Multi-Agent Reinforcement Learning for Heterogeneous UAV Swarm Enabling Detailed Crop Health Assessment

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***Abstract*— Over the last few years, precision agriculture has advanced significantly with the aid of unmanned aerial vehicles (UAVs) and multi-agent systems (MAS). Traditionally, UAVs exhaustively scout the field and predict crop health, but this practice levies higher costs in terms of energy and execution time. In this paper, we propose an alternative approach where UAVs sample only a part of the field to predict the overall crop health. The selection of areas in the field to be sampled is based on different indices such as NDVI (Normalized Difference Vegetation Index), GLI (Green Leaf Index), and NDWI (Water Index). These vegetation indices indicate various factors of plant health. By correlating and quantifying these indices, we can assess the overall health of the crop field. Moreover, the individual indices provide a finer level of detail in precision agriculture, allowing for targeted measures to enhance yield. Our approach employs reinforcement learning and deep learning techniques to autonomously scout and predict the crop health map. Preliminary results show that by sampling only 40% of the field, we can generate a health map with 90% accuracy. This approach reduces labor costs by 4.8 times and increases profits by 36% compared to traditional methods.**

I. Introduction

The rapid growth of the global population and the increasing demand for food necessitates swift advancements in agricultural practices to meet the pressing needs of humanity. Projections indicate that the combination of population expansion and heightened per capita food consumption will require a substantial 70% increase in agricultural yields by the year 2050 [1], [2]. However, the looming challenge of climate change is exacerbating the complexity of farming, as it contributes to stressors on crop health, such as drought, diseases, and pest infestations [3]. These adverse effects are projected to lead to a considerable reduction in crop yields by up to 11% by 2050 [4].

Precision agriculture occupies a pivotal role in meeting the escalating global food demand, as it centers upon the optimized utilization of resources and the maximization of yields through the strategic integration of technology. This, in turn, contributes significantly to the stabilization and reliability of the global food supply chain. Precision agriculture is a promising step toward improving efficiency and reducing adverse impacts of agriculture production [5]. It assesses the variation across the crop fields and divides the field into multiple management zones. So they can be treated efficiently and effectively [6], [7]. The advent of digital agriculture, or data-driven precision agriculture, employs a suite of tools including remote sensors (e.g., satellites and UAVs), in-field sensors (such as embedded soil sensors), and data processing techniques (e.g., machine learning)[8]. This combination informs decisions related to planting, harvesting, and crop treatment, all aimed at maximizing yield and minimizing the environmental impact of agricultural activities. Frequent sensing using these technologies enables the detection of crop health stress due to factors like drought and heat, the identification of diseases, pests, and other harmful phenomena [9], [10], [11], [12]. A pivotal task in digital agriculture involves transforming the collected data into health maps, providing valuable geospatial insights into crop health, and guiding effective crop treatment strategies, commonly referred to as crop scouting.

Traditionally, data acquisition is approached through two main methods: human piloting of UAVs to capture high-resolution images or UAVs autonomously scouting the entire fields. Human pilots, while capable of capturing accurate data, tend to escalate operating costs due to the need for frequent field mapping. Conversely, the autonomous UAV scouting method is cost-effective, but it often leads to redundant data due to a 60-70% side overlap in captured images. Moreover, both approaches necessitate frequent battery replacements due to limited flight times [13], which subsequently extend execution times and have an impact on profit margins.

The UAVs are equipped with various imaging sensors, including RGB, multi-spectral, thermal, and hyper-spectral. RGB cameras are well-suited for tasks such as growth prediction, biomass estimation, and canopy height measurement. On the other hand, multi-spectral cameras excel in early detection of drought stress, identification of pests, yield prediction, and their combination with thermal and hyper-spectral data enables estimation of nutrient status, pathogen presence, and weed detection [14]. Unlike RGB cameras, multi-spectral cameras capture both visible and invisible light spectra, enhancing the assessment of crop conditions and thereby enabling more informed agricultural decisions [15], [16]. Hyper-spectral and thermal cameras capture distinct bands of the invisible light spectrum. Hyper-spectral sensors are particularly effective in the early detection of pathogens and diseases [17], while thermal cameras are effective in identifying drought stress in crops [18]. RGB and multi-spectral cameras are commonly used whereas hyper-spectral and thermal are less common due to relatively higher costs [19].

Given the limited payload capacity of UAVs, they are constrained to carrying only one imaging sensor at a time

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[20]. Consequently, achieving a comprehensive analysis of a crop field necessitates the deployment of multiple drones. However, employing multiple drones for scouting an entire field introduces additional operational and maintenance expenses that may outweigh the potential gains. The increased costs associated with utilizing multiple drones can present a challenge in terms of maintaining profitability.

Contributions: In this paper, we present an efficient method for detailed analysis of whole-field without exhaustively scouting entire field. We employ a swarm of heterogeneous UAVs with distinct capabilities. We utilize multi-agent reinforcement learning to scout crucial areas through competing rewards, as a result battery replacements and payload requirements are minimized. The collected data is combined and extrapolated to provide deeper insights on crop health eliminating the need of exhaustive scouting of the whole field.

II. Methodology

This approach can be divided into two major alternating components: 1) RL algorithm for exploration and sensing, 2) extrapolation algorithm for creating a health map from sensed data. Each UAV will continually cycle between selecting their next location based on the estimated health map and updating the estimated health map by extrapolating from sensed data. Together all agents will pool their results into a combined extrapolated health map.

A. Reinforcement Learning Algorithm

We use a modified version of Q-learning and a MARbLE architecture to select the path to be sensed through multi-agent reinforcement learning [21]. As shown in figure 1 the UAVs explore during the initial phase and then try to maximize the utility of visiting a particular management zone. The states are the x and y coordinates of the management zones and the utility or reward of each action is the error between the predicted values from the CNN and the observed values. Ultimately, the Q-table is updated with the reward from the combined goal and budget preferences from the MARbLE algorithm. These rewards are updated using Bellman's Equation, as shown below.

$$Q(s_i, a_i) = (1-\alpha) * Q(s_i, a_i) + \alpha * [R(s_i, a_i, s_{i+1}) * \gamma \max(Q(s_{i+1}, a_{i+1}))] \quad (1)$$

Equation 1 calculates the maximum reward with learning rate α and a discount factor γ taking into account the immediate and long-term rewards.

To create a generalized and transferable model we use filters while populating the Q-table. The observed rewards are quantified based on their variance such that the observed pattern can be transferred to different fields as well.

B. Extrapolation

While the UAV explores the field, the health map is continuously extrapolated using the newly gathered data at each step. This extrapolation is crucial, as it provides an accurate foundation for decision-making within the RL algorithm. The RL algorithm aims to maximize the percentage error gain between predicted and ground truth values, thereby systematically reducing the error associated with the projected health map. To extrapolate the health maps, we employ Convolutional Neural Networks (CNN). This extrapolation is built on the premise that distinct sensor readings correspond to various aspects of plant health. This concept is akin to human health diagnostics, where different tests reveal diverse health issues that may also be interconnected. For instance, in humans the identification of calcium deficiency through the Total Calcium Test (TCT) can potentially indicate the presence of osteoporosis [22].

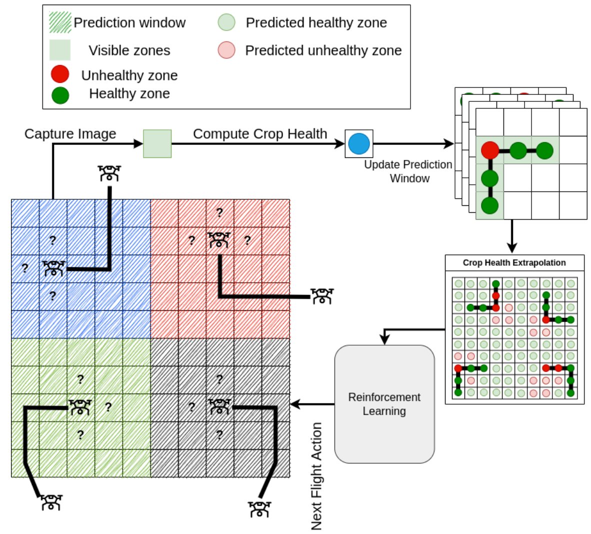

Fig. 1: An illustration of crop scouting using 4 UAVs with distinct capabilities through CNN extrapolation and Reinforcement learning

We quantify comprehensive crop health by combining data from different health indicators such as NDVI, NDWI, and GLI. This combination allows us to present an overarching picture of the crop field's health. Moreover, the extrapolated individual health maps associated with these indicators offer more intricate insights, aiding in the identification of precise measures necessary to enhance the crop's well-being. The quantification of overall health based on different health indicators (NDVI, NDWI, GLI). Furthermore, the overall health map complements the decision making in multi-agent reinforcement learning.

The design of the CNN is based on U-net Architecture [23]. The input to the CNN is observed health maps, and the output is fully predicted health maps.

III. Preliminary Results

Our previous work using RL for crop scouting and CNN for extrapolation with single agent employing RGB camera provide promising results [24]. A health map is predicted with 90% accuracy by scouting only 40% field and hence reducing labor costs 4.8 times and boosting profit by 36%.

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