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Localising Weeds Using a Prototype Weed Sprayer

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***Abstract*—The application of convolutional neural networks (CNNs) to challenging visual recognition tasks has been shown to be highly effective and robust compared to traditional machine vision techniques. The recent development of small, powerful GPUs has enabled embedded systems to incorporate real-time, CNN-based, visual inference. Agriculture is a domain where this technology could be hugely advantageous. One such application within agriculture is precision spraying where only weeds are targeted with herbicide. This approach promises weed control with significant economic and environmental benefits from reduced herbicide usage. While existing research has validated that CNN-based vision methods can accurately discern between weeds and crops, this paper explores how such detections can be used to actuate a prototype precision sprayer that incorporates a CNN-based weed detection system and validates spraying performance in a simplified scenario.**

I. INTRODUCTION

Weeds compete with crops for light, water and nutrients, so weed control is a major concern for farmers. Broadcast spraying, the mainstream approach to weed control, involves spraying an entire field with a herbicide which kills weeds but does not affect crops. In contrast, precision spraying aims to locate and spray only the weeds. This enables weeds to be controlled while dramatically reducing the amount of herbicide required which is beneficial both economically and environmentally.

II. RELATED WORK

Some early research into selective spraying focused on developing systems to spray weeds before crops had been drilled [1]. This meant detection systems merely had to distinguish between soil and plants. There are now commercial examples of systems that can selectively spray areas with no crops such as John Deere's See & Spray Select sprayer [2]. However, more sophisticated detection techniques are required to discern weeds from crops. Early investigations into weed detection used hand-crafted techniques discriminate weeds from crops [3]. More recently, CNNs have been applied to the problem of weed detection and have been shown to outperform methods using hand-crafted features in weed detection tasks [4]. In some studies, CNN-based weed detection was deployed onto embedded hardware including a Raspberry Pi [5] and an Nvidia Jetson TX2 [6], [7]. Research aimed at incorporating embedded detection technology into a prototype precision sprayer to spray weeds in real-time is limited. In [8], weeds were mapped in advance and a precision sprayer, equipped with an RTK–GPS, could then localise the weeds. A drop-on-demand micro-jet sprayer was developed in [9] which detected weeds using colour, shape and texture features and an SVM classifier. They demonstrated the efficacy in a field test by showing a reduction weed coverage, proxied via a reduction in excess greeness, before and after spraying. In [10], a prototype sprayer was proposed, ResNet- and MobileNet-based detection methods were investigated, and deployed on a embedded PC (Raspberry Pi 4 with Intel Neural Computing stick 2). However, no data on the sprayer's performance was published. The work presented here proposes an end-to-end spraying system, explores how CNN-based object detections can be used to actuate sprayer nozzles in real-time, and validates the performance in a simplified spraying scenario.

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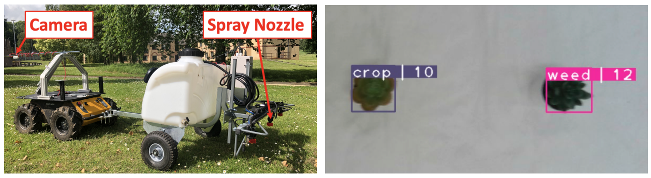

(a) Prototype sprayer (b) Tracker output

Fig. 1

III. METHODOLOGY

An experiment was conducted using a prototype sprayer, shown in Figure 1a, comprised of a Clearpath Husky equipped with a Realsense camera facing down to capture a video stream of the ground ahead of the robot. The husky tows an EnduraMaxx sprayer, filled with water, and fitted with three sprayer nozzles; however, in this experiment we only use the middle nozzle (Arag F110).

A YOLOv5 (CNN) object detection model was trained to detect plastic weeds and crops in the image and circumscribe them using a bounding box. For training, a dataset of labelled images of plastic weeds and crops was divided to create a training set containing 2697 images and a validation set containing 300 images. The model was deployed on an NVIDIA GeForce RTX 3060 Laptop GPU, mounted on the robot, and works as follows: in each frame, crop and weed bounding boxes are detected, they are then fed into a SORT algorithm [11] to associate bounding boxes between frames and track individual plants frame-to-frame. Figure 1b shows tracked weeds and crops with their associated IDs.

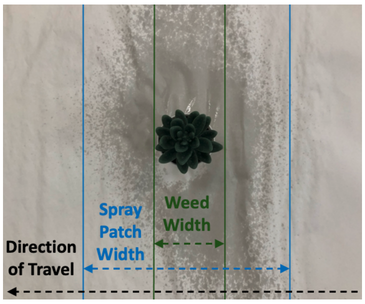

Fig. 2: Measurement procedure

From a given frame, with pixel resolution 1280x720, we can estimate the distance from a detected weed to the spray nozzle at the time the frame was captured. We take the weed's bounding box in the image given by $x_{min}, x_{max}, y_{min}, y_{max}$. In this case, the vehicle is moving in the x-direction, and x_{min} is the edge of the bounding box nearest the sprayer so this is where we aim to start spraying. Since we assume that the centre of the frame represents the area directly below the camera lens, we take the distance from this point to the centre of the image in pixels: $x_{min} - 640$ and convert it from pixels into metres. We established empirically that our camera covers an area of size 1.05x0.59m so the ratio $R = 1.05/1280$ is used to convert pixels into metres. The distance from the centre of the camera lens to the spray nozzle in metres is given by S. Therefore, the distance of the weed from the spray nozzle is estimated to be $D = S + R(x_{min} - 640)$. The pose of the robot at the time the image was taken, obtained from the wheel odometry, is P_t. Assuming the sprayer moves forward in a straight line and accounting for a 0.02m buffer, the pose where the robot should start spraying is $P + D - 0.02$. The estimated pose is updated each time that a weed is detected in a frame.

In order to calculate the length of time to spray a tracked weed, the bounding box with the largest width from all the frames where that weed appears B_{max} is used. The length to spray is $RB_{max} + 0.02$ after converting from pixels to metres and accounting for the 0.02 buffer the other side of the weed. Based on the speed the sprayer (obtained from the wheel odometry) when spraying commences, V, the length of time the sprayer should remain on is $(RB_{max} + 0.02)/V$.

In order to test the accuracy of the sprayer, a simplified model of weed spraying was set up. Two varieties of artificial plants, one to represent crops and the other to represent weeds, were lined up on A1 sheets of papers to resemble a crop row. The distance of each weed from the nozzle at the start was measured. The sprayer was tested by driving in a straight line for 5.2m at approximately 0.32m/s over the crops and weeds. Figure 2 shows location and width of the resulting wet patches on the paper were measured.

IV. RESULTS

The locations of the wet patches relative to the positions of the weeds are plotted in Figure 3. While each of the weeds was fully circumscribed by the patch, the first and last weeds are not centrally located in the patch. Since they are to the left of

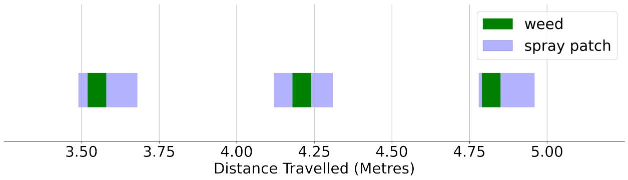

Fig. 3: Results

the patch, this suggests the nozzle turned on slightly too late. Factors that could influence this include accumulated error in the wheel odometry reading and latency in the actuation of the spray nozzles. Addressing these factors, could enable the 0.02m buffer either side of the target area to be reduced which would further reduce area sprayed and thus herbicide usage.

V. CONCLUSIONS

This work demonstrates how a CNN-based detection model can be run in real-time on an embedded system to enable accurate precision spraying. Additionally, by using a simplified weed spraying set-up, its accuracy can be precisely measured. By focusing on when to turn a single spray nozzle on and off, this work investigates precision spraying along a single dimension. In future work, a system with multiple nozzles of varying precision and density could be used to investigate how to further enhance the precision. Additionally, work that more precisely quantifies the area sprayed, taking into account the shape of the patches and the spray deposition across target weeds, could give insights into the potential efficacy of various precision spray strategies.

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