125. Collaboration between aerial and ground robots for weed detection and removal

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Abstract

This paper presents an approach towards the collaboration between aerial and ground robots or autonomous unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) for weed detection and removal. A UAV equipped with a high resolution digital camera was used to collect data from an experimental strawberry plot. The collected data was used to develop machine-learning models to detect weeds in the plot using two different machine-learning architectures that support real-time implementation. The developed algorithms also identify the location of weeds. The location data was then shared with a UGV for weed removal. Accuracies of the machine-learning models in detecting weeds are discussed and experimental results for weed detection and removal are shown.

Keywords: agricultural robotics, autonomy, machine learning, multi-vehicle coordination

Introduction

UAVs can acquire high-resolution aerial imagery for mapping and precision farming. The main advantages of using UAVs are that they can cover a large area in a short amount of time and are cost-effective. UGVs, on the other hand, can be used for crop care operations, chemical application, and harvesting. While UAVs and UGVs are individually advantageous to agricultural applications, the teaming of the two can further help minimize the use of chemicals, reduce cost, and reduce dependencies on human labour (Bhandari *et al.,* 2017). For example, UAVs can provide necessary information about crops such as diseased plants/weeds and their locations to the UGVs, which can use the information provided by the UAVs to autonomously navigate to the area for application of chemicals (herbicides/pesticides) and removal of weeds. UAVs can also be used to spray chemicals. UAVs and UGVs can be helpful for the care of crops when it is difficult in getting people and tractors to the field due to rain and mud. In addition, the information gathered from UAVs and UGVs can be used for high-level decision-making or can help growers build a decision support system by the growers for effective management of farms (Pretto *et al.*, 2021).

Existing literature includes sensor planning for UAV-UGV collaboration for precision agriculture (Tokekar *et al.*, 2016), cooperation between UAVs and UGVs to create vegetation index maps and digital surface models (Potena *et al.*, 2019), and semi-autonomous collaborative UAV-UGV system for identification and cutting of weeds (Baskaran *et al.*, 2017). Collaboration between UAVs and large farming robots such as Bosch BoniRob has also been investigated (Pretto *et al.*, 2021; Walter *et al.,* 2018). However, large ground vehicles cannot effectively be used for all row crops such as strawberry and lettuce. Moreover, using large vehicles results in soil compaction. Using small UGVs instead of large manned or unmanned vehicles is more beneficial for precision farming (Pitla *et al.*, 2020). This paper presents the research on and development of capabilities for the collaborative use of UAVs and UGVs for automated weed detection and removal in real-time. The research goal is to advance the state-of-the-art in aerial and ground robotics and machine-learning techniques for farming automation. The main contribution of this work is the implementation of the developed machine-learning models onboard a UAV for weed detection and sharing of the information provided by the machine-learning models with a UGV for automated weed removal in real-time. Though some works have discussed using collaboration between UAVs and UGVs for farming automations (Valento *et al.,* 2011), the existing literature does not sufficiently address the challenges associated with the integration of machine-learning techniques and UAV-UGV collaboration for the real-time detection and decision-making for farming automation including automated weed detection and removal.

Material and methods

Figure 1 shows the experimental strawberry plot that has a total of three replicate rows. It is a strip-plot design with four nitrogen treatments forming main plots and five irrigation treatments forming subplots. As estimated by evapotranspiration calculations, the subplots were drip irrigated at 0%, 25%, 50%, 75% and 100% irrigation levels. Similarly, the nitrogen treatment was slow-release nitrogen at 0%, 25%, 50% and 100% of the nitrogen recommended for strawberry growth.

UAV, UGV and other hardware

One of the UAVs used is a DJI Phantom 4 (DJI, Shenzhen, Guangdong, P.R. China) equipped with a high-performance real-time kinematics (RTK)-capable global navigation satellite system (GNSS) and a high-resolution camera. It has a maximum take-off weight of 1.391 kg and can fly for 30 minutes at a maximum speed of 58 km/hour. Using an RTK module, it provides real-time positioning data with centimetre-level accuracy. The UAV is capable of autonomous waypoint navigation including auto take-off and auto-landing. The second UAV used is an IF750 UAV (Inspired Flight, San Luis Obispo, CA, USA). The UAV is capable of autonomous waypoint navigation. It has an empty weight of 4.5 kg and can carry a payload of 2.2 kg with a maximum flight time of about 30 minutes. It has been integrated with a Jetson Nano processor board to process the developed machine-learning models for weed detection. Jetson Nano from NVIDIA (Santa Clara, CA, USA) is a small and powerful computer suitable for UAV-based image classification, object detection, and segmentation and for real-time applications.

Attached to the Jetson Nano are two Raspberry Pi Camera Model 2 (Cambridge, UK). These cameras capture the images of the weeds and the crop. The images are fed to the Jetson Nano, which, in turn, processes the machine-learning models to detect weeds. Both cameras are attached to the ends of a meter stick and connected to a mount on the Jetson Nano.

The UGV used is a Husky UGV from Clearpath Robotics (Kitchener, ON, Canada). It is a medium-sized UGV and can be used for variety of applications. It is equipped with cameras, LIDAR, GNSS, a robotic manipulator, and an adaptive robotic hand gripper. The UGV fully supports Robot Operating System (ROS) for research on robotics. Robotic manipulator and adaptive hand gripper facilitate object handling and picking including weed removal. The overall system has been programmed for automated removal of the identified weeds.

Figure 1. Experimental strawberry plot.

The IF750 UAV and the UGV communicate through sockets for the transmission and reception of weed location data in real time. Socket routines create communication channels between the UAV and UGV, and the channel is used to transmit data over a local network.

Data collection and data processing

Images of the strawberry plot were collected using the DJI Phantom 4 UAV from the altitude of 10 to 15 metres. Over one thousand red, green, and blue (RGB) images were collected for testing in a period of two months, while over 200 images were labelled for the training. Each image taken from the UAV has a size of 4000×3000 pixels. The original images were sent to the preprocessing pipeline to splice the images into 800×800 pixel sizes. A given point in the image was calculated using triangulation that uses several angles and reference points to determine the location of the detected images.

To train the model, a conversion tool for computer vision, Roboflow, was first used to label bounding boxes around the regions of interest. Two different labels were used on each image: "strawberry", and "weed". As the name implies, if a strawberry plant was visible in the image, a bounding box would be created around it. Figure 2 on the right shows a post-processed image for training machine-learning models.

Model training

Seventy-six labelled images with over 6000 annotations for both weeds and strawberries were used to train the model. The 76 labelled images were then augmented into more than 3000 images with a difference of exposure of ±5% and sliced into smaller images to support aerial detection. Initially, a model was trained with an SSD (single shot detector) MobileNetV1 architecture as it is compatible with the onboard processor we were using for real-time implementation. However, the detection accuracy was unsatisfactory, resulting in a MAP (mean average precision) of 22%, as discussed later in this paper. Next, YOLOv8 (you only look once version 8), a state-of-the-art convolutional neural network architecture, was chosen for its balance of speed and accuracy. The model was implemented using the Ultralytics framework and deployed on the Jetson Nano for real-time processing. YOLOv8's efficient inference and compatibility with edge devices made it ideal for this application. The model enabled fast and accurate detection in a resource-limited device. YOLOv8's architecture has advanced feature extractions and uses techniques like CSPNet (cross stage partial networks) to reduce redundant computations while improving feature representation compared to SSD MobileNetV1, which combines a single shot multi box detector to detect objects in a single pass and combines the MobileNet backbone as a lightweight convolutional neural network.

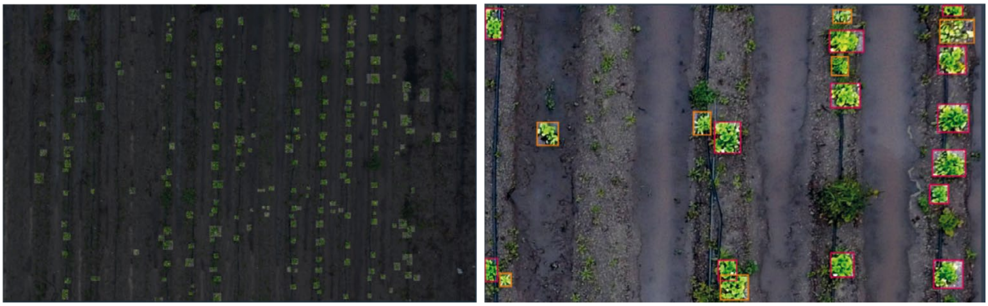

Figure 2. An image taken of the plot from a 10-m altitude (left) and the post-processed image showing strawberry and weed bounding boxes (right).

Autonomous collaboration between UAVs and UGVs

Figure 3 shows the experimental testing at the farm for autonomous collaboration between the UAV and UGV for weed detection and removal. Sockets between the UAV and UGV shared data with each other. The UAV collected the data while flying autonomously and processed the developed models in real-time to detect weeds. The location of the weed was also determined, and the location was sent to the UGV, which then autonomously navigated to the weed location. The UGV's Web user interface (UI) monitored the UGV's planned path.

Operation of the robotic manipulator

The Husky has a UR5e robotic arm from Universal Robots and a 3-finger gripper from Robotiq. This arm is used for weed removal. The operation of the manipulator is performed through a specific programming language called URScript, designed to control the robot. It is operated by sending the URScript through sockets to the control system, which is connected to the Husky through an ethernet cable. This is handled using TCP/IP protocol for communication. A similar operating procedure is used for the gripper, which is configured to operate between 4 modes. The Arm is preconfigured with a pair of poses that were utilized for the weed removal, and this operation was synchronized with the operation of the gripper to grab the detected weeds.

Results

After training the YOLOv8 model with a batch size of 16 and epoch of 100, the model was tested with several test images that weren't a part of the training data set. The trained models were used to detect the weeds in the strawberry plot. Figure 4 shows the detected weeds and strawberries using the images collected from the UAV. The Raspberry Pi cameras that are attached to the Jetson Nano captured the UAV images and fed them to the Jetson Nano for processing. The developed model analyzed the images to identify weeds and strawberries and their locations. The trained YOLOv8 model learned the distinct vision features that differentiate weeds from strawberries, such as colour, shape, texture, and spatial arrangement. The model distinguishes weeds through their irregular shape and tends to vary widely in texture and size compared to the strawberry plants with consistent and more recognizable leaves.

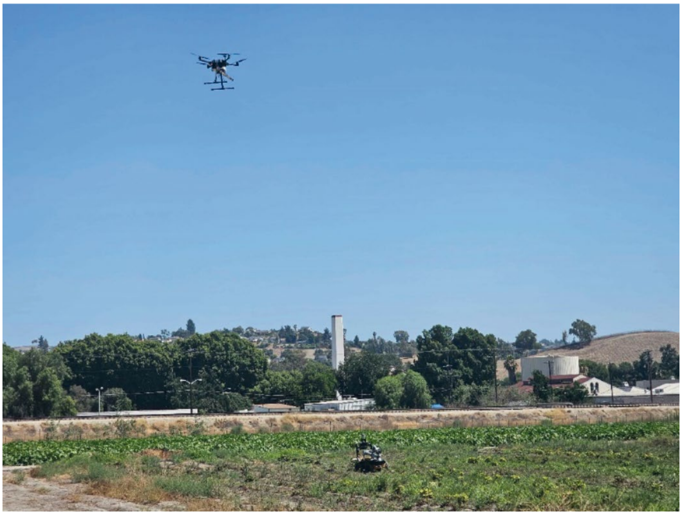

Figure 3. Experimental testing of the UAV-UGV collaboration for weed detection and removal.

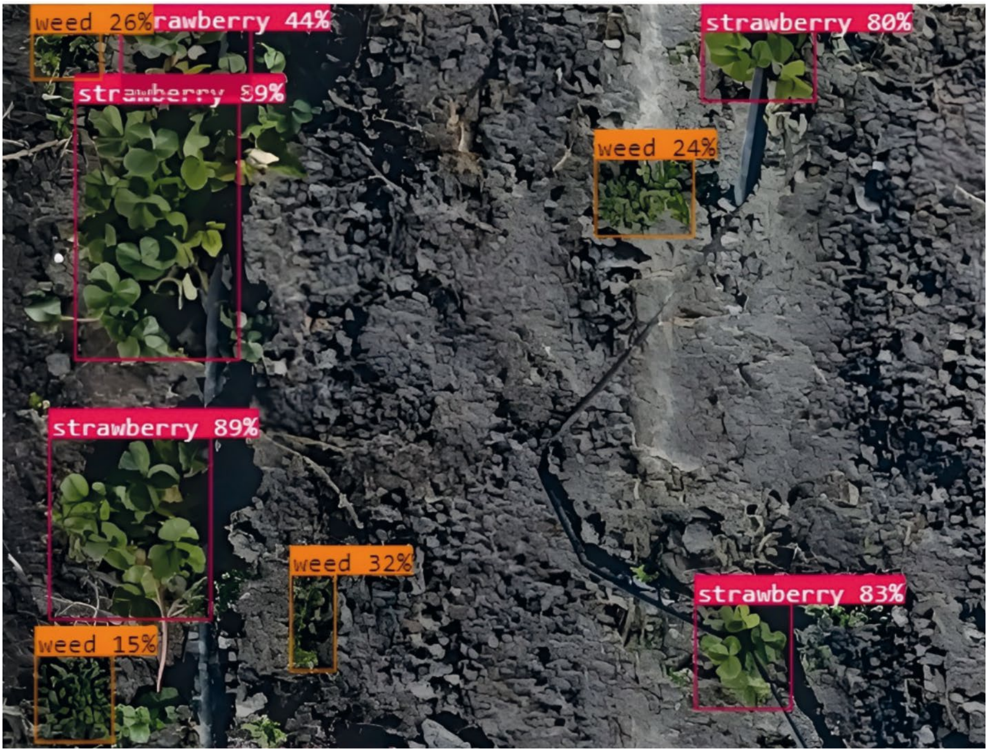

Figure 4. Detected strawberries in pink bounding boxes with weeds in orange bounding boxes.

Compared to the SSDMobileNetV1 trained model, the YOLOv8 performed significantly better due to its feature extraction backbone. The YOLO model significantly increased precision and recall in both classes; however, it also increased the inference time. Table 1 shows the accuracies of the trained models. Strawberry true and false positives were 1074 and 227, respectively whereas weed true and false positives were 435 and 957, respectively.

The YOLOv8 trained model showed improved accuracy at detecting patterns and can accurately detect strawberries and weeds. However, when the model tried to detect smaller weeds in the images, the model would sometimes be confused with the background noise, resulting in a lower confidence for weed detection.

The centre of each box is marked with a dot indicating the location of the weed or strawberry plant. Using triangulation and starting from the centre of the bounding box of the weed, the location of each bounding box relative to the UAV GNSS location was calculated. Each bounding box contains information of the object class, confidence score, location, and dimension. This coordinate was

Table 1. Accuracies of machine-learning models in detecting strawberries and weeds.

Architecture	Image resolution	Strawberry precision	Strawberry recall	Weed precision	Weed recall
YOLOv8	480×640	0.69	0.83	0.51	0.31
SSD MobileNetV1	300×300	0.37	0.29	0.10	0.07

shared with the UGV for autonomous navigation to the weed location. For example, one of the coordinates (latitude, longitude) of a detected weed that was shared with the UGV was (34.0451490, −117.8120469).

Figure 5 shows an example of the UGV successfully extracting a weed from the ground and retracting the arm for disposal.

Discussion

The machine-learning models developed were able to isolate the weeds from strawberry plants and determine the location of the detected weeds. An architecture for autonomous collaboration between UAVs and UGVs for information/data sharing was successfully designed, implemented, and tested. The detection algorithms were processed onboard the UAV to enable real-time identification of weeds, and the information was shared with the UGV in real-time for necessary action that included autonomous navigation to the weed locations. The UGV generates its trajectory autonomously using a combination of GNSS data from the UAV and onboard path-planning algorithm. This coordination can equally be used for other tasks, such as detecting plant diseases and applying herbicides/pesticides.

Future work will involve increasing the accuracy of weed detection models, conducting more experimental testing for further validation of the developed UAV-UGV collaboration technique, and using the collaboration for other on-farm tasks, including the spraying of chemicals. A camera equipped with the UGV will be utilized for navigation and real-time positioning of the robotic manipulator for precise weed removal.

Conclusion

This paper showed a method of collaboration between UAVs and UGVs for detecting and removing weeds. YOLOv8, a convolutional neural network architecture, was used to train the weed detection model and implemented onboard a UAV for real-time detection of weeds. A DJI Phantom 4 UAV equipped with RTK-capable GNSS was used to collect high- resolution images of weeds and strawberry plants for training the detection models. The developed model was able to detect the weeds and strawberry plants. An algorithm was also designed to determine the location of the detected weeds.

A second UAV was equipped with a camera and a high-performance processor to implement the developed models and algorithms so that the weeds could be detected in real-time while the UAVs were flying. Data between the UAV and UGV was shared using network sockets. The UGV, equipped with a robotic manipulator and an adaptive robotic gripper, received the location data from the UAV in real-time for autonomous navigation to the detected weed.

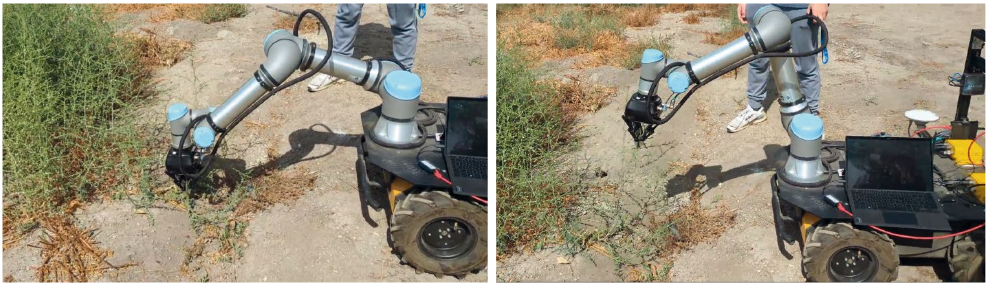

Figure 5. Extraction and disposal of a weed by the UGV.

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