Multi-Objective Scheduling for Agricultural Interventions

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Abstract. Monitoring crops and fields is an important aspect in the agricultural sector to prevent droughts, floods or the spreading of insects and diseases. We introduce an intelligent solution to monitor agricultural environments. The system learns a model of the underlying field which it then uses to plan an optimal monitoring schedule. By interactively querying the preferences of the decision maker, we define a weighting to optimise over multiple objectives in the schedule, such as visiting frequency, intervention frequency and distance. We implement this as an interactive demo, called CropBot, using LEGO Mindstorms.

Keywords: Multi-objective optimisation · Scheduling · Planning

1 Scheduling for Interventions

In an agricultural setting, monitoring crops is important to increase their yield and prevent failures related to climate as well as insects and diseases [3]. A naive monitoring approach can be devised, which scans the field linearly and alerts the decision maker whenever it encounters a reason for them to intervene. Depending on multiple factors, such as the size of the field and vulnerability of the crops, this strategy may, however, be undesirable. We introduce an alternative approach for scheduling monitoring trajectories, leveraging advances in artificial intelligence.

Our system learns a statistical risk model of the field by collecting data such as the relative frequencies of insects, diseases and climate-related problems encountered and uses Bayesian inference to compute the posterior probability of a risk at each cell given the current evidence. The learned model is subsequently used to plan an improved monitoring schedule, similar to methodologies used in model-based reinforcement learning [2]. We highlight that planning a monitoring schedule is a multi-objective decision making problem [4], for which the optimal trade-offs depend on the preferences of the farmer. Therefore, to plan a new route, the field is discretised into cells and the expected value for each cell is computed by optimising over three distinct objectives. Currently, the system supports minimising the time each cell goes unchecked, minimising the travel distance and maximising the number of high-risk cells it visits. The weights for this optimisation process are determined interactively with the decision maker by asking them several questions about relevant trade-offs. Furthermore, these weights can be changed at run time without impacting the learned model of the environment. In the final step, a trajectory is determined which maximises the total value to the end point using the A* path-finding algorithm [1].

2 The CropBot Demo

We introduce a demo designed using the *LEGO Mindstorms Kit*, called CropBot[4]. The CropBot demo consists of two parts, namely the robot itself acting independently in the field and a live dashboard used for interactively determining the preferences of the decision maker and visualising the current belief over the world state of the system. Both components are depicted in Fig. 1.

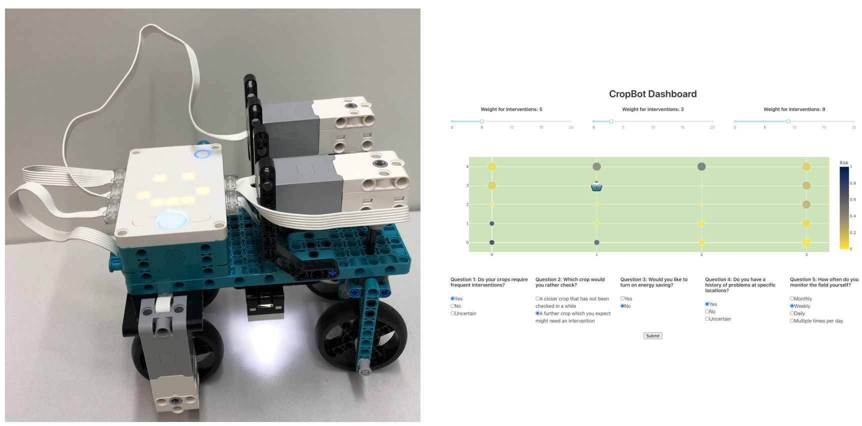

Fig. 1: A side by side view of the robot and the interactive visualisation.

For future work, we intend to focus on three aspects. First, we plan to further improve the preference learning by utilising insights from prior work [6]. Second, we aim to model the setting as a Markov-decision process to apply reinforcement learning for better routing strategies [5]. Lastly, based on the learned model of the environment, the system could move beyond being merely reactive by suggesting adaptations to the farming practices to further increase crop yields.

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[4] A video demonstration is available at `www.youtube.com/watch?v=S94POi-k4IA`.

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