Auction-based Task Allocation Mechanisms for Managing Fruit Harvesting Tasks

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***Abstract*—Multi-robot task allocation mechanisms are designed to distribute a set of activities fairly amongst a set of robots. Frequently, this can be framed as a multi-criteria optimisation problem, for example minimising cost while maximising rewards. In soft fruit farms, tasks, such as picking ripe fruit at harvest time, are assigned to human labourers. The work presented here explores the application of multi-robot task allocation mechanisms to the complex problem of managing a heterogeneous workforce to undertake activities associated with harvesting soft fruit.**

***Index Terms*—Task Allocation Mechanism, Multi-Agent System, Agent-Based Simulation**

I. INTRODUCTION

Multi-robot task allocation (MRTA) problems address situations in which a group of robots must work together to complete a set of tasks. A key challenge is to decide which *tasks* should be assigned to which robots so that a *mission* is accomplished by using resources efficiently and maximising rewards. Auctions are a popular approach because they offer the ability to be flexible and adapt to changes in the environment, as well as balance priorities when multiple criteria need to be considered in the allocation of resources.

As mentioned within the literature [1]–[4], auctions are executed in “rounds” that are typically composed of three phases: (1) tasks are announced to a set of agents, (2) the agents bid on the tasks and (3) an agent is rewarded the task with the winning (e.g. lowest) bid. A prominent strategy in the literature is the *sequential single-item (SSI)* method [5]. SSI is fast (the auction runs in polynomial time in the worst case) and efficient, while also being able to produce an allocation that is close to or within a guaranteed factor away from optimal.

Applying multi-robot teams to *agricultural robotics* [6] has recently been gaining attention. This extremely challenging application domain presents many opportunities to consider not only traditional problems faced in robotics around (e.g.) control, sensing and manipulation, but also emerging issues around human-robot collaboration. One of these challenges is to allocate fruit harvesting tasks to human (and in the near future robotic) labourers efficiently.

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II. METHOD

We have developed a simulation of the harvesting process on a small strawberry farm in which tasks are allocated to workers by applying an auction-based mechanism. Harvesting fruits involves two types of tasks and two types of agents that address those tasks: *pickers* harvest fruit in the field and place the produce in punnets; and *transporters* collect full punnets and deliver them to a centralised location called a pack house.

Our simulation (developed in MASON [7], which is a light-weight, multi-agent simulator) is shown in Fig. 1. The coloured patches represent the picking tasks; the colour indicates the number of ripe fruits: red indicates a relatively high number of ripe fruits and green a low number. Each patch contains information on how many ripe fruits are occluded by the canopy (leaves). This illustration was created based on the yield of one day during the 2020 season. Pickers are represented as grey triangles, starting at the left edge of the field, and transporters are represented as grey circles, starting in the pack house.

We compare three different auction-based mechanisms [8], for allocating picking and transporting tasks: *Round Robin* (RR) assigns the first task to the first agent, the second to the second agent and so forth. After one task has been assigned to each agent, the process is re-iterated to assign each agent another task. This process continues until all tasks have been assigned to an agent. In *Ordered Single Item* (OSI), all agents bid on the first task and the agent with lowest-cost bid is assigned the task. The subsequent task is then auctioned. When all tasks are assigned, the process concludes. For *Sequential Single Item* (SSI), in each round all unassigned tasks are bid on by all agents. The task of the lowest-cost bid is assigned to the agent who placed that bid.

Pickers are defined by the tuple $p = \{v, l, S^p\}$, where

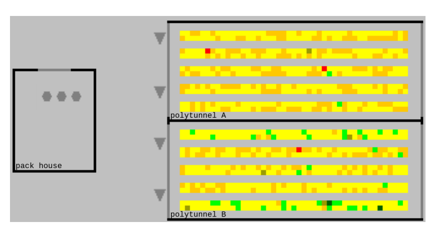


Fig. 1. Our strawberry farm within the simulation. See text for explanation.

l is the agent's initial location and v its navigation speed; $S^p = \{s^o, s^u\}$, the agent's occluded (s^o) and unoccluded (s^u) fruit picking speed. The cost of a picking bid is the number of timesteps it takes the picker to navigate to the picking location, pick the ripe occluded and unoccluded fruits, and, when necessary, wait for a transporter. After a picker has filled a punnet with strawberries, it cannot pick any further fruits, and so a transport task is generated.

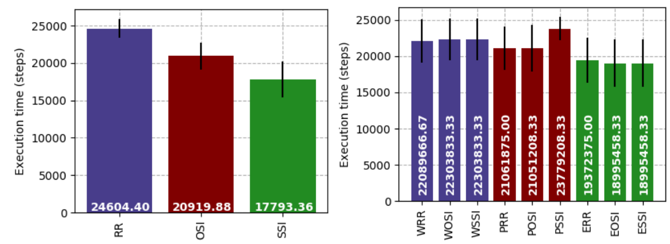
Transporters have a navigation speed and an initial location, i.e., $r = \{v, l\}$. The cost of a transporting bid is the time it takes the agent to navigate to the picker, collect the filled punnet and take the punnet to the pack house. Three different modes were implemented for allocating tasks to transporters. For all 3 modes, implementations of RR, SSI and OSI were developed. To differentiate between these and the mechanisms implemented for allocating picking tasks, each adds a prefix to the mechanism name (e.g. WRR):

- *Whilst scheduling picking* (W): Transporters can be scheduled as soon as a transport task is created. This enables a picker's bid to include the time spent waiting for the transporter.
- *Post scheduling picking* (P): The transporters can be scheduled after all transport tasks have been created (i.e. all picking tasks have all been assigned). This could result in the creation of a closer to optimal schedule for the transporters (but potentially at the expense of the pickers).
- *whilst Executing picking* (E): Alternatively, transporters can be scheduled during execution, which facilitates delays (e.g., due to collision avoidance) to be accounted for within the transporters' schedules.

The aisles (i.e. the spaces between the crop rows) are too narrow for agents to pass side-by-side; therefore, two agents of the same type cannot be within the same aisle, and transporters can only enter an aisle if the picker they are assisting is performing the task they require assistance with. If an agent cannot enter an aisle, it waits beside the aisle. These rules can cause deadlocks to occur as transporters and/or pickers could be delayed and blocked from entering an aisle. To prevent deadlocks, a transporter swaps its current task with a task that appears later in its own, or another transporter's, schedule. Collisions in open spaces are avoided by the agents making adjustments to their paths or waiting.

III. Results

We performed a series of experiments, with four different picker configurations (i.e. picking speeds and initial locations) and two random assignments of ripe fruits (that were counted during the 2020 picking season) to fruit patches. These experiments employed 4 pickers and 3 transporters. We compare the three auction mechanisms used for scheduling pickers (RR, OSI and SSI) and nine mechanisms for scheduling transporters ($\{\mathsf{RR}, \mathsf{OSI}, \mathsf{SSI}\} \times \{\mathsf{W}, \mathsf{P}, \mathsf{E}\}$). The results were analysed using factor analysis in order to determine the influence of picker or transporter mechanisms individually or in combination. As expected, SSI results in the shortest execution time (i.e. time it takes to perform the mission). Figure 2a illustrates that there are statistically significant differences for the execution time. Figure 2b shows the ablated results for all combinations of transport task scheduling modes and auction mechanisms, demonstrating that ESSI and EOSI results in the shortest execution times. ESSI and EOSI are equivalent since only one task is available to auction each time the auction is run. Overall, when the results for each picker scheduling mechanism and each transporter scheduling mechanism and mode are ablated, SSI is the superior auction mechanism for assigning picker tasks and E with OSI or SSI is the superior mode for assigning transporter tasks.



(a) Picker scheduling mechanisms ($H = 150.04, p = 0.00$). (b) Transporter scheduling modes and mechanisms ($H = 45.40, p = 0.00$).

Fig. 2. Factor analysis. The statistical significance (H and p statistics), calculated by running Kruskal-Wallis tests [9], are reported in the captions.

IV. Conclusion

The experiments presented here explore the application of auction-inspired task-allocation mechanisms to assigning strawberry harvesting task to pickers and transporters. A data-backed simulation of a real-world soft fruit farm is presented. Our current work involves scaling the results to larger farms, using data recently obtained from two commercial farms with over 500 pickers at each farm in the height of the season. Early results indicate that the trends seen here will hold.

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