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ROBOTICS IN COTTON HARVESTING

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ABSTRACT

Advances in computer vision, artificial intelligence, and mechatronics have resulted in the introduction of autonomous machines and mobile robots in agricultural production. Cotton Incorporated has recently sponsored research projects focused on robotics for cotton harvesting, resulting in (1) data on potential yield and quality benefits from frequent harvest events rather than once-over harvesting, (2) the ability of a small robot to traverse a field through crop rows based on GPS and other sensors, (3) machine vision to detect cotton bolls under defoliated conditions, and (4) design of a robotic "end-effector" for removing cotton from bolls in the field.

INTRODUCTION

Because mechanical harvesting is conducted only once at the end of the growing season, early maturing cotton bolls are left exposed to weathering for weeks while the upper position bolls are maturing and waiting to open. In cotton growing areas where increased rainfall and major storms commonly occur in the fall, like much of the U.S. cotton growing region, lint quality can be significantly reduced, and yield can be devastated by storms. Robotic harvesting would allow for a timely seed cotton harvest as the bolls open, preserving yield as well as fiber and seed quality.

Technological advances in machine vision, computing, and electromechanical controls are beginning to lead to commercialization of automation and robotics in agricultural production and procession. Numerous farm machinery companies have (a) conducted research and developed intellectual property in automation, (b) announced plans to provide increasing levels of automation in their machinery, (c) developed prototype autonomous machines, and (d) fielded numerous technologies that automate critical farm processes (Thomasson et al., 2018). Barnes et al. (2019) discussed how conducting multiple harvests after first open boll could improve fiber quality by minimizing weathering and reduce yield loss due to extreme weather events. The objective of this paper is to provide an update and overview of robotic cotton harvesting projects currently supported by Cotton Incorporated.

FREQUENT HARVEST STUDIES TO ESTABLISH POTENTIAL BENEFITS

Research at Texas A&M, University of Georgia, and University of Tennessee. To quantify the value of frequent harvest, hand harvest studies were conducted in 2018 and 2019 at two sites in Texas (irrigated site near College Station; non-irrigated site near Vernon) and one in Georgia (near Tifton). In 2019 another site was added in western Tennessee. The goal was to harvest two times per week after first open boll, but actual harvest events depended on the weather. Three primary treatments were conducted at each site: (i) frequent harvesting by hand throughout the season (no defoliants applied), (ii) hand harvesting one time at the end of the season, and (iii) machine harvesting one time at the end of the season following accepted defoliation practices. All sites collected data across two cotton varieties with the exception of Georgia in 2018, which had one variety in 2018 and two in 2019. Measurement of yield and fiber quality (HVI and AFIS) was conducted at all four sites.

Ten hand harvests were conducted throughout the season in Georgia in 2018 (Figure 1A) and 2019 (Figure 1B). The first hand harvest in 2019 had high yield because rainfall had delayed it significantly. Multiple harvests in 2018 provided a significant yield benefit over a single harvest, whether it be by hand picking or machine picking (Figure 2A). Hurricane Michael hit the region before the crop was defoliated but after many bolls had opened, so the storm played a significant role in the difference between multiple and single harvest in 2018. In 2019 no major storm caused an appreciable loss of seed cotton, but multiple harvests still had higher overall yield than the one-time machine harvest (Figure 2B).

Two cotton varieties with different maturities were used in Texas. In 2018, no significant yield differences between multiple and single harvests were observed. Figure 3 shows reflectance by harvest event. Machine harvesting resulted in inferior fiber quality relative to hand harvesting, and single harvesting resulted in inferior HVI measurements of trash, reflectance, and yellowness relative to multiple harvests. Micronaire, uniformity, strength, and length also decreased throughout the season, but some of this reduction is attributed to harvesting higher boll positions on the plant (Bradow and Bauer, 1997; Kothari et al., 2017; Bauer et al., 2000; Davidonis et al., 2004). Overall, first position bolls represented 52% of the overall hand harvested yield, second position 25%, and third position and vegetative bolls 23% (Figure 4). The greatest quality difference was poorer color grades that resulted after 9 inches of September rainfall. Machine harvested cotton had lower value than multiple harvested cotton by 10 cents per pound in 2018 and 5 cents in 2019.

Initial data from western Texas and Tennessee in 2019 indicated a small yield impact with harvest method (Figure 5). Weather conditions after first open boll are important in determining the amount of yield advantage with multiple harvests, but overall the results indicate that the ability to harvest bolls in a timely manner after they open can improve yield and fiber quality.

ROBOTIC COTTON HARVESTING RESEARCH

Conceptual Approaches for a Robotic Harvest System. All of the work reported herein was accomplished in less than two years, and there is still significant work to be done before a practical prototype harvester is tested. One conceptual design is picture in Figure 6. The black arrows represent a retractable array of “arms” that can be extended when a cotton boll is detected at that height on the plant. The end of each arm would have an end-effector to grasp and remove seed cotton from the boll. The red arrow represents an arm that has been extended to harvest a cotton boll (side view). This only requires one degree of freedom of control when machine speed is accounted for and should allow a desired harvest rate of four bolls per second. Looking from the top view, the array of arms are set up to harvest plants on both sides of the machine and are at an oblique angle to the row to allow them to be longer than if perpendicular to the machine (minimizes machine width to fit between the rows). A system with a forward-looking detection system allows more processing time before the end-effector (e.g., a spindle) needs to be triggered and also allows multiple view angles of the plant so bolls behind leaves or stems can be detected. The doffing action occurs when the spear is retracted into the housing – the boll is dislodged and falls to the bottom of the unit (boll catcher). The boll catcher could then mechanically convey seed cotton to a small trailer behind the unit. The trailer would then empty to a “boll buggy” robot at the end of the row that could then deposit the seed cotton into a stationary module builder at the end of the field. This concept assumes a small independent robot as the harvester, similar to the Clemson ClearPath unit (Figure 7). Alternatively, the system in Figure 6 could be treated as a row unit and several units mounted on a system similar to the UGA Red Rover platform (Figure 8). With a high clearance platform, the system should still be capable of multi-harvest without significant plant damage.

This is only one concept under consideration. Another example is one in which there is non-selective harvest of a limited part of the plant (e.g., the bottom 5 nodes in the first harvest cycle) at a high rate of speed (no boll detection). A slower “gleaner” robot then follows using a machine vision system to collect any bolls that were not captured. Additional concepts are under development, and the economic models described in a following section will be an important component in ranking various concepts.

Clemson University: Robotic Platform for Cotton Harvesting. Commercial small Unmanned Ground Vehicles (UGV) or mobile ground robots with a navigation sensing modality provide a platform to increase farm management efficiency. The platform used in this work (Husky from Clearpath Robotics) can be retrofitted with different manifolds that perform specific tasks; e.g. spraying, scouting (with multiple sensors), phenotyping, weeding, harvesting, etc. An autonomous map-based robot navigation system (Figure 7) 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 of cotton harvesting was performed in terms of how effectively the harvester removed the cotton bolls and the effective distance between suction nozzle and boll (Burce et al., 2019).

University of Georgia: Machine Vision System for Boll IDENTIFICATION. A machine vision system was developed that includes a stereoscopic camera, machine vision processing, a deep learning network model (YOLOv3) and an embedded computer to manage analysis of the images. A Red Rover was used as the platform for testing the system as illustrated in Figure 9. Results have shown that bolls were identified and located with a high level of confidence with one camera looking downward when there was sparse foliage later in the season (Fue et al., 2020).

Cotton boll images used for training the YOLOv3 deep neural network (DNN) model were augmented 27 times with CLoDSA,.an open-source image augmentation library for object classification, localization, detection, semantic segmentation, and instance segmentation (https://github.com/joheras/CLoDSA). A total of 2085 images were collected and labeled, and images were augmented to provide a new labeled dataset of 56,295 images.

The YOLOv3 model was used to train the dataset with a Lambda Server (Intel Core i9-9960X; 16 Cores, 3.10 GHz) with two GPUs (RTX 2080 Ti Blowers with NVLink and Memory of 128 GB, Lambda Computers, San Francisco, CA 94107). A thousand iterations provided optimal performance for YOLOv3, and the training took only 4 hours.

One of the main advances made in 2019 was the development and testing of the navigation system of the rover. A modified path-following technique was instituted based on the geometry of the rover. Detailed equations for calculating path curvature were developed (Fue et al., 2020). The navigation system consisted of an embedded computer (NVIDIA Xavier) and a rover navigation controller. The rover used two algorithms to control navigation, modified pure pursuit and PID control. The system used a predefined path based on the RTK-GPS signal to navigate through the rows. The path was obtained by recording the rover path as it drove through the cotton rows. The predefined path was then used by the rover to navigate while harvesting.

Since the rover used 5 sensors (two IMUs, two encoders, and RTK-GPS) to navigate (Figure 8), the Extended Kalman Filter was implemented for simultaneous localization and navigation. It was achieved by using the open-source library "Robot localization," which provided sensor fusion and nonlinear state estimation for IMUs, encoders and GPS. “Robot Localization” was implemented in ROS (Robot Operating System), which is robotics middleware used for robot software development. The IMUs “publish” two ROS topics (imu_link1/data and imu_link2/data), encoders publish wheel odometry (/wheel_odom) and RTK-GPS publishes /gps/fix signal. The EKF localization used the nav_sat_transform library to integrate fix data from the RTK-GPS. Basically, “navsat_transform_node” required three sources of information: the robot’s current pose estimate in its world frame, an earth-referenced heading, and a geographic coordinate expressed as a latitude/longitude pair with optional altitude (http://docs.ros.org/).

Initial testing was conducted on a grassy field in Tifton, GA. This rover achieved pure pursuit tracking by following six steps: determine the current location of the rover, find the path point closest to the rover, find the goal location, transform the goal location to rover coordinates, calculate the curvature and request the rover to set the steering to that curvature and then update the vehicle’s position. The rover had an absolute mean error of 0.189 m, median of 0.172 m, a standard deviation of 0.137 m and a maximum error of 0.986 m. Most of the path error occurred during turning when it was more challenging to maintain absolute path tracking.

Boll picking used the combination of navigation and boll localization to control the x-y position of the cartesian arm with an end-effector. Initial testing was performed on a grassy field with cotton stalks in 12.5cm dia, pots. Three bolls were randomly placed on cotton stems in a row of 6 pots for a total of 18 bolls to harvest)Fue et al., 2019). Running the rover over the bolls for six repetitions, with boll arrangements changed for each test, resulted in all bolls' being detected and located, a mean of 16 bolls' being successfully picked with an average cycle time of 17.3 seconds per boll.

A test in the field was conducted two times late in the growing seasony. In each of these tests, bolls were picked as found in the field without cotton plant defoliation; however, the field tests were late in the season when foliage was sparse and not representative of early season harvesting. In each test, approximately 5.3 m of row was picked. Results showed that for the first test, the robot picked 67 and left behind 17 bolls, which means the Action Success Ratio (ASR) was 80%. The rover was able to reach (Manipulator Reaching ratio (MRR) 94% of the bolls (79 bolls). For the second test, the robot picked 89 and left behind 26 bolls which means the ASR was 77%. The rover was able to reach (MRR) 96% of the bolls. The average ASR was 78.5%, and the average MRR was 95%.

Texas A&M University and Mississippi State University: Boll Removal. A key requirement of a robotic cotton harvester is an appropriate end effector. Lab tests were conducted to estimate the power requirements for a suction end effector and found a minimum of 1 kW was required. Because solar-recharged batteries would be ideal for multiple field robots, this level of power requirements appears to be excessive for in-field solar robots. Multiple potential versions of an energy-efficient end effector based on mechanical picking have been considered. Each of these would require doffing and transfer of picked seed-cotton. A challenge for both suction and mechanical approaches is the cotton boll orientation. Three potential solutions exist to deal with this issue: (1) utilizing a high degree of freedom manipulator that can face the cotton boll along with artificial intelligence to calculate control actions; (2) adding auxiliary components to the end effector to force the cotton boll to change its orientation; and (3) designing an end effector that can pick seed cotton without considering cotton boll orientation. A combination of these solutions is also possible. Major orientations have been categorized for cotton bolls on a plant (Figure 10), and a preliminary design of a five-spindle end effector developed (Figure 11). This design has two main limitations: (1) sometimes the spindle may not pick all the seed-cotton; and (2) seed-cotton wound on two or more spindles could cause problems; e.g., a branch could get stuck among the spindles, keeping the end effector from being pulled away from the plant.

A subsequent preliminary design has two-directional moving teeth (Figure 11) and could pick cotton bolls facing either the tip or side. The picked seed-cotton would be transferred through the fingers and would be doffed at the endpoint of the fingers. Evaluation of this approach is still in process.

SUMMARY AND CONCLUSIONS

Advances in machine vision, mobile computing and controllers have led to increasing automation of many agricultural processes. Initial data collect at multiple locations in the U.S. confirmed the hypothesis that cotton yield and quality could be improved with frequent harvest, depending on the environment. Initial efforts to develop autonomous equipment to automatically and selectively harvest cotton bolls have been successful. A new end-effector is being developed and will contribute to continued progress in automated cotton harvest. This work is still in its initial phases and more attention to overall system design and economic feasibility must be considered.

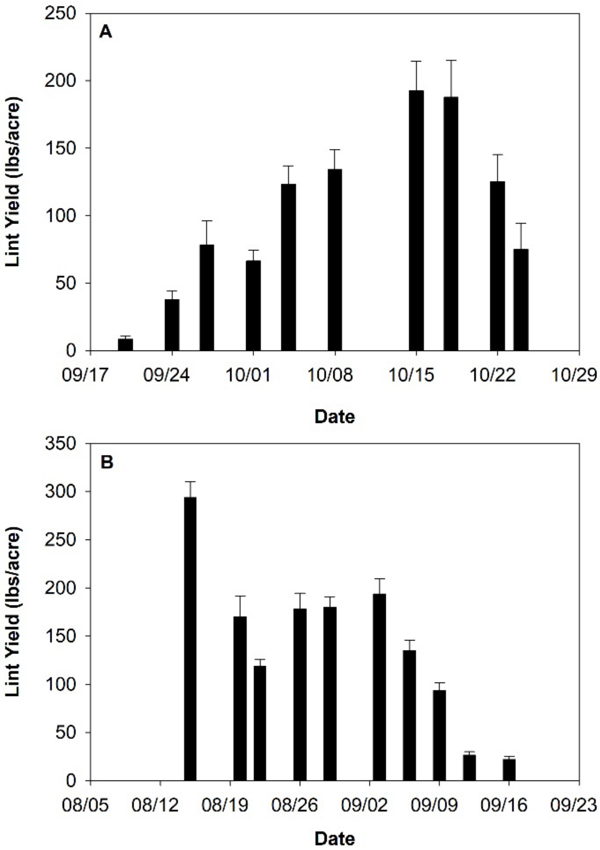

Figure 1. Lint yield for multiple sequential harvest dates during the 2018 (A) and 2019 (B) growing seasons near Tifton, GA. Values are means ± standard error (n = 12).

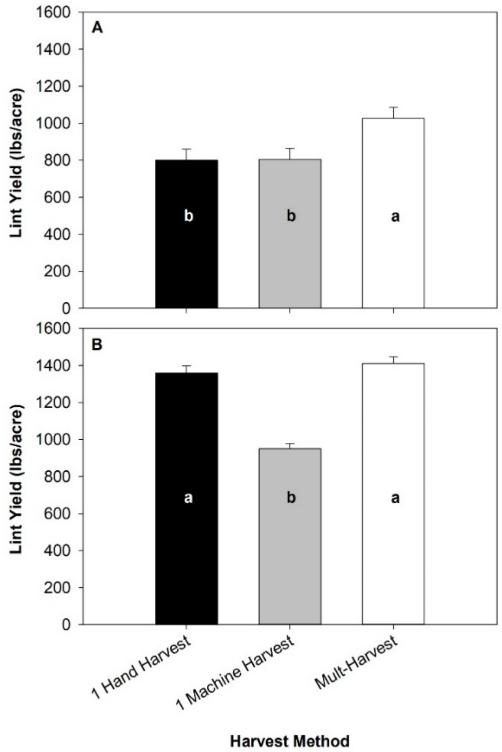

Figure 2. Lint yield for three different harvest methods during the 2018 (A) and 2019 (B) growing seasons near Tifton, GA. Values are means ± standard error (n = 12).

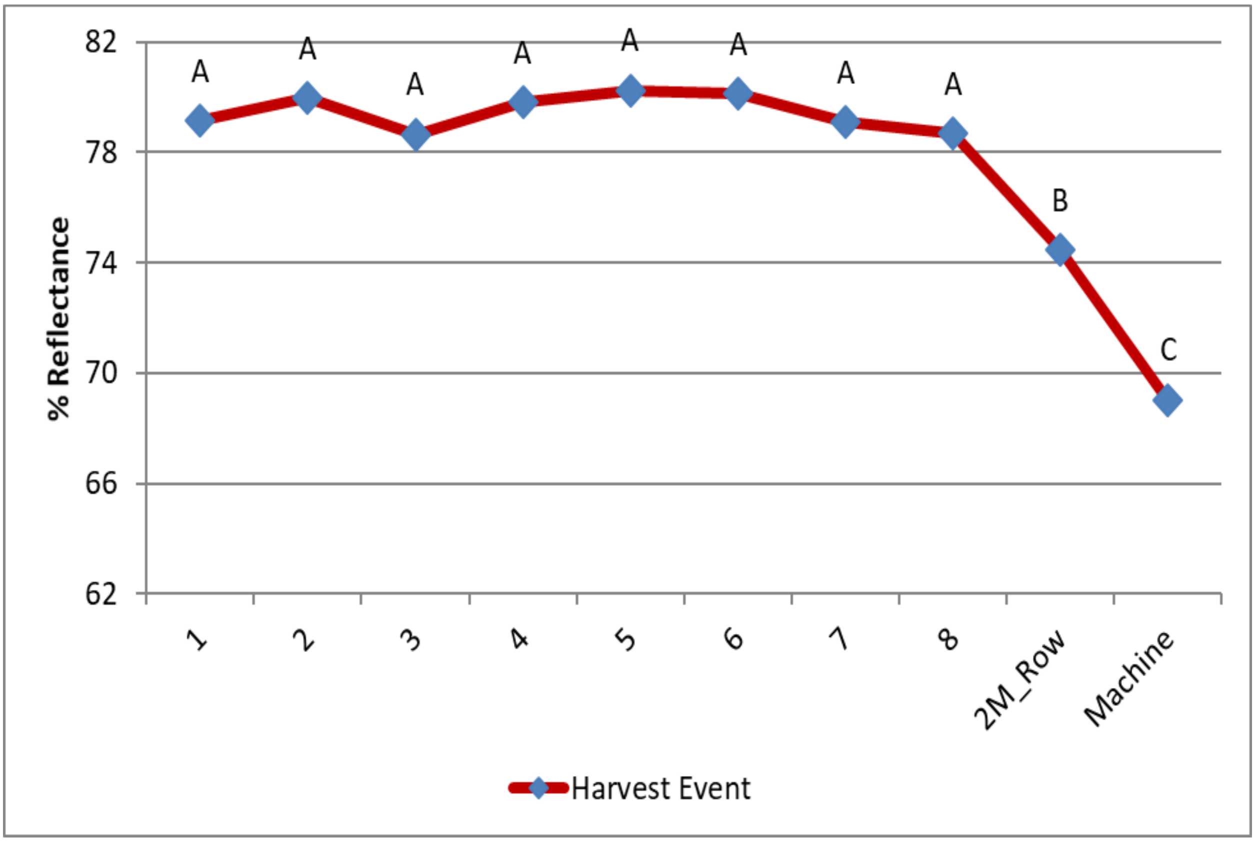

Figure 3. 2019 Reflectance percentage from HVI for each harvest timing and method at the College Station, TX.

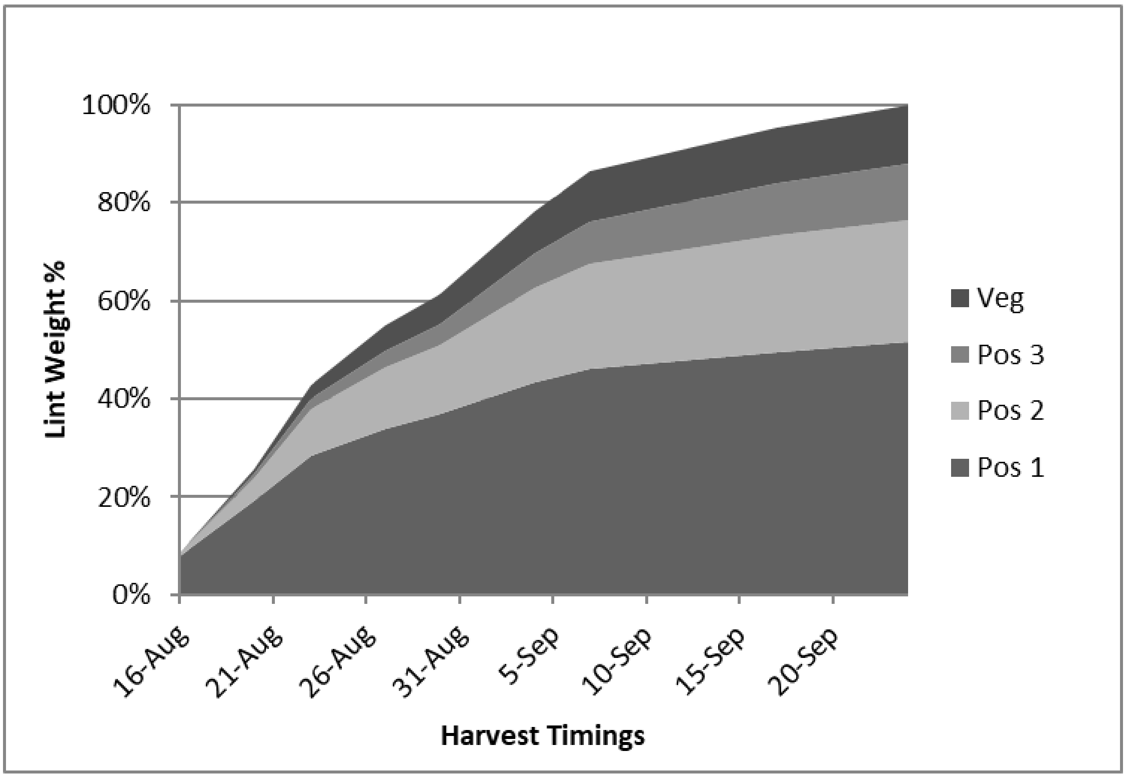

Figure 4. 2019 Cumulative Percentage of lint weight for each harvest and for each position at College Station, TX.

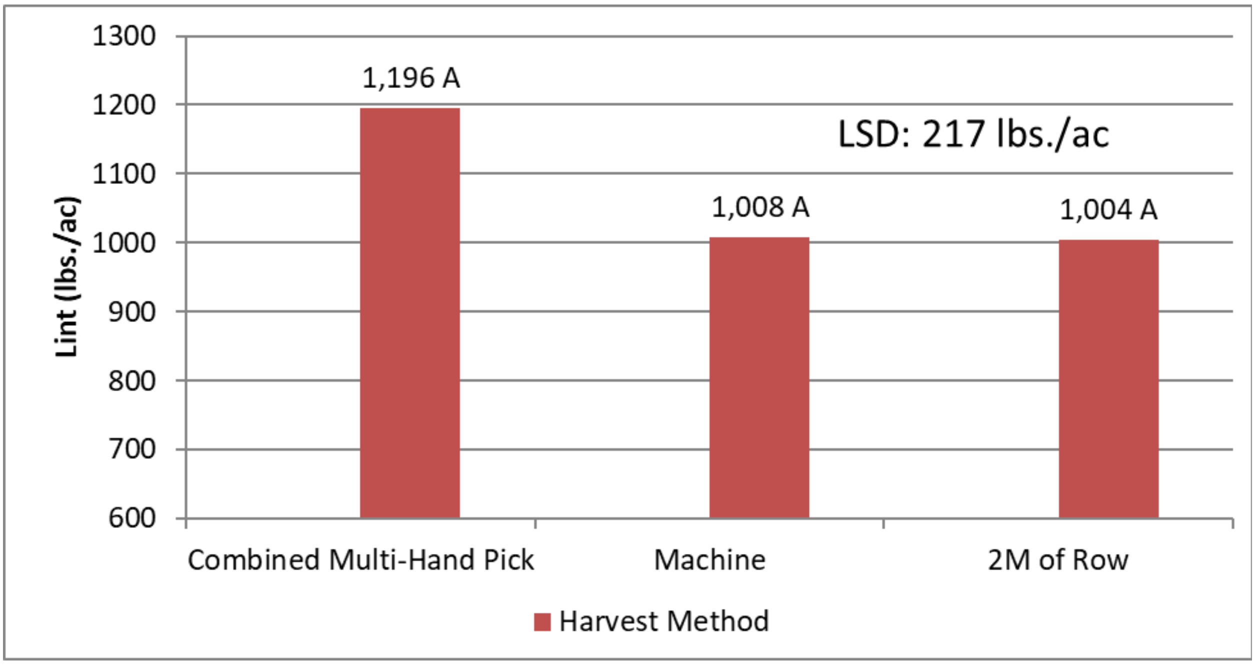

Figure 5. Combined lint yields for 2018 and 2019 for each harvest method in College Station, TX.

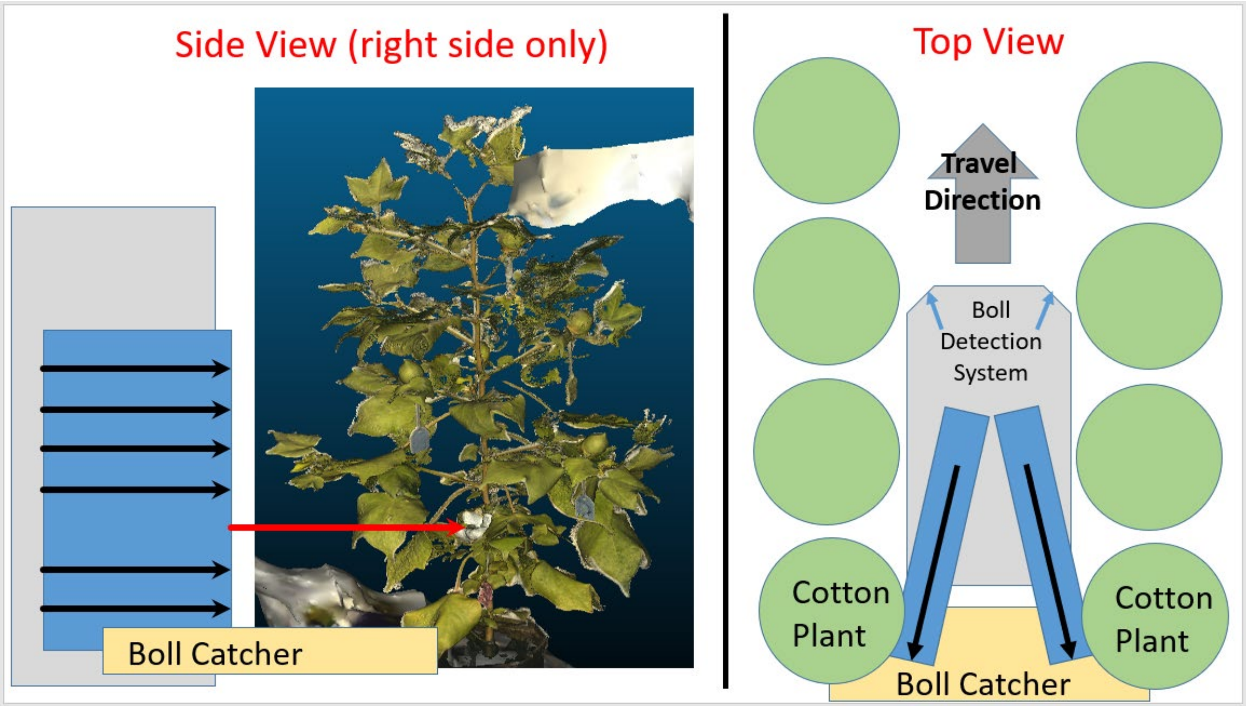

Figure 6. Conceptual robotic cotton harvest system (cotton plant representation complements of the USDA-ARS, Maricopa, AZ).

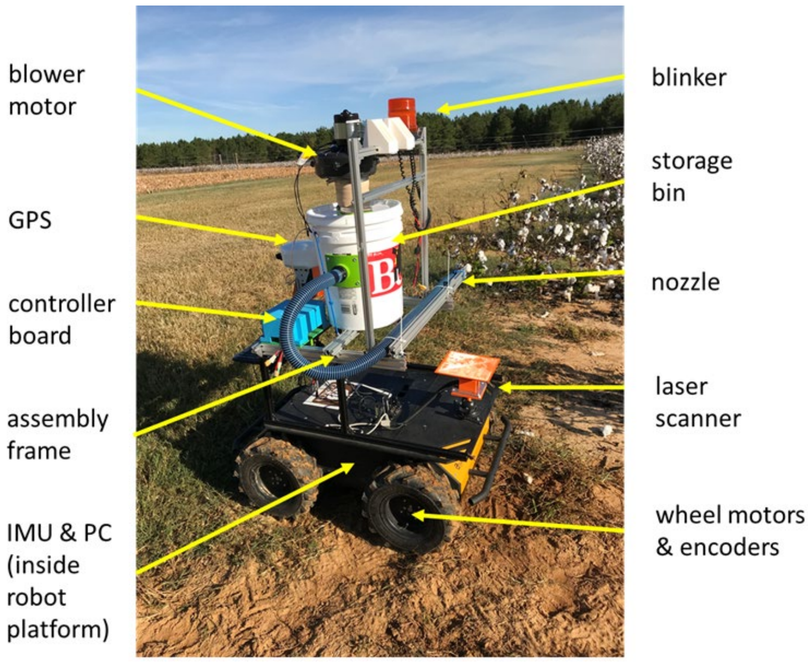

Figure 7. Mobile Robot Platform with a harvester module prototype for cotton.

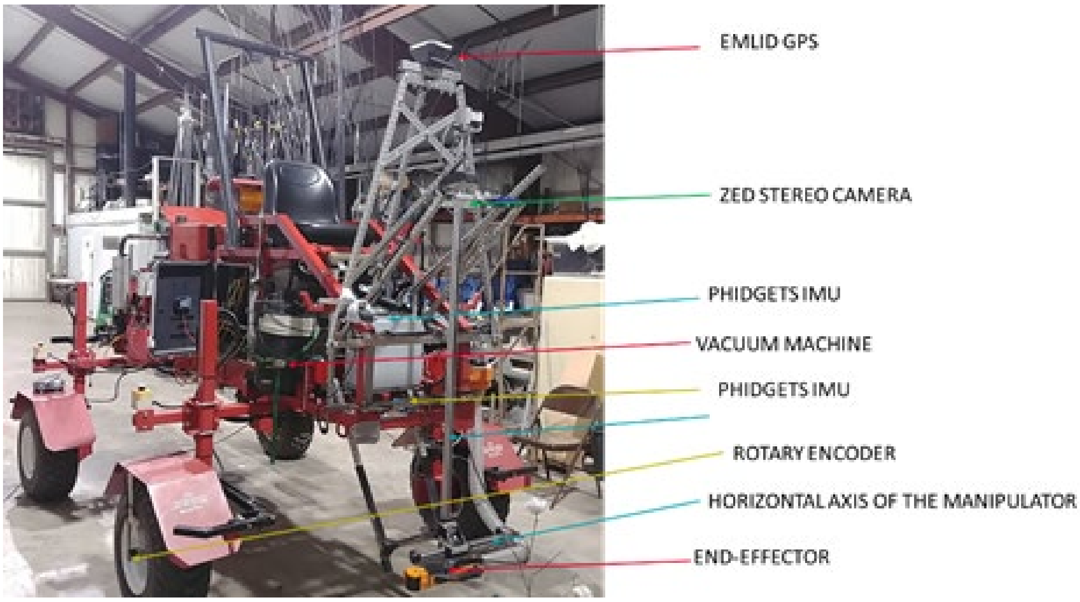

Figure 8. Red Rover platform for testing cotton harvesting system.

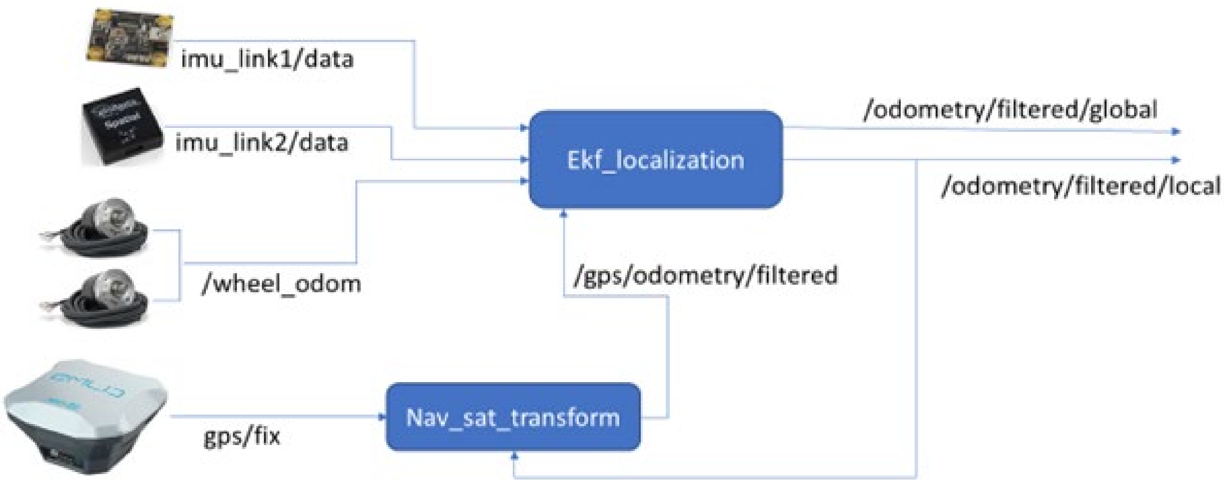

Figure 9. Simultaneous localization and navigation of red rover using a dual extended kalman filter.

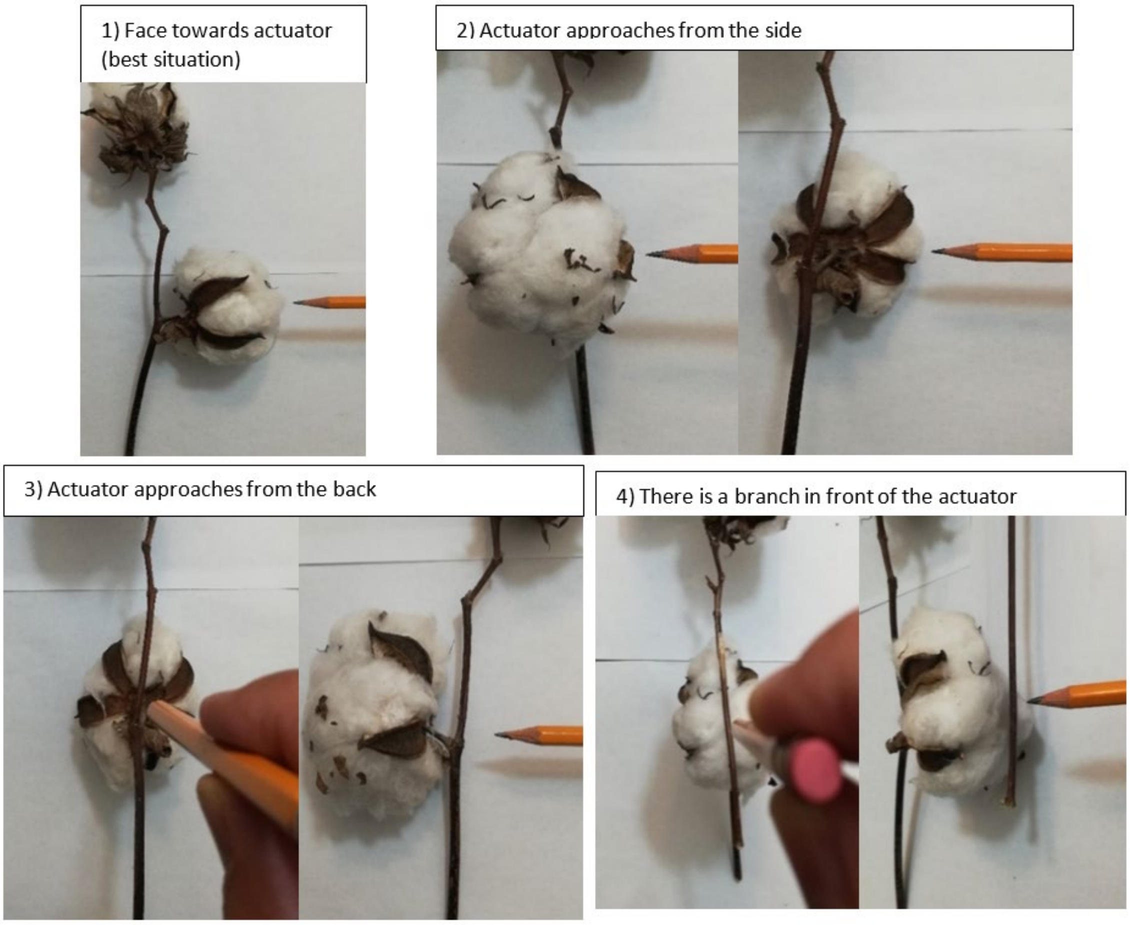

Figure 10. Different orientations and situations of a cotton boll on the plant.

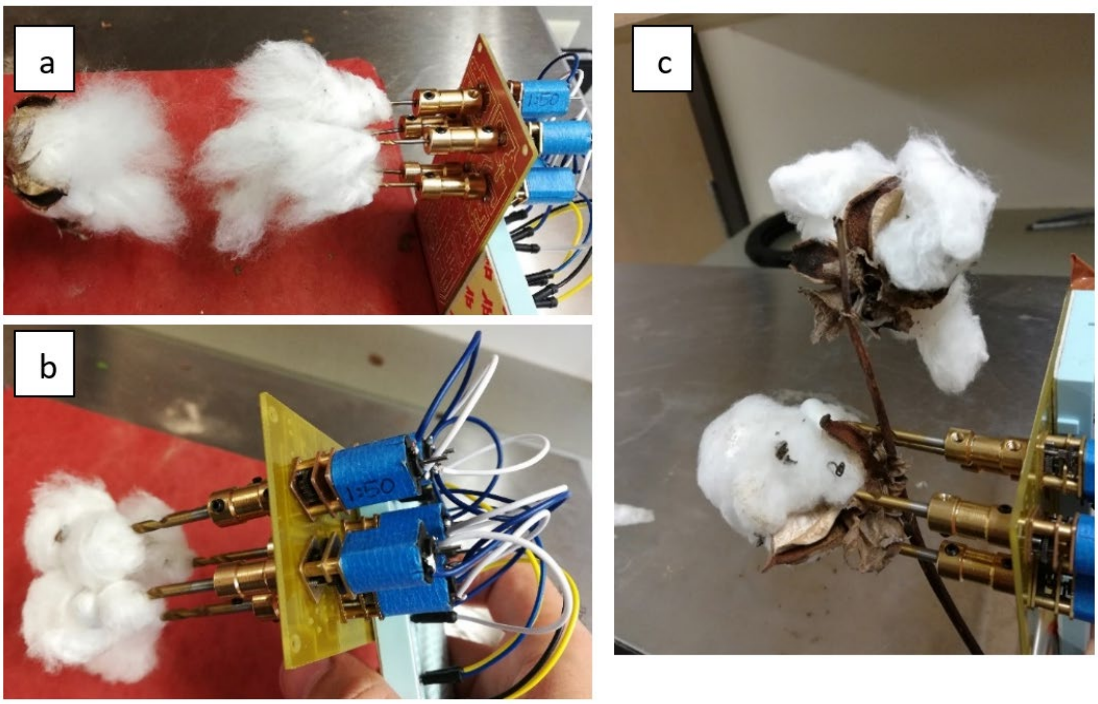

Figure 11. A five-spindle end-effector, a: seed-cotton isn't plucked completely, b: seed-cotton is wounded on two or more spindles at the same time which cased spindle bending, c: a branch got stuck among spindles.

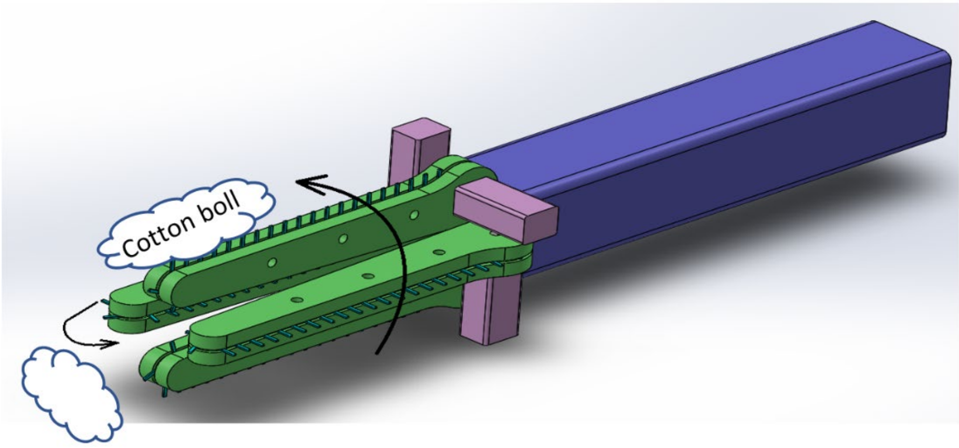

Figure 12. A computer aided design model of the end-effector which has two-directional moving teeth.

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