{W_R} = (\varphi_{W_{FR}} + \varphi_{W_{RR}})/ 2 \quad (4)$$

$$\omega_{W_L} = (\omega_{W_{FL}} + \omega_{W_{RL}})/ 2 \quad (5)$$

$$\omega_{W_R} = (\omega_{W_{FR}} + \omega_{W_{RR}})/ 2 \quad (6)$$

The robot’s angular speed and position are shown in Equations (7) and (8),

$$\alpha = (\varphi_{W_R} - \varphi_{W_L}) \times (r / l_2) \quad (7)$$

$$\acute{\alpha} = d\alpha / dt \quad (8)$$

and Equations (9) and (10) computes the robot’s x and y component,

$$\dot{x}_c = (v_L + \acute{\alpha}(l_2/2)) \cos(\alpha) \quad (9)$$

$$\dot{y}_c = (v_L + \acute{\alpha}(l_2/2)) \sin(\alpha) \quad (10)$$

and to get the actual position we compute Equations (11) and (12),

$$x_c = \int_0^t \dot{x}_c \, dt \quad (11)$$

$$y_c = \int_0^t \dot{y}_c \, dt \quad (12)$$

ROS Navigation Stack

The ROS Navigation Stack is an integrated framework of individual software or algorithmic packages bundled together as nodes for steering the robot from one point to the next, as shown in Figure 3. Users configure the navigation stack by either plugging-in built-in or custom-built packages in any of the navigation stack nodes. Estimation of the robot's odometry is therefore handled internally by the nodes in the navigation stack that automatically loads, reference, and updates the configuration file during runtime execution of the robot.

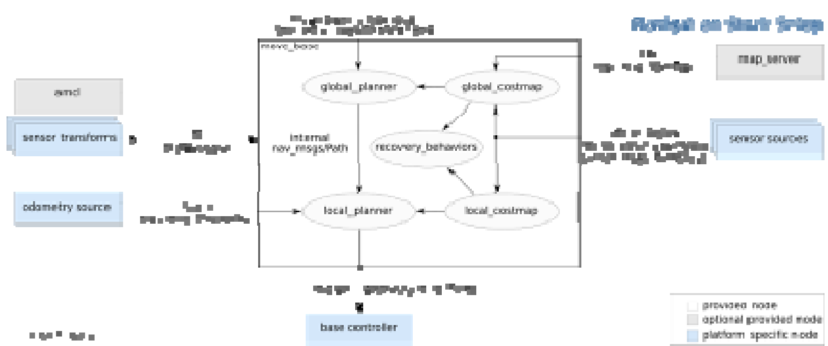


Figure 3. The ROS Navigation Stack.

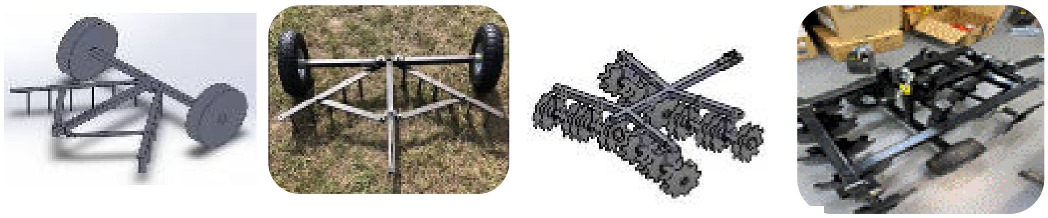
Study Site

The field trials occurred at two separate locations, Edisto Research and Education Center [Edisto-REC] (33°21'26.6"N, 81°19'39.9"W) and Coastal Research and Education Center (32°47'27.2"N, 80°03'37.6"W) [Coastal-REC] of Clemson University in July ~ August of 2018, 2019, and early 2020. Before the field trials, the navigation of the mobile robot was tested in the months of April ~ June. The row spacing of the cotton plants was approximately 96 cm and 10 cm in-row plant spacing. For these trials, standard skip-row planting configurations were implemented with alternate rows. Seeding was done in early May and harvesting in the first week of December. Regular crop management practices were applied during the growing season.

During the field trials, the mobile robot was tested twice per month through 5,000 sq. m, without critical issues on the platform. Most of the issues during the trials were attributed to the mechanical vibrations that loosen the IMU from its holder, wheel nuts, and the ball joint holder loosening. The problem with loose IMU was not detected early on as its location was obscured. ROS has a useful command line, rosbag, which can be used both to record and replay bag files. Bag file is a file format in ROS for storing data. Examining the bag files provides a clue on why the mobile robot was acting weird on some of the prior test.

Weeder Prototype

Two different weeder modules were designed, built, and tested. The first design (Figure 4a), V-shaped, has six individual prongs on each side, where each prong measured approximately six inches. The prong was designed to penetrate about 3.8 cm (1.5 inches) into the soil. Two wheels were used to ensure the prongs would be kept at a constant depth into the ground. A slider mechanism was designed to make the width of the two-prong holder adjustable. The second weeder (Figure 4b) was an adjustable harrow disk, where the disk holder can be adjusted at a certain angle with no wheels to support the disk. Since the disk used was off the shelf and heavy, it was retrofitted with two wheels to minimize the mobile robot's force to pull the weeder.



(a) (b)

Figure 4. Two weeder designs were tested for this work: (a) Weeder with V-shaped and (b) Weeder with adjustable harrow disk.

New Harvesting Module Design

The new harvesting module design was based on the stripper design used by big machinery in cotton harvesting. Prior to the final harvester module, the stripper enclosure (Fig. 5a) was first placed on the front of Husky with two setups (Horizontal and Vertical stripper), as shown in Figure 5b. Unfortunately, with this setup, the lidar sensor will have to be relocated, including the GPS antenna located in the front.

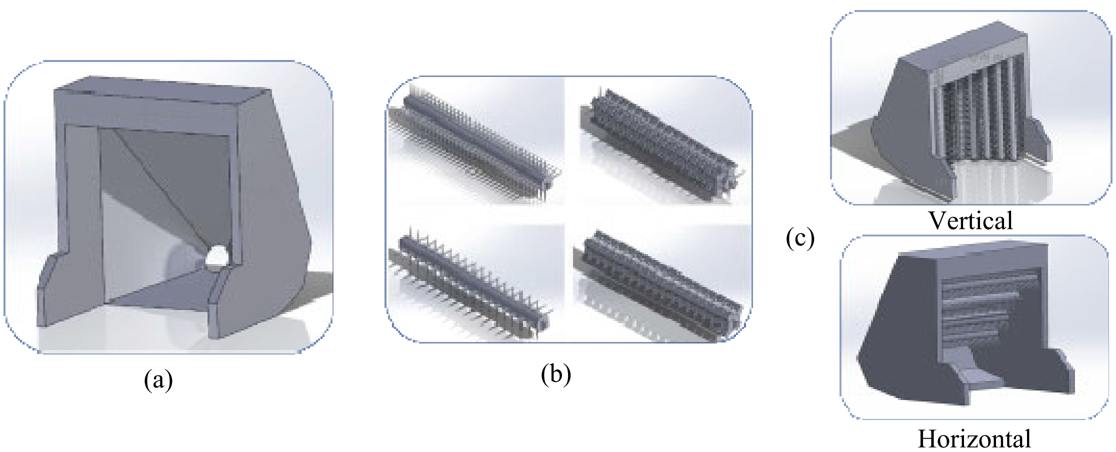


Figure 5. Preliminary design of harvesting module which comprise of the (a) enclosure, (b) stripper, and (c) stripper placement.

Moreover, another problem was the bucket location that collects the harvested bolls and the high torque requirement needed for the robot to push the plants while harvesting. An additional mechanism is required to perform cutting the stem after harvesting, which makes this design complicated—relocating the harvesting enclosure to the side of Husky. This new design (Fig. 6b) addresses all the issues mentioned above. Sensors, e.g., lidar, and GPS will not be relocated, and there are minimal changes on the mount for the harvesting bucket previously used on the first harvesting prototype (Fig. 6a).

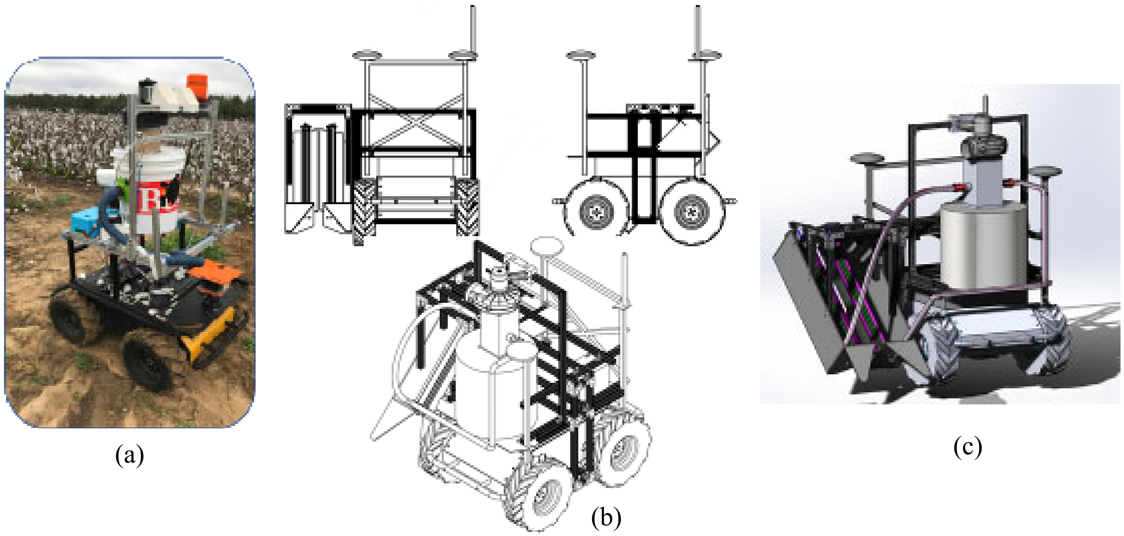


Figure 6. (a) First harvester prototype, (b) New harvester design and (c) 3D rendition of the harvester on the robot.

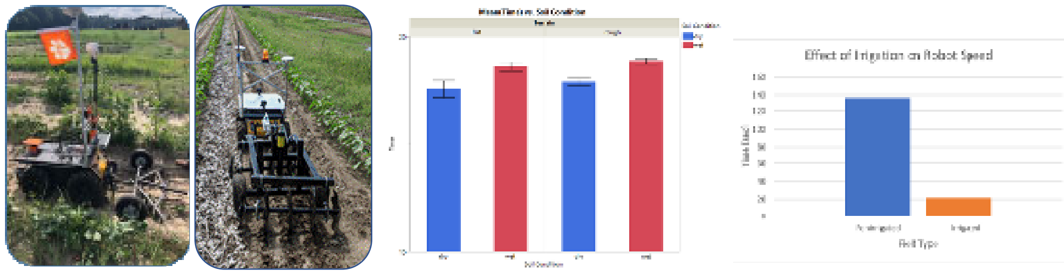
The fabrication of this design will start in the first quarter of 2021. Performance testing will be done in the laboratory before testing in the field.

Weeder Field Trials
The mobile robot speed (with and without the weeder) was tested in two terrain types (rough and flat) and two distinct soil moisture types (irrigated and non-irrigated) using a randomized block with three replications. The preliminary test was set to 30 meters. The speed was held constant at startup to 0.5 m/s but will compensate if slippage was detected during travel. The slippage compensation was set to a maximum of 2 seconds where if the robot does not change its displacement, the robot will increment by 0.1 m/s, until a displacement occurred. The mobile robot will stop the motors if the set speed reaches 1 m/s. with no displacement. This will prevent the platform from either destroying the motors caused by slippage or heavy load. The travel times were recorded for both irrigated and non-irrigated.

The second trial focused on weed control. At the Edisto-REC trial, the speed was set to around 0.75 m/s, while in the Coastal-REC, the speed was set to 1 m/s for ground covered with mat of killed ryegrass and 0.75 m/s without the cover. Weed at the Edisto-REC comprised goosegrass, palmer amaranth, and purslane, while at the Coastal-REC were Carpet weed and crabgrass.

Results and Discussion

Weeder Field Trials
The soil moisture average on the two months trial was around 20%. The results shown in Figure 7c indicate that the mobile robot's travel times were the same for both dry and wet soil. The same test was replicated with the weeder attached, and the results (Figure 7d) showed that, on average, travel time with wet soil is similar to without the weeder. Still, there was a significant travel time with the weeder on dry soil (~138 seconds). Figure 7a and 7b show the two weeders tested during the field trial. The field test showed that the average time of the mobile robot's travel only has a minimal difference between the two irrigated rows (10% saturation and 65% saturation) but has a significant difference between irrigated and non-irrigated.



(a) (b) (c) (d)

Figure 7. The two weeders being tested: (a) V-shaped and (b)Harrow-disk. Results for the travel time (c)with or without the weeder and (d) irrigated and non-irrigated.

The V-shaped weeder was not effective in weed control (Figure 8a) during the preliminary test. Weight was added to maintain the penetration but its connection to the hitch eventually broke. Succeeding field trials on the weed control was only focused on the harrow disk. Approximately 10%~15% weed control was observed at the Edisto-REC field trials (Figure 8b). There were three different weeds found in this area (goosegrass, palmer amaranth, and purslane). The terrain in this location is not flat, and thus the lower weed control results. The Coastal-REC field trials resulted in higher weed control was observed (80%). Note that the robot was tested on two different ground covers, and the terrain on this location was flat.

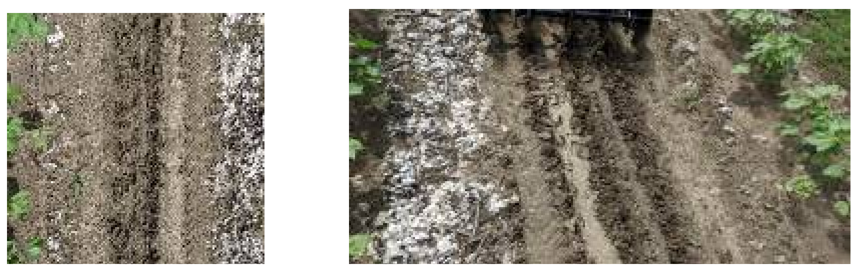


Figure 8. Weed control feed trials results for (a) V-shaped weeder and (b) Harrow disk weeder.

(a) (b)

Summary

This work demonstrated the mobile platform with two different weeders for weed management for cotton. The mobile platform was successfully deployed in the cotton field at two different field sites. Data collected from the trials were used to measure the efficacy of the two weeding modules and future designs of the weeding mechanism. Due to the available robot platform, the design constraint for the weeding module was that it must be a pull behind type. Although there are many mobile platforms, most of these systems are large or can only be used for one specific operation, e.g., weeding or spraying. The one used in this work addresses weaknesses in other designs and fills a niche as a compact and easily transportable. The mobile platform also used the popular ROS, which can easily be adapted to another platform that used the same operating system. Equally crucial for this work was the autonomous navigation of the platform, which has been field-tested rigorously. Results for flat terrain were very promising, and new designs were already in the works to be tested in the future. As noted on the new harvester module discussion, fabrication and testing will be done in 2021. Although the focus for this work was on cotton, the same system could be deployed for other crops as well.

Acknowledgements

This project was funded by Cotton Inc. under Project No. 17-029 and by NIFA/USDA under project number SC-1700543.

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