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PROGRAM BOOK

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Day 1, May 20 (Mon.) | Scientific Program

S3-3 Technical Section 3: Plant Production

16:30 - 18:00 Halla A (3F)

Chair(s): REZA EHSANI (University of California at Merced)

S3-3-01
16:30-16:45

Optimizing accuracy in AI models: balancing real and synthetic data

Author: DAEUN CHOI (University of Florida)

Co-author(s): OMEED MIRBOD (University of Florida)

S3-3-02
16:45-17:00

The innovation and application of precision agriculture technology in citrus orchards: a multidimensional study based on UAV remote sensing and deep learning

Author: YALI ZHANG (South China Agricultural University)

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HAOXIN TIAN (South China Agricultural University)
XIPENG FANG (South China Agricultural University)
SHIZHOU WANG (South China Agricultural University)

S3-3-03
17:00-17:15

An Improvement to the CNN-Based semantic segmentation algorithm for better estimation of crop cultivation areas in Jeju Island

Author: DONG-WOOK KIM (Seoul National University)

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YONG SUK CHUNG (Jeju National University)

S3-3-04
17:15-17:30

Reinforcement Learning-Based optimization of spraying paths: an End-to-End approach for comprehensive tree coverage in orchard robotics

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KYEONG-HWAN LEE (Chonnam national University)

S3-3-05
17:30-17:45

Optimizing inclined plate seed metering device performance using artificial neural network

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S3-3-06
17:45-18:00

Damage classification of castor seeds based on modified AlexNet

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Reinforcement Learning-Based Optimization of Spraying Paths: An End-to-End Approach for Comprehensive Tree Coverage in Orchard Robotics

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Abstract

In the field of modern agricultural automation, autonomous spraying robots have become a key solution to alleviate the workload of farmers.[1] Traditionally, these robots rely on dense GPS mapping for path planning. However, this method is cumbersome and requires frequent updates due to continuous environmental changes.[2] Our research introduces an innovative end-to-end path generation model that employs deep reinforcement learning to achieve efficient and comprehensive coverage in orchard environments.

During the training phase, the method initially uses drones to collect elevation maps of the orchard to establish a training environment. Subsequently, combining multiscale maps and simulated obstacle detection sensor data as inputs to the deep reinforcement learning environment, a reinforcement learning agent equipped with a spraying simulator explores and generates paths within the environment. In the inference phase, the model only needs the orchard's elevation and tree position information to generate a path that ensures maximum coverage of the orchard trees with minimal distance. Thus, our approach only requires an elevation map with tree position information and a predefined starting point to autonomously plan the optimal

Keywords: Automatic Spraying Robots, Reinforcement Learning, End-to-End Path Generation, Agricultural Automation.

1. Introduction

As global population growth drives increased demands on food production, advancements in agricultural automation have become critical. Among these, autonomous spraying robots are pivotal for enhancing crop management efficiency and reducing labor needs. Traditionally reliant on dense GPS mapping, these robots face operational complexities and require frequent updates, limiting their practicality in dynamic agricultural settings.

Our study introduces an innovative end-to-end path generation model using deep reinforcement learning, enabling these robots to efficiently navigate orchards without dense GPS data. The model's training involves collecting orchard elevation maps via drones, using these maps in conjunction with a reinforcement learning agent equipped with obstacle detection and spraying simulation to identify optimal paths. In the inference phase, the model requires only orchard elevation and tree position data to generate paths that maximize coverage with minimal travel.

This approach aims to enhance agricultural automation's efficiency and reliability, supporting sustainable agriculture and spurring further technological innovations.

2. Materials and Methods

This paper introduces an innovative end-to-end path generation method that utilizes unmanned aerial vehicles (UAVs) to acquire topographic and tree position information of orchards, integrating these data into a deep reinforcement learning environment to enable an agent to learn and generate navigational paths through reward-based exploration. Initially, the UAVs collect topographic and tree position data, which are then transmitted to the deep reinforcement learning system. Here, the agent continuously explores using the model, environmental feedback, and reward signals, ultimately learning a path generation model. In the inference phase, this model can directly generate global paths suitable for practical navigation.

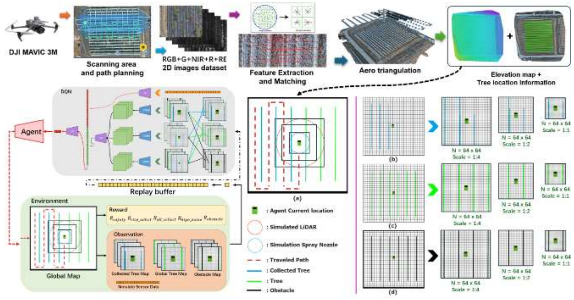

Figure 1. Path Generation System

2.1. Observational Space for the Deep Reinforcement Learning Network on Tree Coverage

To enable the agent to effectively learn paths covering the trees, we designed a specific observational space, mapped to feature representations suitable for neural network inputs. We prepared three maps: one with the location information of all collected trees, one showing the locations of all obstacles, and a global tree map containing all tree locations. These maps are represented as two-dimensional grid networks to accurately express the current state information of the agent. Additionally, to enhance the model's versa tility, we designed multi-scale maps centered on the agent's current position as the observational space. This introduction of multi-scale maps aims to maximize the retention of map information without needing to input all map details into the network, allowing the model to be applicable to various map sizes.

2.2. Action Space for the Deep Reinforcement Learning Network on Tree Coverage

In our learning environment, we employed a discrete action space including left turn by 9 degrees, right turn by 9 degrees, and moving straight. This selection of actions helps maintain the smoothness and stability of the agent during turns.

2.3. Reward Functions for the Deep Reinforcement Learning Network on Tree Coverage

Our goal is for the agent to cover all tree areas. To this end, we defined two reward functions: one based on the total number of trees collected at each time step, and another based on the ratio of the number of trees currently collected to the total number of trees in the map. To ensure the safety of the path, we also designed a safety reward based on the distance between the agent and the nearest obstacle, and a high negative reward when the agent encounters an obstacle. Additionally, using the DBSCAN clustering method, we determined approximate lengths and widths of trees, and based on this information, we set an additional reward for the opposite trees of each collected tree. Based on the dimensions from clustering and the agent's speed information, we also set a time constraint, granting additional rewards only if the agent completes the task within the set time, thereby motivating the agent to complete the task of fully covering the tree path in the shortest time.

3. Results and Discussion

As illustrated in Figure 2, this paper describes the input process, training process, and inference process using a deep reinforcement learning system. During the input stage, to enhance the model's generalization ability, we trained the system by randomly selecting from five different maps. As observed in Figure 2, the model progressively explored the largest map during the training process, and the reward changes depicted in Figure 3 indicate that the model was gradually converging.

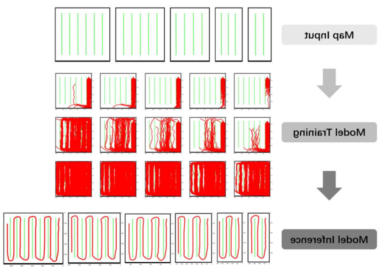

Figure 2. Model training process and inference results

That is, it could stably achieve full coverage for each map. After the training was completed, we validated the model using the original five maps and an additional new, larger map. The validation results, as shown in Figure 2, demonstrate that the model is capable of generating the shortest path that fully covers the trees on all maps.

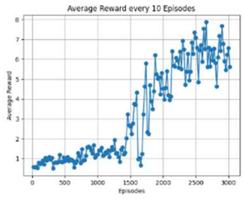

Figure 3. Average reward per 10 episodes of episodes during training

Conclusions

We propose an end-to-end method for generating the shortest comprehensive tree coverage paths based on map elevation and tree position information, specifically tailored to address the challenge of automating global shortest tree coverage path generation in orchard environments. This method enhances adaptability to orchard maps of varying sizes through the use of multiscale maps and boosts model performance by introducing a novel reward mechanism. Specifically, we optimize the reward function using the DBSCAN clustering method, enabling the agent to efficiently explore and determine the shortest comprehensive coverage paths. This approach, based on deep reinforcement learning, has been validated through simulation to accurately generate global shortest tree coverage paths.

Acknowledgements

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