AUTOMATING ORCHARDS: A SYSTEM OF AUTONOMOUS TRACTORS FOR ORCHARD MAINTENANCE

Stewart J. Moorehead, Carl K. Wellington, Brian J. Gilmore and Carlos Vallespi

***Abstract*— This paper presents results from an extended field test of an autonomous multi-tractor system that performs mowing and spraying operations in a citrus orchard in Southern Florida. The system includes two autonomous tractors and uses a remote, human supervisor to assign tasks and help when needed. Each autonomous tractor detects obstacles with a perception system using ladar and cameras. The perception system makes use of both a geometric-based detector and an appearance-based classifier to detect hazards in the cluttered orchard environment and guide the tractors down the center of the tree rows. A mission planner uses a map of the orchard to produce optimized paths that cover the area requested by the supervisor. The paper also describes how the autonomous tractors fit into the existing orchard operations and how current practices used during manual spraying can improve the overall safeguarding of the autonomous tractor system by restricting access to areas of operation. The autonomous tractors have shown significant productivity improvements and have driven over 1,500 km, mowing and spraying, during field tests in the orchard.**

I. INTRODUCTION

Orchards require a great deal of maintenance throughout the year, from pruning to bloom thinning to spraying for insects and disease to just mowing the grass between the trees. Harvest is a major logistical event, requiring the transport of large quantities of fragile fruit and large numbers of seasonal workers. These activities make up a significant portion of operating expenses and improvements in efficiency can directly improve an orchard's productivity.

Many orchards are owned by large, vertically integrated agricultural companies who operate processing plants, such as a juice factory, in addition to growing the fruit. These companies have realized significant productivity improvements in their processing plants through the use of industrial automation, and are eager to utilize this technology in the field. In addition to productivity improvements, these growers recognize the potential for automation to reduce chemical exposure to their employees during spraying and help reduce the logistical difficulties of finding sufficient, skilled, seasonal labor.

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Figure 1 Autonomous tractors working in the orchard showing alternating bed rows (left) and swale rows (right)

Harvest is the most expensive and complex part of the seasonal cycle and the desire to automate this process is very high. However, skilled human pickers are able to pick fruit from trees very quickly and current robotic systems are much slower. Automation can aid the people picking fruit though, and work to develop automated, mobile picking platforms to replace ladders and automated vehicles to remove the fruit from the tree rows after picking, have shown great productivity improvements and made the work safer for the orchard employees [3][9].

Automation and advanced sensing in orchards can also provide greater information for the farmer. Multi-spectral imaging is being used to determine if trees are diseased [2]. Laser scanners are being used to measure tree canopy volume and predict fruit yields, control spray patterns and just keep track of how many trees are in the orchard [1][12][13]. These types of information have great potential to improve overall operational efficiency and can be combined with existing, manually operated tractors.

This paper presents an autonomous multi-tractor system that is currently being used to mow the grass and spray chemicals in a 1,300 hectare citrus orchard in Florida, USA (see Figure 1). Both mowing and spraying require a tractor to drive through the orchard and control the tractor power take-off (PTO) that drives the mower and sprayer implements. Further, both mowing and spraying occur regularly throughout the year, providing good utilization of the automated equipment. Automating spraying has the added benefit of removing people from a dangerous activity that is uncomfortable for current operators due to the large amount of protective gear that they must wear.

II. Environmental and Customer Requirements

As shown in Figure 2 the orchard is laid out using parallel rows of trees widely spaced, with the canopy of the trees pruned so that the spacing at the top of the trees is wider than at the base. This ensures maximum light penetration to the leaves, and has the nice side effect that it also provides good sky visibility for GPS.

The orchard used for testing in this paper had rows alternating between flat beds which are 22’ wide and swales which are small ditches for drainage and are 28’ wide as shown in Figure 1. Due to the different widths of these rows, the mowing uses different sized mowers – 10’ for beds and 15’ for swales. As can be seen in Figure 3 the orchard has many lagoons and wild areas, roads and canals. Additionally, the trees are laid out in blocks which are then combined into regions called pump zones (based on the location of irrigation pumps). The block and pump zone designation is how orchard operations are scheduled and so any automation system should also allow the orchard supervisor to set tasks for the autonomous tractors by block and pump zone. The autonomous tractors must understand the bed and swale structure so that paths are planned appropriately for the mower implement attached to the tractor.

Figure 2 Planting configuration

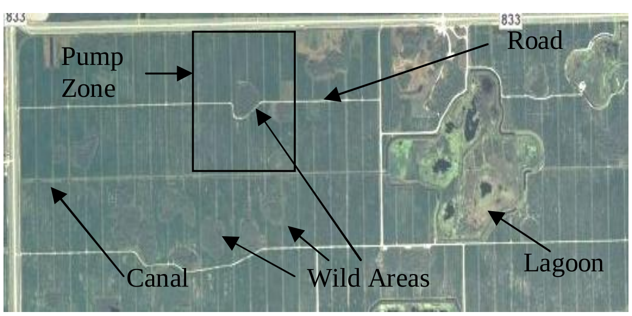

Figure 3 Satellite view of orchard

In addition to the trees, the orchard has many types of obstacles that an automated tractor must be aware of. They can be divided into two groups—fixed and moveable. Fixed obstacles such as canals, telephone poles and irrigation pumping stations are part of the orchard structure and can be incorporated into the orchard map. Paths can then be planned to ensure that these objects are not in the way. Examples of fixed obstacles are shown in Figure 4. Moveable obstacles cannot be placed in the orchard map, which makes them more challenging to deal with. They include other vehicles, people, orange picking bins and other equipment such as ladders. These objects can either be detected by sensors on the tractor or operational practices can be instituted that ensure no such objects are present in the orchard while autonomous vehicles are operating. These practices are similar to those already used while spraying is being done manually and include signage, physical barriers and communications to all employees at the start of the day. In practice, it is likely that a combination of the two methods will be employed.

Figure 5 shows a process map for the citrus orchard operations performed in the orchard throughout one year. As the diagram shows, spraying and mowing operations happen frequently and concurrently throughout the year. The continuous nature of this task makes it economical to automate since it ensures high usage of an expensive capital investment for an autonomous multi-tractor system.

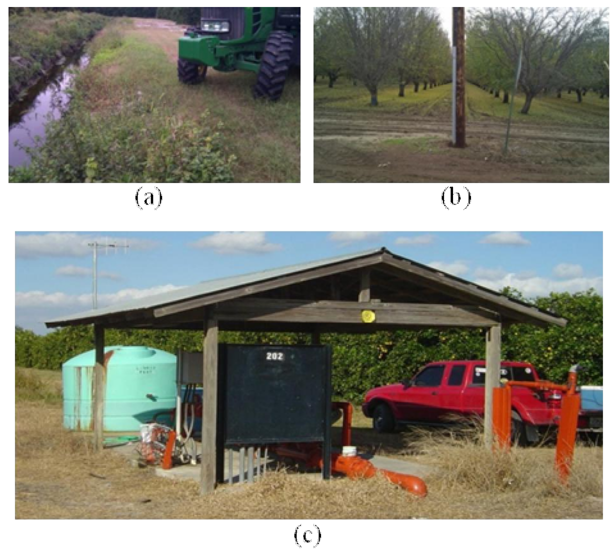

Figure 4 Example obstacles (fixed infrastructure): (a) Canal to left of tractor (b) Telephone pole in lane (c) Irrigation pump station

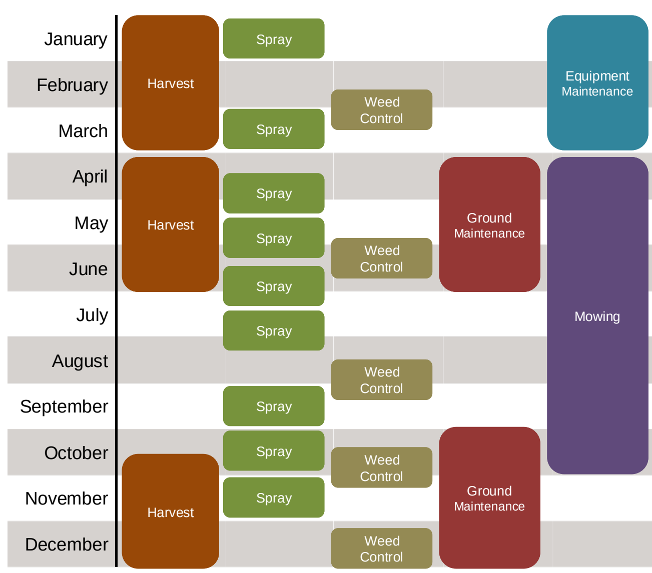

Figure 5 Example citrus orchard process map

III. AUTONOMOUS SYSTEM

The autonomous system implemented in the Florida orchard consists of two tractors that are capable of driving autonomously. Each tractor has a perception system to detect unexpected obstacles in the orchard, RTK GPS for localization to accurately follow the planned path and the ability to control the tractor functions such as the PTO and propulsion with an onboard computer [7].

While each tractor is capable of autonomous operations, they are part of a larger system that includes a remote supervisor [10]. The supervisor has several roles. First, the supervisor assigns each vehicle a task. This task is to mow or spray a block, set of blocks or entire pump zones. Secondly, the supervisor responds to requests from the tractor when the perception system is uncertain about what is in front of it, as described in greater detail below. Finally, the supervisor is able to track and observe what the autonomous tractors are doing at any time. The supervisor, however, is not a remote control operator controlling every action of the tractor, nor is he watching a video stream of the tractor, trying to detect hazards. The tractors operate autonomously and only contact the supervisor if there is a problem. This allows the autonomy system to focus on the repetitive simple parts of the application and err on the side of caution when something is unexpected, letting the human supervisor handle the complex parts of the application. The system layout is illustrated in Figure 6 and as the figure shows, the architecture is not limited to two tractors, but can support many tractors, limited only by the communications system and how frequently the supervisor must intervene with each tractor.

To facilitate communications between the supervisor and the multiple tractors in the 1,300 hectare orchard, two separate communication links are used. The first is a 900 MHz link that provides low bandwidth communications for mission critical data and heartbeat messages. The 900 MHz link has good coverage throughout the orchard and good penetration through the foliage of the trees. It ensures that there is always some communications between the supervisor and each vehicle. If this communication link drops for whatever reason, the autonomous tractor will stop. For the transmission of images and video, a 2.4 GHz network is used that provides the needed bandwidth but has poor penetration of foliage, requiring repeaters to get coverage throughout the orchard.

Each of the autonomous tractors has a computer mounted onboard called the Intelligent Vehicle Controller (IVC) which communicates to the remote supervisor over the wireless communications network, receiving tasks to complete and sending back status information. The IVC then controls the tractor functions such as speed, steering and PTO over a CAN bus. These commands utilize the ISO 11783 standard which is setup to allow implements to talk with a tractor. So, the IVC appears as an implement to the tractor. This architecture is described in greater detail in [6].

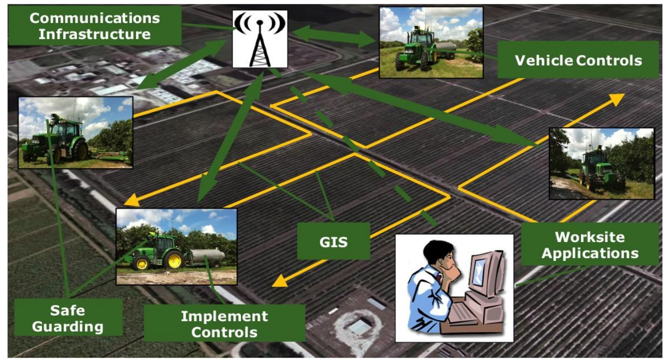

Figure 6 Autonomous system configuration

Each autonomous tractor has a perception system that allows it to see and understand the environment that it is operating in. While the operating processes described in Section V help to ensure that no people or vehicles are present in the area around the tractor and the path plans will keep the tractor away from fixed objects such as those shown in Figure 4, unexpected things such as fallen trees or a washed out canal bank can happen and should be detected.

To perceive the environment, the autonomous tractors use a laser scanner and color cameras registered with GPS. The laser scanner is mounted to a motor that nods the entire sensor up and down to create a full 3D view of the world. The color cameras need to have a very high dynamic range since the orchard has deep shadows next to bright sunshine. The use of multiple sensors provides much more information than a single type of sensor and each sensor can compensate for weaknesses in the others. These sensors can be seen in Figure 7.

Figure 7 Autonomous tractor perception head

Figure 8 shows the perception software architecture. The software needs to take the information from the sensors and decide if the tractor can continue driving or if it should slow down or even stop. Due to the constricted nature of the tree rows, it is rarely possible to drive around any obstacle so avoidance is not required. Thus the output of the system is a safe speed for the tractor. Slowing down when uncertain has the advantage that objects are seen more frequently before the tractor gets to them, helping determine if something is just a branch that the tractor can brush against, or if it is something it should stop for.

The perception system has access to the orchard maps that the path planner used to create the mission. This map indicates where the tree rows are (but not individual trees), fixed obstacles, roads and canals. This information is used in the Prior Obstacle Map of Figure 8 to detect pre-mapped hazards and provide context for the onboard sensor data.

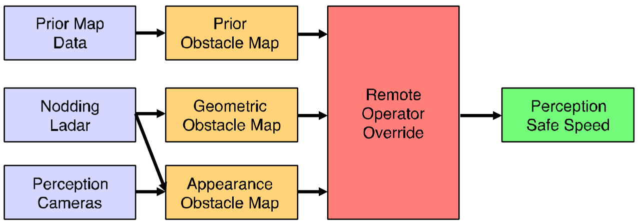

Figure 8 Autonomous tractor perception software architecture

The nodding ladar data is fed into the Geometric Detector that looks for obstacles based on the geometric properties of the scene [4]. This is a common way of performing obstacle detection and works well for detecting obstacles in areas without a lot of clutter. An example of the Geometric Detector output is shown on the top row of Figure 9 where a utility vehicle on the road is detected and shown in red in the rightmost image, and the canal dropoff is detected and shown in black.

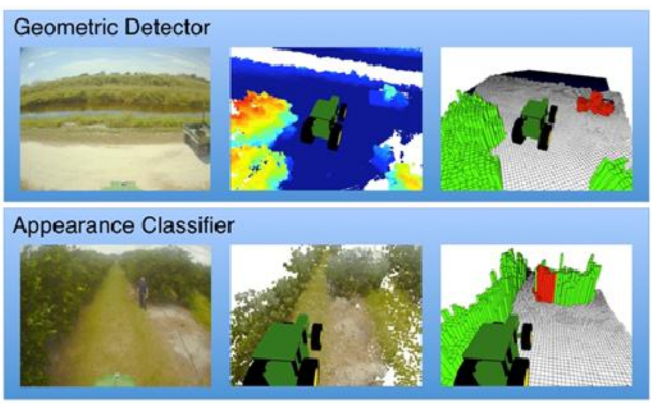

Figure 9 Example outputs of the Geometric Detector and Appearance Classifier. In both rows the leftmost image shows the scene and the middle image shows the sensor data (ladar height in the top row and colorized ladar points in the bottom row). The rightmost image shows the classified output of each algorithm with white being drivable, green is tree, red is obstacle, and black is a ditch.

While geometric-based obstacle detection works well in open areas where obstacles generally stand out, it has more difficulty in areas near the trees or with tall grass where the obstacle geometry mingles with the surrounding area. Both are common occurrences when mowing grass in an orchard. For these reasons, the perception system also makes use of an Appearance Classifier that combines camera and ladar data to detect obstacles based on their geometric properties and appearance. The Appearance Classifier is trained using large quantities of data from typical operations as well as labeled obstacles in different scenarios to optimize the system to distinguish between drivable ground, weeds, trees and obstacles.

An example of the complexity of the problem is shown in the bottom row of Figure 9. The detection of the person standing next to the tree poses a challenging case for a Geometric Detector since geometric cues may not be unique enough to distinguish the person from the trees. However, the Appearance Classifier can also use texture and color information cues to properly classify the person as an obstacle.

Using a combination of the Prior Obstacle Map, Geometric Detector, and Appearance Classifier, the perception system is able to operate in many challenging conditions, but the complex environment of the orchard means that the autonomous tractors are not always able to confidently decide that the route ahead is passable. Especially in areas where the weeds are very tall, during challenging lighting conditions, or in turns that require pushing into the trees or driving very close to the canals, the perception system may stop the tractor and signal the remote supervisor for help to determine if the path is clear.

Once perception safe speed goes to zero and the tractor stops, a message pops up on the remote supervisor's interface. The message, as seen in Figure 10, shows camera views to the front and both sides of the vehicle as well as an overhead map, providing context to the supervisor. The perception system identifies the potential obstacle by coloring it red in the images. The supervisor looks at the images and determines whether there is an obstacle or if this is a false positive and it is actually safe for the tractor to proceed. If the path is clear, the supervisor clicks on the Override Obstacle button, which masks out the detection and causes perception safe speed to rise, allowing the remote supervisor to initiate the motion approval process. If the supervisor is busy or unavailable when the tractor sends the obstacle message, the tractor will remain stopped until the supervisor is able to focus on the images and resolve the situation. This combination of autonomy with occasional requests for help allows one supervisor to oversee multiple tractors at once while keeping the perception problem tractable.

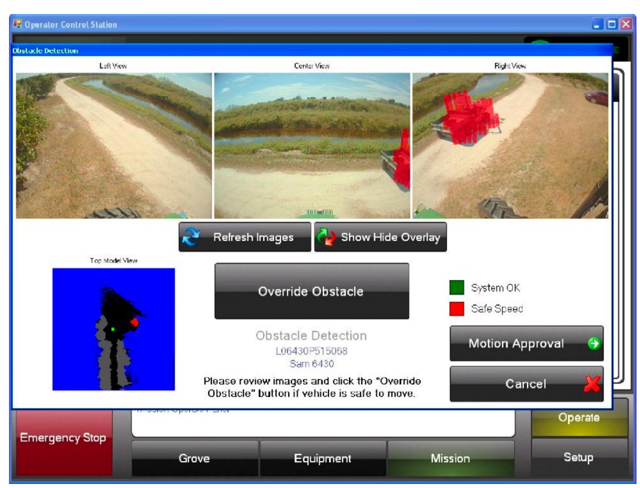

Figure 10 Screen shot from supervisor's interface showing a possible obstacle

IV. PATH PLANNING AND NAVIGATION

When the supervisor assigns a tractor a particular task, he also specifies the area to perform that task in. Individual tree rows can be selected, but more commonly a group of blocks or an entire pump zone is selected. Once the region and task are defined, a path planner generates a near-optimal coverage path for the tractor.

A person driving the tractor will normally perform a greedy search plan, typically just driving from one row to the next adjacent row. This works well for areas of the orchard without any obstructions, but as shown in Figure 3 there are often many untraversable areas that make it more challenging to determine the most efficient route. The path planner has the advantages of a complete map of the orchard and the ability to easily track where it has already traveled, so it can optimize over the entire job and perform more complex paths that can result in significant time savings.

The goal of the planner is to visit every row while minimizing overall operation time. This can be viewed as a Generalized Traveling Salesman Problem (GTSP) with each row treated as a city that can be entered from the top or the bottom. We use an efficient dynamic programming approach to turn the GTSP into a normal TSP, but the traveling salesman problem is combinatorial and NP-hard in the general case. We require optimization over approximately 40 rows, so computing the guaranteed optimal solution is intractable. However, the orchard has a lot of structure and in most cases neighboring rows are traversed sequentially. We therefore initialize the planner using a greedy solution, and then perform a heuristic neighborhood search that swaps the order and direction of rows and blocks of rows to find a near-optimal solution to the TSP quickly (under 10 seconds to optimize a pump zone on a standard laptop).

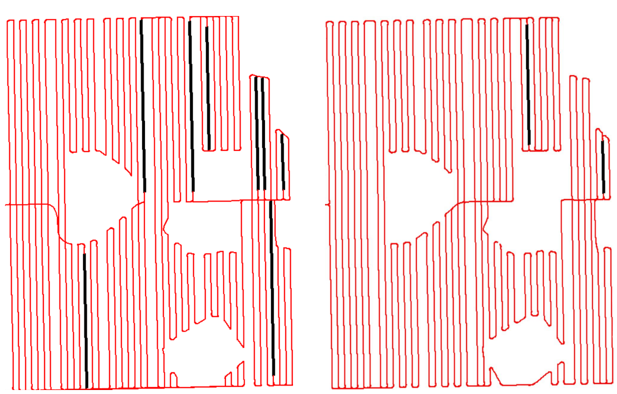

Figure 11 (a) Path plan for pump zone 203 using greedy search. (b) Path plan for pump zone 203 using optimized planner. Rows that are traversed twice are shown in black. The optimized path is 9.6% shorter.

Figure 11 shows plans for an entire pump zone as generated by a greedy search algorithm and the optimized planner. The total length of the greedy plan is 32,703m and would take the tractor 5 hours and 14 minutes to complete with no stops. The optimized plan has fewer duplicate rows where the tractor is driving down a row without performing work and is only 28,686m long, which would take 4 hours and 44 minutes to complete. This is a 9.6% time savings for a single pump zone.

Once the path plan is generated, it is downloaded to the tractor which proceeds to execute the plan. The vehicle uses RTK GPS and is able to very accurately follow the paths. However, the trees grow at different rates and are often manually hedged so relying only on RTK GPS for autonomous tractor guidance along straight row segments often resulted in the tractor pushing into the trees.

Other researchers have used cameras for guidance in agricultural applications by detecting various lines in the crop or field and computing a heading offset to keep the vehicle aligned with the crop – see [5] for a recent example or [8] for a summary of earlier work in this area. These approaches generally focus on using the detected lines to guide the heading of the vehicle, but in this application the lateral offset within the tree rows is more important, similar to [11], which tries to maintain an offset from detected trees using a height threshold from a ladar scan or a simple color classification from a camera image.

A similar approach to row guidance is used in this paper, leveraging the 3D ladar data from the perception system on the tractor, but expanded to include a tree classifier that combines ladar and camera data to differentiate between trees and tall weeds that are common in an orchard. The row guidance algorithm uses the computed tree map to find the lateral offset within the row relative to the original planned path that will keep the tractor from running into trees on either side. This offset is computed continuously and is applied to the original planned path to create a new path for the tractor to follow, as shown in Figure 12.

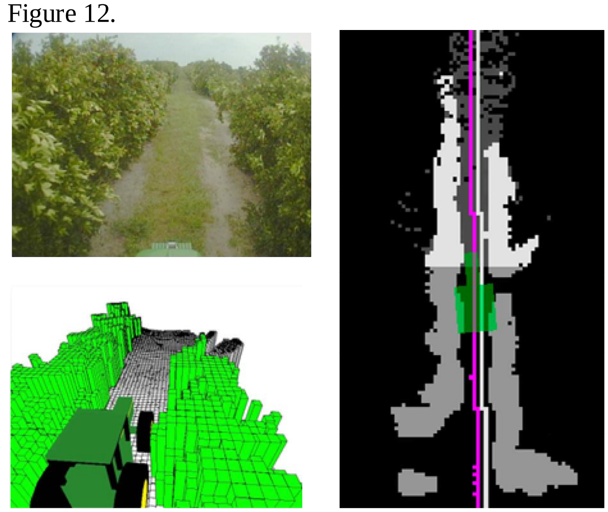

Figure 12 Example of row guidance. Top left shows tree row. Bottom left shows computed tree map with tree cells colored green. Right image shows original path as white line and row guidance adjusted path as pink line.

V. INTEGRATION INTO ORCHARD OPERATIONS

The autonomous tractor system needs to be integrated with current customer operations for the greater orchard worksite. The points of integration include: access control practices, Global Information System (GIS) integration, worksite applications and documentation or data management systems.

The orchard we operated in has an existing set of access control rules that have been setup to prevent the spread of disease and to safeguard employees from dangerous chemicals. The orchard has only one entrance where everything coming in and out is logged and sprayed to prevent the spread of canker disease. The rest of the orchard perimeter is either fenced or has a canal that happens to be full of alligators – providing a natural deterrent to casual guests. Inside the orchard, processes exist to restrict access to areas that are being sprayed. This includes signage at the restricted area, physical barriers across the road and verbal communications to all employees at the start of the day informing them of work to be done in the orchard that day. For the autonomous tractor system, these access control processes have several important factors. During the morning "all-hands" planning meeting, the robots can be assigned their tasks and given keep out areas by the supervisor. The other employees are also then made aware of areas an autonomous vehicle is operating and treat it as they would a chemical sprayer and stay away. The autonomous tractors can also make use of similar physical barriers and signage as used in spraying to further prevent entry. And finally the single access point to the orchard further restricts the chance of any people or vehicles being present in an area of autonomous operation. These process and perimeter defenses add to the total safety of the autonomous tractor system.

GIS integration takes place through the path plans required by the autonomous system. The orchard is mapped for passable beds and swales (areas that the tractor traverses), headlands, roadways and obstacles or hazards like telephone poles, pump houses, trees and canals. For mowing operations, separate path plans are developed for the beds and swales to accommodate the different implement sizes. Since the orchard is mapped, the paths can be tested for maneuverability by the tractor and the implement and adjusted if required. The mowers are stopped and lifted to cross the roads to minimize damage to the mower blades and the road. Due to the cost of the spray material, the sprayer nozzles are turned off at points in the orchard where a gap in the rows of the trees exist. Initially, this was achieved using a stand-alone commercial sprayer that uses ultrasonic sensors to sense if trees are present. However, as an alternative to show added value in the autonomy system, the tractor perception system has been integrated with a CAN bus controlled sprayer to automatically control individual nozzles based on the perception tree maps, thus avoiding the cost of the ultrasonic sensors needed for the commercial sprayer [13].

Through "worksite apps" the system has been fully integrated into orchard operations. Worksite Apps are created for each field operation, like mowing. In these Worksite Apps, the remote supervisor assigns the tractor and implement pair to an orchard pump zone and sends the command to execute the desired work-plan. A day's worth of work can be planned in a very short time.

Documentation and data management is becoming more important to farms as they seek to maintain compliance with government regulations, try to understand how different practices affect yield, track where various crops were grown and respond to customer desire to know more about how their food is grown. The autonomous tractor system provides an ideal platform to collect, systematically and reliably, information about how the orchard is being maintained, what chemicals are applied, when, where, and how much. Since each autonomous tractor has RTK GPS, they are able to tag all information gathered with a very accurate position and time that is valuable for data storage. All of the operations of the autonomous tractors are logged, providing historical data for analysis. Finally, the obstacle detection system is able to record when obstacles are present as well as high resolution maps of the trees, providing a way to track growth, inventory and perhaps even tree health through volume of canopy [1][13].

While it was important to understand how the orchard currently operates to ensure a complete design of the autonomous tractor system, it was also important to compare its performance with the existing manual method of mowing and spraying the orchard. This comparison provides a quantitative estimate of autonomous tractor productivity gains.

A manually-operated tractor was instrumented with a GPS receiver to measure its speed as an indicator of productivity. The speed records of an autonomous tractor and manual tractor are compared by their speed histograms. Figure 12 shows the speed histograms for each tractor plotted as cumulative percentiles. The plot shows that the manually-operated tractor spends 74% of its time at 5 km/h or below, while the autonomous tractor spends less than 35% of its time at 5 km/h or below. The autonomous system operates at its maximum speed range for 65% of the time, while the manually-operated tractor speeds less than 5% of its time at its maximum speed range. As with many manual operations there is time allocated for breaks and other personal needs. In addition to the stops, the manually-driven vehicle has greater variation in drive speed than the autonomous one. By maintaining a constant travel speed and not stopping for breaks, the autonomous tractor is able to perform more work in a shorter period of time, while reducing fuel usage.

Productivity is also gained through efficient path planning as described in Section IV. Figure 14 shows a GPS location trace for a manual operation. As characteristic of manual operations (and similar to the greedy path in Figure 11) there are segments in the path that are not required to accomplish the task. Autonomous paths are generally shorter than those generated manually and since the path planner does not forget where it has been, the planner can optimize the paths by skipping rows to catch them later on, which is difficult for people to do. Skipping rows can eliminate sharp turns at the ends of the rows which may require backing up to complete, which takes significant time. In irregularly shaped areas, skipping rows can reduce the need to backtrack (redo a row) while covering the area.

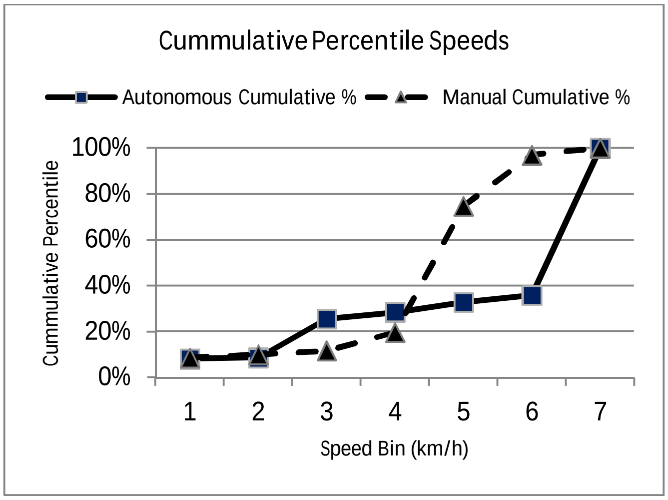

Figure 13 Cummulative percentile tractor speed histograms. Graph shows the percentage of the total mission time that the tractor drove at the particular speed or lower. For example, the value shown for speed bin 4 is the amount of time spent driving at 4 km/h or slower. The percent of time spent driving at 4 km/h can be found by subtracting the amount shown in speed bin 3 from that in speed bin 4. The graph shows that the autonomous tractors spent much more of their time at maximum speed than did the manually driven tractor.

Figure 14 GPS trace of manual operation

The combination of a constant driving speed, no breaks, more optimal path plans and the elimination of backing up all add up to a significant productivity improvement of a single autonomous tractor over a single manually-driven one. With multiple tractors supervised by a single person as described in this paper, the productivity gains continue to increase. Data collected over several months of field testing in a Florida citrus orchard show significant productivity improvements based on number of acres covered in a day when comparing the autonomous system versus a human operator. These results are shown in Figure 15.

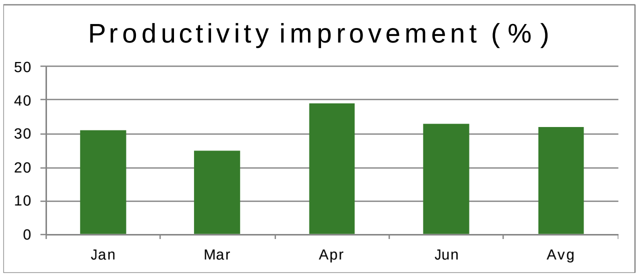

Figure 15 Productivity improvement due to autonomous operation

VI. CONCLUSION

This paper described an autonomous multi-tractor system being used to mow the grass and spray in a citrus orchard located in Southern Florida, USA. The system uses a remote, supervised autonomy methodology where a person acts as a supervisor to assign tasks to individual tractors and to provide assistance to a tractor when it is unable to determine if the path forward is clear.

Orchards are a very promising environment for autonomous tractors. With existing processes in place to keep people out of orchards during spraying and the strong structure of the environment, it is possible to operate autonomous tractors safely. Many orchard owners also operate processing plants to create juice or other processed products and are familiar with industrial automation and the potential of robotics. Additionally, the sensors on the autonomous tractor can be combined with GPS to enable other precision agriculture applications such as yield prediction, tree inventory, disease detection, spray control, traceability, and monitoring to occur while mowing or spraying operations are being performed, increasing the data available to the grower to improve orchard efficiency at all levels.

Extensive field testing has shown the orchard to be a challenging environment for autonomous vehicles. Growers maximize the number of trees by keeping the space in the headlands between the end of the tree row and the canals as small as possible, making it challenging to reliably make turns without hitting trees with the implement or getting too close to the canals. Swales can fill with water and mud that gets the tractor stuck. Tall trees in the unplanted sections of the orchard block radio signals and make communications a challenge. Tall, thick grass and weeds grow between the tree rows and the tractor must drive over this while mowing. The trees create sharp shadows next to bright sunlight and missing trees and changing sun angles cause these shadow patterns to change, making everything look different. All of these factors make perception challenging.

Despite these challenges, the autonomous tractors described in this paper have operated over much of the orchard and provided value to the grower by mowing and spraying as part of their normal operations. By leveraging a single supervisor to oversee the team of autonomous tractors, each tractor is able to handle the simple cases and err on the side of caution, relying on the human supervisor to help with the hard cases. As the autonomous system performance improves, the workload on the supervisor decreases, allowing them to oversee more tractors at once. This architecture has proven to work well and over the last 18 months, these two autonomous tractors have driven over 1,500 km while mowing and spraying in the orchard and shown a significant productivity improvement over traditional methods.

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