Intelligent In-Orchard Bin-Managing System for Tree Fruit Production

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***Abstract*— The labor-intensive nature of harvest in the tree fruit industry makes it particularly sensitive to labor shortages. Technological innovation is thus critical in order to meet current demands without significantly increasing prices. This paper introduces a robotic system to help human workers during fruit harvest. A second-generation prototype is currently being built and simulation results demonstrate potential improvement in productivity.**

I. Introduction

Effective and efficient production is becoming a greater challenge to the tree fruit industry in the United States due to its heavy use of labor during harvest season. Harvest is a labor-intensive process, and labor shortages threaten the viability of the tree fruit industry in the long term. To overcome this problem and maintain the industry's competitiveness in the global marketplace, technological innovation is required.

A traditional tree fruit harvest consists of four steps: in-orchard bin-positioning, fruit picking, bin-filling, and bin-transporting. In the first step, human workers use a forklift-like machine to place empty bins at different locations within the orchard. Next, the workers pick fruits from the tree and unload them to the nearest bin. Once a bin is full, it is transported to a collecting point (repository) by a forklift. Among those four steps, bin-positioning and fruit picking are the most labor-intensive tasks with high associated costs. Our (unpublished) preliminary study shows that human workers typically spend less than half of their time picking fruit. The rest of their time is used to move, reset, climb ladders, and walk to and from bins. Therefore, there is a critical need to reduce labor cost by utilizing autonomous robots to assist workers during these processes.

Current robotics technology is capable of meeting this need by providing a robotic self-propelled fruit bin carrier system for transporting bins [1]. Our work aims to develop a multi-robot system to assist human workers in placing and moving bins in the orchard to allow for efficient harvest (Fig. 1). The most significant challenges are: (1) building a fully autonomous bin carrier capable of traveling through different terrain, (2) precise localization and navigation inside orchards, and (3) efficient coordination among multiple robots. To achieve this, we have designed a mechanical prototype, engineered a localization and navigation system, and created a simulation for an auction-based approach for multi-robot coordination.

Fig. 1. Autonomous bin-managing system to assist harvest in orchards.

II. Hardware Design

Our robotic bin-management system will be tested in the Pacific Northwest region of the U.S. Most tree orchards in that area are structured with parallel rows of trees separated by empty lanes that allow access for vehicles and fruit pickers. At the ends of the tree rows there is typically a free area known as the 'headland' that allows access to the lanes and turning space for vehicles. Typically, lanes between tree rows are 2.2-3.5 m wide, and the headland area is 4.0-6.0 m wide. A robot operating in an orchard would be expected to navigate along rows and make turns in the headland without collision.

To address the challenge of navigating a robot in this environment, we focus on four problems. First, the ground surface in the lanes between tree rows is typically wet or dry soil with low compaction. Wheeled vehicles operating in this environment suffer from frequent wheel slip due to low soil strength and insufficient normal force. Second, narrow headland areas and spacing of tree rows makes collision-free navigation difficult. Third, an L-shape turning pattern with narrow row entrances may be difficult. Fourth, in order to successfully locate, contact, and lift a bin, the robotic platform requires accurate estimates of the relative bin position.

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Fig. 2. Mechanical structure of the concept-approval testing prototype of the proposed bin-dog robot

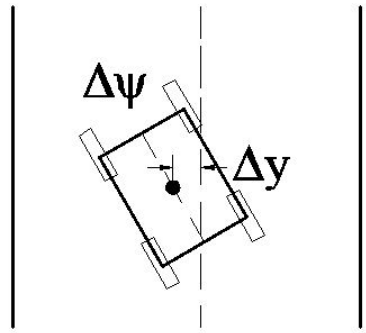

Fig. 3. The dashed line is the desired straight line of the trajectory. Based on the location of the robot, we calculate the distance offset value Δy and the heading angle error $\Delta\Psi$.

To fulfill the requirements, as shown in Figure 2, a concept-approval testing prototype of the proposed bin management robot ('Bin-dog') was designed and fabricated in 2013. The mechanical structure of this prototype consists of four subsystems of driving, steering, bin lifting, and frame leveling. The prototype was powered using a 9.7 kW gas engine, with all the implementing subsystems driven by electronically controlled hydraulic systems via bidirectional proportional control valves.

The robot features a 'bin-straddling' design. This allows it to drive over a bin so that it does not need to change its path when there is a bin blocking the way. To further improve the maneuverability of the conceptual-approval platform, a wheel-ground engagement system (WGES) and a four-wheel independent steering (4WIS) system will be added to the current prototype. The WGES will be developed to improve the maneuverability of the robot by reducing wheel slip ratios, which will solve inaccurate execution of maneuvering actions on the robot. The 4WIS system will be developed to maximize maneuverability in orchard environment by providing steering modes such as four wheel coordinated steering, crab steering and spinning.

III. Autonomous Navigation

The navigation module will be responsible for controlling the movement of robots both outside the tree rows (using differential GPS) and between tree rows (using local sensors). We focus on the second, more difficult case.

A. Localization Methods

To achieve effective localization between tree rows (where GPS is unreliable), the relative distances of objects is used. The relative distance data (relative location), will be collected from laser scanners, as was done in previous work [2]. The data will be analyzed to quickly estimate the distance from the center of the tree row and its relative orientation to the row. We are currently using an LMS 111, a laser scanner from SICK, to design and test our sensing algorithms.

Ultrasonic sensors, a type of unidirectional distance sensors, will also be tested. Multiple ultrasonic sensors can be mounted on the two sides of the robot to directly sense the distances toward tree rows. Because of the spacing between the leaves, data will be noisy, and different filtering techniques will be tried. We currently focus on using a simple Kalman Filter by treating the spatial distribution of leaves on the tree as noise. Although much less reliable than a laser scanner, ultrasonic sensors are orders of magnitude less expensive. If successful, they could significantly reduce the cost of the unit, or provide additional sensing for a small increase in the price.

B. Navigation Modes

After a robot's trajectory is determined, we define several navigation modes to specify the use of sensors and control of the robot.

Straight-line tracking: First we need to make sure that the robot moves forward straight along the planned trajectory. When running on open field, we can generally trust the absolute location data collected by GPS. But when operating between tree rows, we calculate the trajectory-tracing error based on the relative location data. During the robot movements, the navigation algorithm calculates the real-time running error. It then sends the running error (offset and heading angle) to the mechanical control units, and the units produce the actual control signals to the mechanical actuators. With this method, the robot is capable of following the planned trajectory. Figure 3 shows a simple working situation and how we quantify the running error.

Turning: Turning along a desired trajectory is more complicated because the actual control of actuators can vary due to the motion status changing. Turning actions take place on the headland when the robot needs to access the working area between trees. Since there are no landmarks to help the robot turn, it will need to calculate the tracking error using absolute location data supplies by the GPS receiver.

Bin Operation: Once the robot is close to a bin, the bin can be used as a reference to adjust its relative position. Besides the laser scanner, ultrasonic sensors are mounted on the front side of the robot. These ultrasonic sensors can perceive the relative position of the target bin. Instead of relying on the distance towards lateral trees, the robot can simply start to activate the front sensors to collect data to successfully approach and lift the bin. Once the bin is lifted, navigation can be resumed as normal.

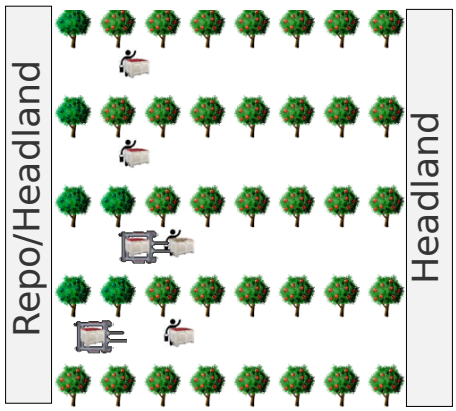

Fig. 4. Layout of the orchard environment in the simulation.

IV. Multi-Robot Coordination

We propose our multi-robot approach for the problem in this section. We focus on how to coordinate multi-robot efficiently, so the bin management can be improved.

A. Simulation Setup

To test a number of multi-robot coordination approaches, we create a simulation of the typical orchard conditions in the real world. The remainder of this section provides the detailed parameters and variables of the simulator.

Figure 4 shows the layout of the simulation environment as a 10×5 grid world. The leftmost and rightmost column are headland. The repository (i.e., a collecting point) is located in the leftmost column. Robots can move horizontally within the harvest area and are only allowed to move vertically in the leftmost and rightmost columns.

According to our conversations with orchard managers, they are working to make the distribution of fruit uniform. In the simulation, we assume that the fruit are uniformly distributed, with enough fruits in one grid to fill two bins. Usually, 5 pickers work together in a group to fill one bin. In our simulation, the number of groups is set to 4 and 8 with 5 pickers in each group. Thus, there are 20 and 40 pickers in total. In the real world, 1 to 5 pickers usually work together to fill one bin. Since each picker can fill one bin in one hour, a bin can be filled in roughly 12 minutes if 5 pickers work together. A picker can usually fill 8 to 10 bins per day. To simplify the problem in our simulation, one group consisting of 5 pickers can fill one bin in two time steps. Since one of the goals of this project is to have a scalable approach, we use 2 to 20 robots in our simulation.

The robot's speed depends on whether it is carrying a full bin. A bin-carrier with a full bin moves slower than without a workload. In our simulation, a robot moves 2 grids per each time step while not carrying a full bin and 1 grid otherwise. At this early stage of research, all robots are assumed to have unlimited communication range within the environment.

B. Problem Statement

Groups of simulated workers are initialized randomly within the harvest area in the orchard. Bins are placed at locations where there are workers. All robots start from the top-left grid. Once the simulation starts, workers begin filling the bin at their location. When the bin is full, the workers request a new bin, which will be delivered by a robot. If there is no more fruit in a location, the workers move to a new location, sending a new bin request for that location. Workers cannot harvest fruit if there is no bin at their location, and they must instead wait for a bin to be delivered.

A robot in our system thus has to make two decisions: (1) which (potentially) full bin should be picked up (and returned to the repository), and (2) where it should carry a new bin (a robot can only take a new bin if it is at the repository in the leftmost column). Once it makes a decision, it proceeds to complete its task and only makes another decision when it has finished its current task.

C. Algorithm Design

Our approach makes robots coordinate with each other using auctions based on the market framework [3]. Before discussing the detailed algorithm, we first explain a baseline algorithm.

The baseline algorithm is designed to use a greedy approach. An idle robot selects the closest full bin from its current location to pick up. If there are no full bins in the orchard, the robot estimates the closest bin that will be filled soonest based on the number of workers at the bin's location. Once it selects a bin, the other robots cannot choose to pick up the bin, even if their distance to the bin is closer than the first robot. Selecting a new location is also done greedily: an idle robot selects the earliest (unfulfilled) request made. A robot only considers taking a new bin to a requested location if it does not see any bin that can be picked up because all bins in the harvest area are, or will be, taken by the other robots.

One potential improvement to the greedy baseline approach is in the bin selection process. Instead of a single robot greedily selecting the closest (potentially) full bin, we want the robots to perform some coordination to achieve a more optimal solution. In our current implementation this coordination is done using one-turn English auction [4].

An idle robot scans the orchard environment to identify possible bins to pick up, which will be subsequently called *idle bins*. A bin is considered idle if there is no robot that is on the way to pick it up and it is not being carried by another robot. The robot then makes a list of plans to pick up one of the idle bins and assign a cost to each plan. The cost C to pick up the bin in plan p is formally defined as:

$$C_p = T_t + T_w$$

where T_t is the time required to reach the target bin and T_w is the estimated time of the robot to wait for the target bin to be filled. Each idle robot then sorts its plans based on the associated cost, with the plan with the lowest cost being the most preferable.

Once all idle robots construct their plans, they broadcast their plans to each other. If their most preferred plans conflict, the robot with the lowest plan cost wins the auction.

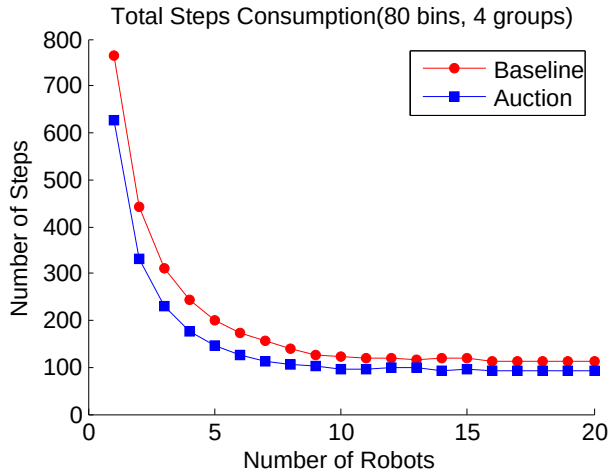

Fig. 5. The number of steps required by different numbers of robots to retrieve all bins to the repository.

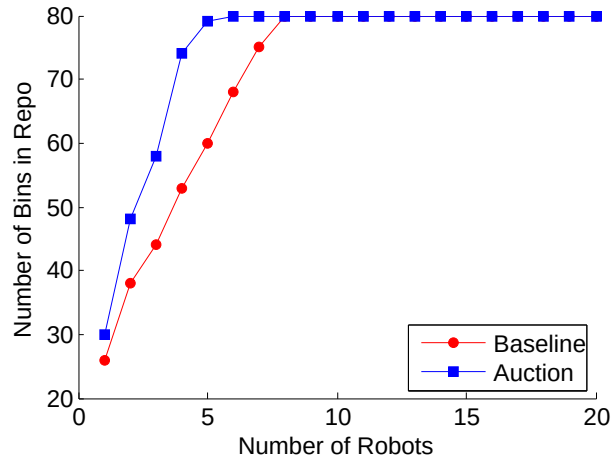

Fig. 6. The number of full bins returned to the repository by different algorithms in 150 step limits.

The other robots then remove the auctioned plan from their list and start broadcasting their next preferred plans. This process is repeated until all idle robots have a plan to execute. However, if a robot cannot win any plan, then it will not pick up any bin.

After the plan selection process, a robot also considers carrying a new bin to a requested location. If the robot has a target bin to pick up, it estimates whether there will still be fruit at the target bin's location. If so, the robot takes a new bin to that location. Otherwise, it has to make another decision to choose a requested location to deliver a new bin to. In the case where a robot does not have a target bin, it chooses to carry a new bin to the closest requested location.

A straightforward way to select a requested location is to calculate the time required to travel between the target bin and the requested location. A seemingly efficient method is to choose the closest requested location to the target bin.

D. Experimental Results

We evaluate our algorithm with different simulation setups to observe its scalability. We observe its performance in a 5×10 grid world with 4 groups of workers. With this setup, fruit in the orchard will fill a maximum of 80 bins. As can be seen in Figure 5, the number of steps required to finish harvesting by the baseline and autonomous robots with auction-based coordination converge slowly, although our proposed algorithm still produces better results (i.e., fewer number of steps) compared to the baseline.

Figure 6 shows the number of full bins returned to the repository within a 15 step limit. The maximum number of bins is 80 — systems with large numbers of robots finished harvesting in fewer number of steps. As can be seen from the figure, our proposed algorithm consistently outperforms the baseline algorithm.

V. Conclusion and Future Work

In this paper we design a robotic system to help transport bins in tree fruit harvest. We describe the challenges and the current hardware design. We also describe the navigation setup. We develop a multi-robot coordination algorithm and analyze some preliminary results.

As the next step in hardware design, we will add a coordinate control system to intelligently determine steering modes and driving speeds based on the level of posture error (offset error and heading error) and its current task. For navigation, we will specify instruction codes used as the communication protocol between the navigation level and the mechanical level. We will also focus on realization and improvement of the perception sensors on the real prototype. We need to test the reliability and efficiency of the navigation modes and instruction set to improve the actual navigation control of the robot. Finally, we will explore learning methods to determine the humans picking speeds, potentially yielding more efficient coordination between humans and robots.

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