



# Field evaluations of a deep learning-based intelligent spraying robot with flow control for pear orchards

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## Abstract

This study proposes a deep learning-based real-time variable flow control system using the segmentation of fruit trees in a pear orchard. The real-time flow rate control, undesired pressure fluctuation and theoretical modeling may differ from those in the real world. Therefore, two types of preliminary experiments were conducted to examine the linear relationship of the flow rate modeling. Through preliminary experiments, the parameters of the pulse width modulation (PWM) controller were optimized, and a field experiment was conducted to confirm the performance of the variable flow rate control system. The field test was conducted for three cases: all open, on/off control, and variable flow rate control, showing results of 56.15 ( $\pm 17.24$ )%, 68.95 ( $\pm 21.12$ )% and 57.33 ( $\pm 21.73$ )% for each control. The result revealed that the proposed system performed satisfactorily, showing that pesticide use and the risk of pesticide exposure could be reduced.

**Keywords** Variable flow rate control · Deep learning · Field experiments · Pulse width modulation

## Introduction

With the looming threat of serious environmental problems, precision agriculture has received increased research attention. In particular, pesticide spraying has caused serious damage to human health, the environment, and ecosystems over the past decades. Thus, research on agricultural robots for precision agriculture is underway (Kim et al. 2019) with

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the agricultural robots being increasingly being used for tending crops in smart farms. In addition, various harvesting robots (Bac et al. 2014; Jun et al. 2021) and spray (Kim et al. 2020) are operating in field and orchard environments. Most agricultural robots have not been commercialized and are still in the research stage. However, in the field of agriculture, robots can be used for various purposes, and research using unmanned aerial vehicles and unmanned ground vehicles to increase the efficiency of agricultural work by utilizing multiple robots (Kim and Son 2020; Ju and Son 2019) is in progress. Precision spraying through agricultural robots can solve this problem by accurately and efficiently applying pesticides to the target area, greatly reducing the use of pesticides while maintaining crop loss prevention.

In agriculture, pesticide spraying improves the productivity and quality of cultivated crops and prevents losses by up to 45% of the global food supply (Mahmud et al. 2021), especially in orchards, where pest control is essential for increasing yield (Gao et al. 2018). However, pesticide spraying control requires extensive spraying owing to the probability of pest occurrence and corresponding irregularities. Speed sprayers (SS), which are mainly used in orchards, spray pesticides in all directions irrespective of the surrounding environment. This type of spraying may induce changes in the soil owing to the pesticide abuse, as many pesticides are indiscriminately controlled, and workers may also be exposed to pesticides and get poisoned (Berenstein and Edan 2017; Guan et al. 2015). Therefore, an intelligent spraying control system is required that sprays an appropriate amount of pesticides based on the environmental awareness for stability and economic benefits for farmers and workers (Salcedo et al. 2020; Manandhar et al. 2020).

During pesticide spray applications using air-assisted sprayers on fruit crops, only a small portion of the total spray volume reaches the target canopy (Escolà et al. 2013). This spraying type requires extensive use of pesticides to improve the control performance (Chen et al. 2012). Therefore, an intelligent spraying system that recognizes the surrounding environment and individual nozzle control according to environmental conditions is required. In this case, the pear orchard environment is not well-organized; therefore, fruit trees must be recognized more robustly while ensuring that the system is not affected by the surrounding environment. In Xiao et al. (2017), an intelligent pesticide spray technique based on a depth-of-field extraction algorithm was developed. Microsoft's Kinect camera was used to calculate the average distance between the camera and a fruit tree, as well as the leaf wall area density. Wei et al. (2016), proposed a targeting air-assisted sprayer based on an infrared detection system. This spraying system could reduce spray volumes and ground deposition; however the spray deposition and the canopy coverage were also reduced. Furthermore, the target measurement method simply used the depth data and echo of the infrared sensor. This is not suitable for environments with obstacles and other environmental factors.

In Shen et al. (2013) and Chen et al. (2011) a lidar-guided air-assisted variable-rate spraying system was developed for tree and fruit crop applications. However, it was unclear how trees were distinguished from other obstacles in an orchard environment. Moreover, the spray on-target experiment was conducted only under laboratory conditions. Laser and lidar sensors have the problem of high initial costs. Researchers have developed vision and spray systems, and a moving platform for the target sprayer (Zhou et al. 2018). The crop is recognized based on color transformation and the Ostu automatic threshold algorithm; the rectangle of the recognized binary image is calculated as the spray area. The test results reveal that the use of pesticides can be reduced by approximately 46% by introducing the prevention system developed herein, and the correct spray action was 99.1% accurate. Spraying experiments were conducted in a well-organized environment;

therefore, experiments do not guarantee satisfactory results in a not well-organized field. In Zeng et al. (2020), the canopy was recognized by a 3D lidar-based system at the individual trees for precision agriculture. The proposed a 3D point cloud data processing algorithm shows an accuracy of 88.6%, 82.1%, and 94.7% for three tree condition, and provides reference information for precision orchard work such as precision spraying in the future. However, it is difficult to prove that the algorithm improves the performance of precision sprays without spray testing.

For intelligent spraying, the environment must be recognized in real time, and a system that calculates and sprays an appropriate control amount of pesticide based on the acquired image data is required. Researches have been conducted to confirm the presence or absence of negligence and selectively on/off control; however, this method still uses plenty of pesticides. In addition, there is a problem that the crop condition is overlooked. Since the on/off method sprays at a constant flow rate while “on”, selective on/off control cannot be considered a representative of intelligent control systems. In addition, there is a problem in that drift occurs because the same flow rate is maintained. Therefore, recent studies have been conducted to control spray amount considering the variability of the canopy (Liu et al. 2014; Giles et al. 2011; Berk et al. 2016).

In Liu et al. (2014), a flow control system was developed to achieve variations in spray outputs based on the structure and movement speed of trees precisely control the flow rate in orchards and nurseries. However, because this was not tested in the field, it is difficult to prove the performance in practice according to the structure of the tree and the moving speed of the platform. A site-specific orchard sprayer was developed to apply an accurate amount of pesticide by sensing the green canopy of trees based on RGB and to increase the efficiency of pesticide use in the orchard (Asaei et al. 2019). The sprayer used an on/off control when more than 10% of the scene is captured as green pixels. However, it is difficult to determine the precise spraying amount based on the condition of the fruit tree because the environment and conditions were not sufficiently considered.

In Butts et al. (2019), the droplet size was controlled to increase the efficiency of the control device and minimize the risk of scattering. The droplet size was determined by pulse width modulation (PWM) control, and optimal PWM was determined by identifying the droplet size distribution and nozzle tip pressure according to duty cycle, nozzle type, and gauge pressure. Droplet deposition and distribution of artificial fruit trees with different canopy densities were studied by simulation (Cheng et al. 2019). The fruit tree canopy image was subdivided based on the FCM-R algorithm and split to obtain an image containing only the canopy portion of the fruit tree using the Retinex lighting model and fuzzy C-mean clustering. Considering droplet deposition and distribution characteristics, the criteria for pesticide application based on the ratio of gaps and canopy density were presented. In Shen et al. (2017), Chen et al. (2019, 2012), Cai et al. (2019) and Osterman et al. (2013), a variable-rate precision sprayer was developed with a high-speed laser scanning sensor to control the spray output of individual nozzles in real time. Spraying was performed with the spray amount for each nozzle being determined according to the grid volume. However, the target tree used in the experiment was artificial, and the experiment was not conducted in an orchard environment.

The objectives of this paper were: (a) to build an automated vision-based system which recognize pear tree canopy and orchard environment. The system should be applicable to field conditions and invariant to time; (b) to perform spraying autonomously based on the established vision system. The spraying must be controlled precisely on the target; (c) to conduct field test evaluating the system to see if it achieves the objectives stated in (a) and (b). The research hypothesis was that such a system will be shown good performance for

intelligent agriculture spraying if deep learning-based vision and PWM-based variable flow rate spraying were applied. To prove this hypothesis, this study developed an intelligent spraying system that reduces the amount of pesticides used in pear orchards and improves spraying performance. The work was performed according to engineering method guidelines focused on problem definition, data collection, and system building and evaluation. For more information on the engineering method process (Koen 1988).

## Contributions

The contributions and novelty of the study are summarized below:

- (1) This study proposed a real-time variable flow control system to enhance spraying performance. This intelligent spraying system was designed through a preliminary experiment. In the preliminary experiment, the flow rate was modeled, control parameters were determined, and the proposed variable flow rate control system was optimized according to the orchard environment.
- (2) The field experiment was performed in a pear orchard to evaluate the variable flow rate control system. Since the pear orchard was not a well-organized environment for field experiments, the proposed intelligent spray system is more reliable.
- (3) This paper utilized fruit tree perception based on deep learning that was also used in a previous study (Kim et al. 2020). Various datasets were constructed by acquiring data for 2 years.

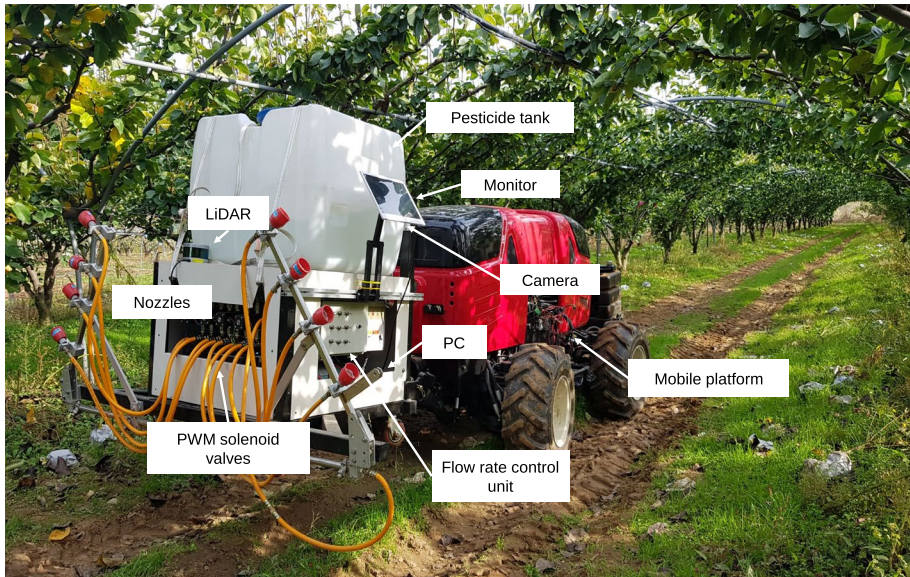
## Structure of paper

The remainder of this paper is organized as follows: in the section Intelligent Spraying system description, the paper introduces the intelligent spraying system and fruit tree perception based on deep learning, a method of fusion of depth data. In the section Real-time Variable Flow Rate Nozzle Control, a real-time variable flow rate nozzle control method is presented, as developed through a preliminary experiment. In Field Experiments, the paper presents the experimental setup and results for the verification and evaluation of the proposed real-time variable flow rate control system in a pear orchard. In the Discussion section, the experimental results and challenges for future work are discussed. Finally, in Conclusions, the paper concludes the study and provide directions for future research.

## Intelligent spraying system description

### Intelligent spraying system

The intelligent spraying system is shown in Fig. 1. The spraying system was connected through a three-point hitch link to a mobile platform, that can freely drive on unstructured roads, such as those in agricultural fields. The spraying systems and computing platforms received power from 24 V batteries. The spraying systems were equipped with a 300 L pesticide tank, computing platform, and spray boom with a total of eight nozzles. Two RGB-D cameras were attached to the frame, with one on each side of the platform, and the data were transmitted between the computing platform and the cameras.



**Fig. 1** Intelligent spraying system

To control each nozzle individually in the orchard, the image obtained from the camera ( $1280 \times 256$ ) was divided and mapped considering the location of the nozzle. Because there are four nozzles on each side, the image was divided into four areas, each mapped to one nozzle. The flow rate of each nozzle was determined using deep learning-based fruit tree recognition and depth data with information on the region obtained from the camera.

### Fruit tree perception

This study recognized fruit trees in orchard environments based on the developed in Kim et al. (2020). A brief summary of the semantic segmentation for fruit tree perception with a fusion of depth data to prevent spraying in undesired areas is provided below. Further details can be obtained in Kim et al. (2020).

### Dataset

The dataset was acquired over 2 years (2019–2020) from pear orchards using Intel RealSense D435 cameras. A total of 2 000 images with a resolution of  $1280 \times 256$  were obtained. Training images were captured at various distances from the fruit trees for variations in the canopy. Images were acquired at different times of the day because the light intensity and shadow in the images varied depending on the position of the sun. Therefore, generality was maintained by providing sufficient variation in tree topology, leaf density, and leaf characteristics. The fruit of the Korean pear tree is grown in wrapped in paper bags to prevent worm and germ infestation and improve quality. The learning process assigns a fruit class to the wrapped paper bags.

Considering an actual outdoor environment was used, it was essential to subdivide the classes for deep learning training. There are five classes in the dataset, as acquired from the

training: tree (leaf + branch + trunk), fruit, ground, sky, and pipe. The spraying system only sprayed areas with fruit and trees. The components of trees (leaf, branch, and trunk) were grouped into a single class without further division based on details. However, the fruit was grouped into a separate class from the tree because, depending on the season, the trees may not always have it.

### Semantic segmentation results

In a previous study, Kim et al. (2020) performed semantic segmentation for fruit tree perception. Image semantic segmentation is the classification of every pixel in an image into a corresponding predefined number of classes. In this study, it was used to identify the presence of trees and to recognize trees to accurately spray pesticides on them. Among the deep learning models commonly used for semantic segmentation are U-Net, SegNet, ICNet, and DeepLab v3. The acquired dataset was trained and tested on different deep learning models. The model-specific accuracy is listed in Table 1. The perception was performed using the SegNet model, which had the highest accuracy among the trained models.

### Fusion of depth data with fruit tree segmentation

A pear orchard has trees planted in rows so that the background of one tree can contain other trees. Thus, post-processing was performed using depth data from the RGB-D camera to prevent the trees in the background from being detected. The distance between the camera (which is on the platform) and the tree is approximately 1.2 m, and the total depth of the canopy of the tree, including the branches and leaves, is 0.8 m. The output data from deep learning with more than 2 m of depth data based on the camera were voided. This prevented the background trees from being segmented and ensured that only the trees that should be sprayed were segmented.

### Real-time variable flow rate nozzle control

The flow rate of each nozzle was designed by controlling the installed solenoid valve in real time from the recognized camera image. When controlling each nozzle with this real-time control system, a fluctuation in the spray pressure of the nozzle tip near the solenoid valve mounted near each nozzle tip occurred (Chen et al. 2012). These pressure fluctuations can cause unintended changes in the flow output and droplet size. These problems can differ greatly between the theoretical modeling of the flow rate and the modeling of the actual flow rate. To properly control the solenoid valve, a PWM-based controller is designed, and parameter values for utilizing image information and depth data, which are input data, must be designed and optimized. Therefore, herein, a variable flow rate control system was experimentally modeled and optimized as follows.

**Table 1** Accuracy performance of segmentation models

Model	SegNet	U-Net	ICNet	DeepLab v3
Accuracy (%)	83.79	66.47	72.54	75.31

## Preliminary experiment

The flow rate can be controlled according to the PWM duty cycle. However, The effective spraying coverage area and the spraying performance reduce with the reduction in the duty cycle. This means that the pesticides do not reach the fruit trees when the flow rate is reduced. Here, the duty cycle is the fraction of “on” period in which the signal or system is active. Therefore, an intelligent spraying system should be experimentally developed before application to an actual orchard.

The preliminary experimental results are evaluated through the pesticide adhesion rate  $R_p$ , where the pesticide attaches to the water-sensitive paper, which is defined as follows (Kim et al. 2020):

$$R_p = \frac{A_s}{A_w} \times 100 = \frac{\sum_{i=0}^{r-1} \sum_{j=0}^{c-1} p(i,j)}{r \times c} \times 100, \quad (1)$$

where  $A_s$  is the sprayed area of the water-sensitive paper,  $A_w$  is the area of the water-sensitive paper, and  $r$  and  $c$  are row and column pixels with RGB values corresponding to the sprayed area, respectively.

The preliminary experiments were designed as follows and are shown in Table 2.

### Preliminary experiment 1: evaluation of spraying coverage area

The spray angle decreased as the duty cycle was adjusted. Low-duty cycles may not fully cover the desired coverage area. To check whether the spraying was evenly performed in all duty cycles, the duty cycle was set as a variable, and an appropriate duty cycle was optimized by comparing  $R_p$ . An experiment was designed to find an appropriate duty cycle based on the fruit tree distribution area recognized by the camera. The design of the experiment is shown in Fig. 2, and preliminary experiment 1 was conducted on the second nozzle, which showed the most diverse area distribution among the four nozzles. The duty cycle was increased from 75 to 100%, each fruit tree area was divided from 30 to 100 in 10% increments, and four sheets of water-sensitive paper were attached to the corresponding area to compare the  $R_p$  according to the duty cycle.

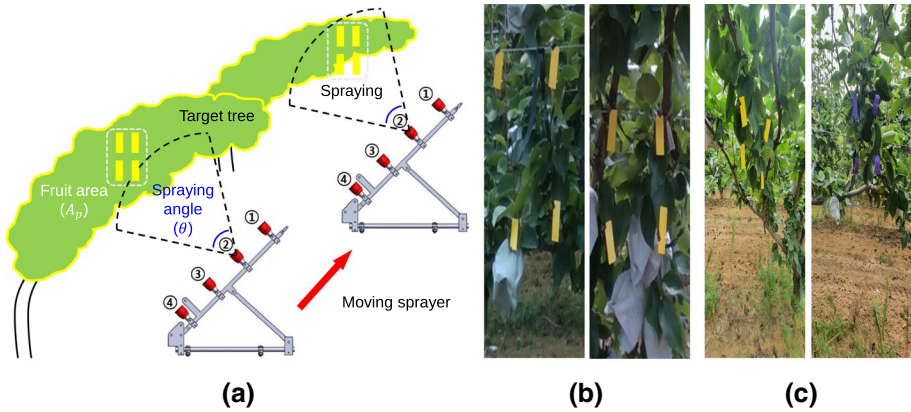
Figure 3 shows the results of preliminary experiment 1, wherein at a duty cycle of 90% or above, the area was sufficiently covered. As the duty cycle increases,  $R_p$  increases; and at a duty cycle that is too low, the desired area is in sufficiently covered. This not only results in insufficient flow but also does not reach the area with the corresponding flow rate. Therefore, the results must be derived according to distance.

### Preliminary experiment 2: evaluation of spraying distance

The spray distance decreased as the duty cycle was adjusted. The spray distance decreased as the duty cycle was adjusted. As the effective spraying range decreases to optimize the duty cycle by comparing  $R_p$ . An experiment was conducted to find an appropriate duty cycle based on the depth data recognized by the camera. Preliminary experiment 2 setup is shown in Fig. 4, and the experiment was conducted by attaching a model tree to the mobile

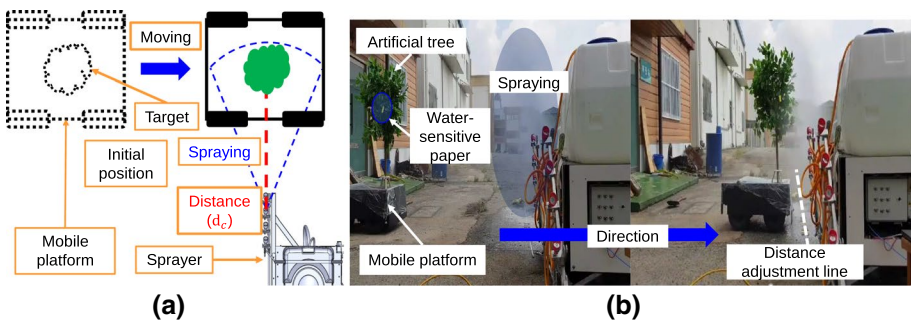
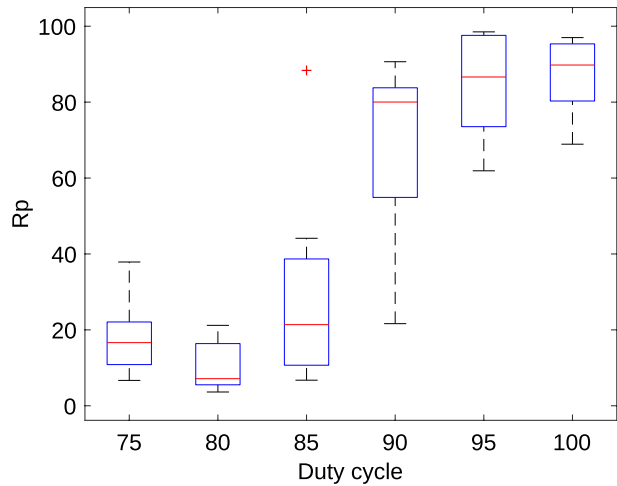
**Table 2** Preliminary experiment design

Category	Case
	Preliminary experiment 1
Objective	Evaluation of spraying coverage area according to duty cycle to optimize spraying control
Process	<i>The fruit area is changed from 30 to 100%, the duty cycle is changed from 75 to 100%, and the sprayer is moved forward</i>
Result	Analysis of spraying coverage area according to duty cycle by pesticide adhesion rate
	Preliminary experiment 2
Objective	Evaluation of spraying distance according to duty cycle to optimize spraying control
Process	<i>The distance is changed from 70 to 160 cm, the duty cycle is changed from 75 to 100%, and the mobile platform is moved with an artificial tree</i>
Result	Analysis of spraying distance according to duty cycle by pesticide adhesion rate



**Fig. 2** Preliminary experiment 1 setup. **a** Configuration of preliminary experiment 1 for spraying performance evaluation. **b** Attached water-sensitive paper according to fruit tree area from 30 to 100%, 50% (left) and 90% (right). **c** Results of spraying: before spraying (left), after spraying (right)

**Fig. 3** Preliminary experiment 1 results



**Fig. 4** Preliminary experiment 2 setup. **a** Configuration of preliminary experiment 2 for spraying performance evaluation. **b** Field view of experiment

platform, with a total of six cases ranging from 75 to 100% based on the duty cycle. The distance was set according to the environment of the orchard in which the experiment was conducted. The distance between the nozzle and the target was increased in small increments of 30 cm, from 70 to 160 cm.

The results of preliminary experiment 2 are presented in Fig. 5. At a duty cycle of 90% or above, the area was almost covered. At a close distance, it shows sufficient coverage, even at a low duty cycle. Therefore, it is important to design an optimal duty cycle according to the distance to appropriately determine the amount of pesticides used to improve spraying performance.

### Variable flow control design

The flow rate was determined by controlling the proportional solenoid valve. The discharge flow rate was determined by controlling the plunger position of the proportional solenoid valve, and the flow rate could be controlled in real time. A proportional solenoid valve was achieved through the PWM control method, which is used to obtain a linear relationship between the fluid flow and the input signal using a proportional solenoid valve in a fluid power system (Le et al. 2010).

The PWM-based controller control diagram is presented in Fig. 6. The working process of the intelligent spraying system is illustrated in Fig. 6a. In detail, the image acquired from the camera, depth information of the fruit tree, and fruit tree area were calculated. Then, the spray was determined based on whether it satisfied the threshold value set.  $V_{PWM}$  was determined by the PWM-based controller, and the determined  $V_{PWM}$  was generated through the PWM generator. The output signal  $V_{PWM}$  was transmitted to the solenoid valve to adjust the plunger position. A flowchart of the intelligent spraying system, providing an overview of the spraying procedure, is shown in Fig. 7.

The total flow rate is equal to the sum of the flow rates of each nozzle. The average flow rate of each proportional valve when the valve opens can be expressed as

$$Q_n = C_n \cdot A_n \cdot x_n(t) \cdot \sqrt{\frac{2 \cdot P_n}{\rho}}, \tag{2}$$

where  $C_n$  is the discharge coefficient,  $A_n$  is the throat area of the annular orifice,  $x_n(t)$  is the proportional valve plunger position, and  $P_n$  is the pressure.

The flow rate of each nozzle was controlled by the degree of opening and closing of the proportional valve. This can be controlled according to the valve plunger position, which is related to the control voltage input  $V_{PWM}$  and can be defined as:

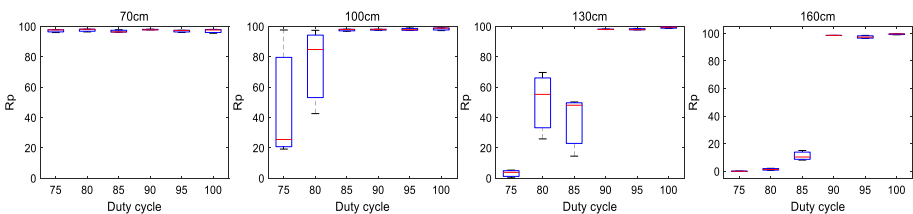
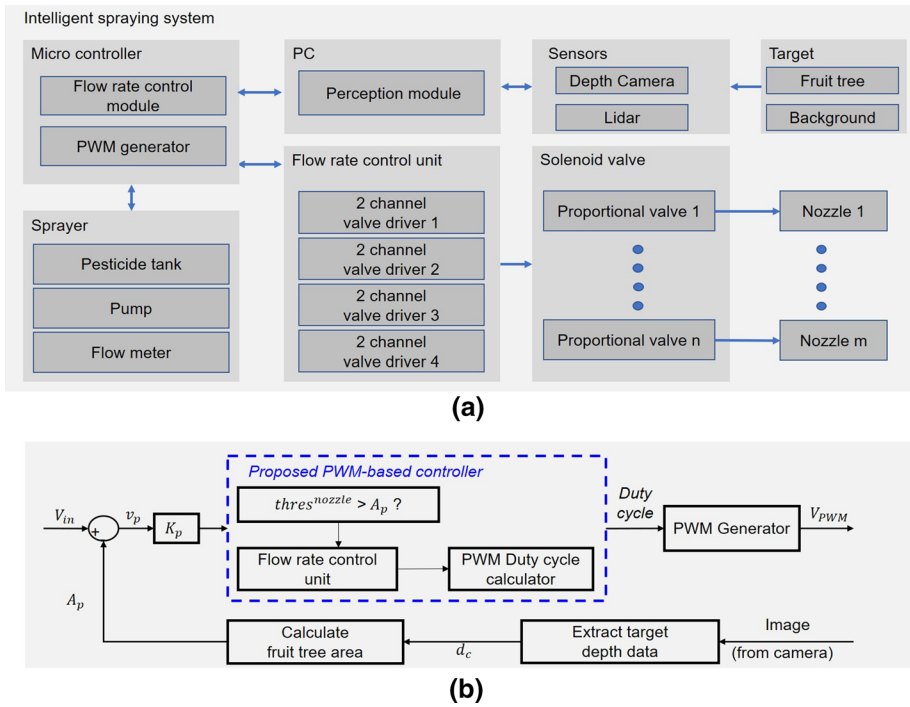
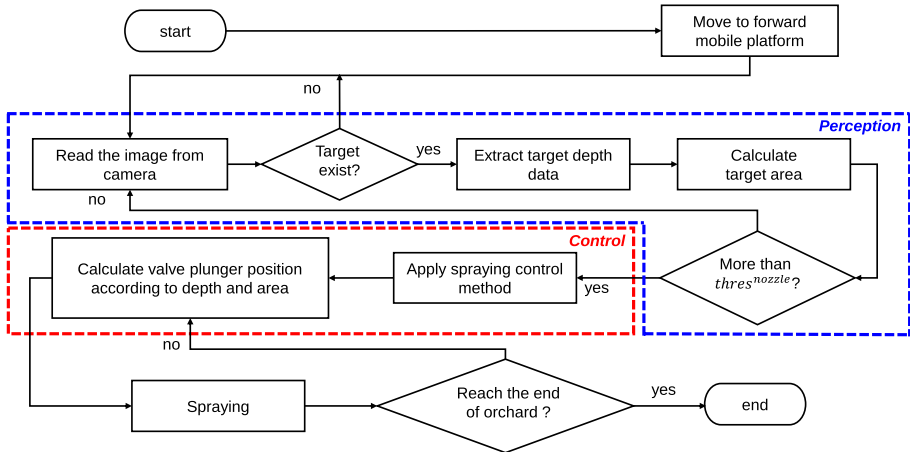


Fig. 5 Preliminary experiment 2 results



**Fig. 6** PWM-based variable flow rate control diagram. **a** Operating process of intelligent spraying system. **b** Proposed PWM-based controller



**Fig. 7** Flow chart of intelligent spraying system

$$x_n(t) = f(A_p, d_c, v_p, V_{PWM}), \quad (3)$$

where  $A_p$  is the area of the fruit tree,  $d_c$  is the distance between the sprayer and the camera,  $v_p$  is the velocity of the platform, and  $V_{PWM}$  is the control input PWM duty cycle.

$V_{PWM}$  was determined using the control method. This was divided into on/off control and variable flow rate control in real time. In the case of on/off control, the state of the valve was determined by  $thres^{nozzle}$  based on a predetermined threshold (Kim et al. 2020). In this study, this value was set to 10%, and the control input  $V_{PWM}$  was determined as follows according to the acquired fruit tree area: If the value was less than 10%, then the valve was kept in the OFF state; above 10% the valve was maintained in the ON state.

$$V_{PWM} = \begin{cases} 0\% & \text{if } A_p \leq thres^{nozzle} \\ 100\% & \text{else} \end{cases}, \quad (4)$$

where  $thres^{nozzle}$  is the percentage of pixels that determines whether the nozzle is open.

The variable flow rate control in real time was controlled by a PWM signal to the flow rate control unit. The PWM control input was determined by  $K_p$ ,  $A_p$ ,  $d_c$ , and  $C_v$ .

$$V_{PWM} = \begin{cases} 75\% & \text{if } d_c \leq 0.9 \text{ (m)} \\ K_p \times A_p \times d_c + C_v\% & \text{else} \end{cases}, \quad (5)$$

where  $K_p$  is the proportional constant, and  $C_v$  is the dead zone according to the valve dynamic characteristics.

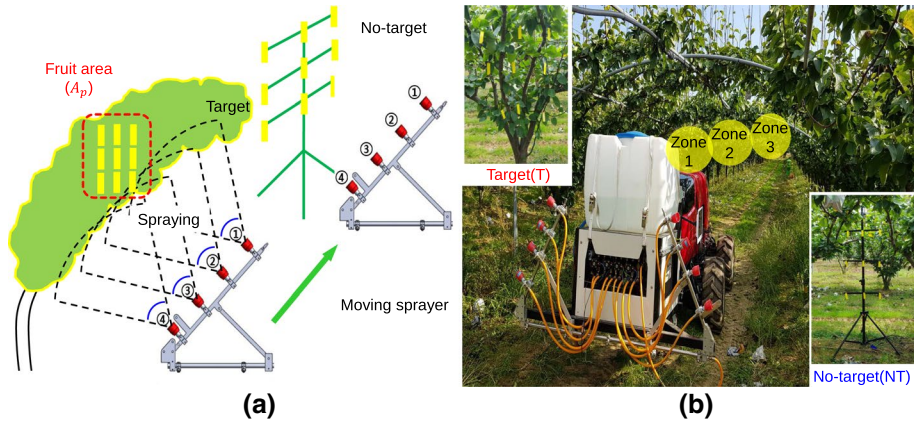
The variable flow rate control significantly influences the control performance according to the design of the control input  $V_{PWM}$ . Control parameters were optimized based on preliminary experiments. According to preliminary experiment 1, the performance was the best when the duty cycle was more than 90%, and there was no significant difference at a higher duty cycle. According to preliminary experiment 2, since the entire area is covered even at a low duty cycle at a distance of 0.9 m or less, the minimum spraying amount is determined.

Based on the preliminary experiment, the flow rate was determined as shown in Eq. 5, and it was also necessary to tune the proportional constant  $K_p$  gain. Owing to the dynamic characteristic of the valve, it does not become spraying at a duty cycle of less than 75%, it was adjusted so that the spray could be sprayed according to the distance and when it should be sprayed. At a close distance, all areas were well covered regardless of the spraying area, and the proportional gain value was adjusted according to the spraying distance. This was set to 0.8 through preliminary experiments 1 and 2.

## Field experiments

### Experiment

Field experiments on the variable spraying system were conducted at a pear orchard in Bonghwang, Naju, South Korea. As introduced in the Intelligent spraying system subsection, the variable spraying system was attached as an intelligent spraying system to a mobile platform, and the environment was configured as shown in Fig. 8. A total of nine water-sensitive paper were attached by divided into target (T) and no-target (NT) in a total of three zones.



**Fig. 8** Field experiment setup. **a** Configuration of field experiment for each control spraying performance evaluation. **b** The environment consisted of zone 3, where each zone was divided into target and no-target. A target is should be sprayed because there is a fruit tree present. Nine water-sensitive papers were attached to the target tree. No-target does not require a spraying area because there is no fruit tree present. Nine water-sensitive papers were attached to the no-target

The experiment was conducted with three controls:

- (1) *Control 1* all nozzles open (spraying without applying an intelligent spraying system),
- (2) *Control 2* on/off control (spraying while applying an intelligent spraying system),
- (3) *Control 3* variable flow rate control (spraying while applying a variable spraying system).

## Results

Figures 9, 10, 11, 12, 13 and 14 and Tables 3, 4 and 5 show the spraying performance of each control in the field experiment. Figure 15 and Table 6 summarize the spraying performance of each control. The performances of three different experiments were analyzed

**Table 3** Results of control 1: all nozzles open

$R_p$ (%)		Mean ( $\pm$ SD)	Max	Min
Trial 1	T	53.27 (19.53)	72.37	14.85
	NT	58.88 (19.56)	89.77	12.25
Trial 2	T	59.03 (14.40)	79.09	18.14
	NT	58.72 (13.95)	90.11	30.53

**Table 4** Results of Control 2: on/off control

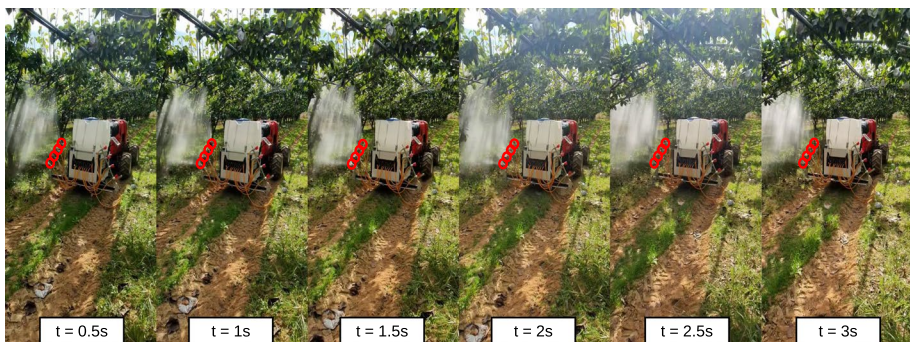
$R_p$ (%)		Mean ( $\pm$ SD)	Max	Min
Trial 1	T	54.29 (17.40)	75.69	6.80
	NT	31.72 (22.14)	61.55	2.81
Trial 2	T	83.60 (12.67)	95.36	48.77
	NT	47.01 (28.71)	87.78	6.69

**Table 5** Results of Control 3: Variable flow rate control

$R_p$ (%)		Mean ( $\pm$ SD)	Max	Min
Trial 1	T	54.43 (21.00)	84.45	19.92
	NT	10.63 (6.50)	29.25	0.77
Trial 2	T	60.23 (22.46)	96.92	11.08
	NT	5.54 (4.11)	13.65	1.01

**Table 6** Results of field experiment

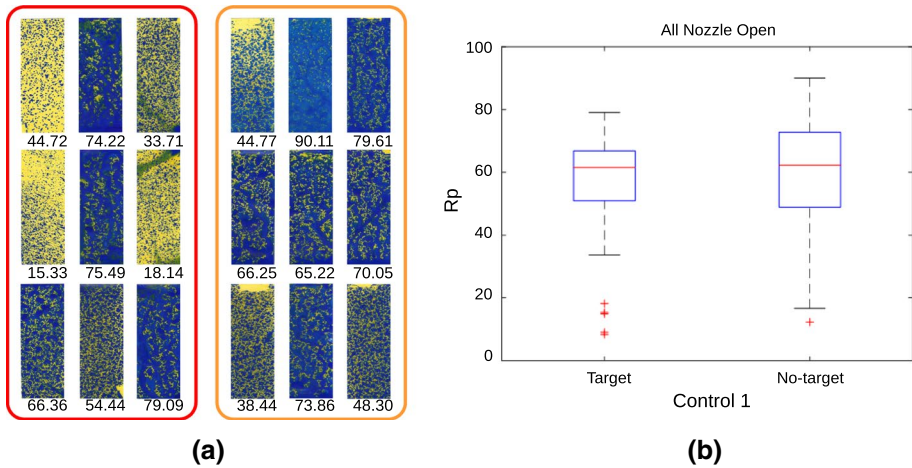
$R_p$ (%)		Mean ( $\pm$ SD)	Max	Min
Control 1	T	56.15 (17.24)	79.09	8.31
	NT	58.80 (16.83)	90.11	12.25
Control 2	T	68.95(21.12)	93.74	6.80
	NT	39.37 (26.54)	83.19	2.51
Control 3	T	57.33(21.73)	96.91	11.08
	NT	8.08 (5.97)	19.00	0.78

**Fig. 9** Control 1 of snapshots from 0.5 to 3 s of spraying. The circle indicates a fully open nozzle

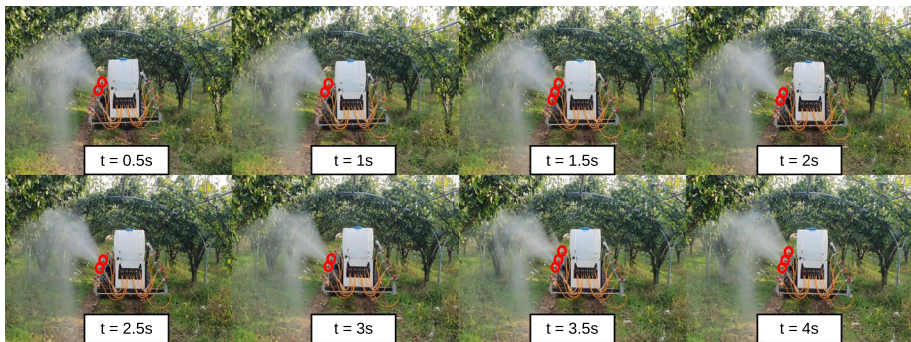
using  $R_p$  according to each control. Figures 9, 11, and 13 show snapshots of each control experiment.

### Control 1: all nozzles open

The first experiment was conducted to confirm the degree of pesticide adhesion to the water-sensitive paper when all the nozzles were opened. The intelligent control system could evaluate the spraying performance by comparing  $R_p$  sprayed on the desired area, as in an experiment where control was not performed. In addition, it was possible to see how much the pesticide has decreased by comparing  $R_p$  in the NT area, which is an undesired area, and by comparing the pesticide consumed to control the entire area to see the degree to which the pesticide decreased. Figure 9 shows snapshots from 0.5 to 3 s of spraying. Control 1 was always open regardless of whether the fruit tree was recognized. Each nozzle was always fully open, according to Control 1. The red circle indicates a fully open nozzle.



**Fig. 10** Spraying result in Control 1—all nozzles open. **a** Example of water-sensitive paper result: Target (left) and No-target (right), and **b** box plots display median, interquartile range, maximum, and minimum values

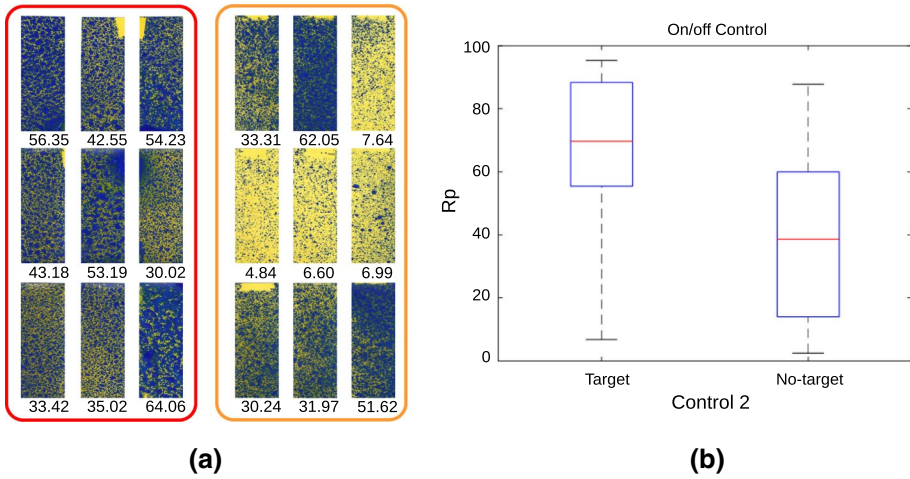


**Fig. 11** Control 2 of snapshots from 0.5 to 4 s of spraying. Each nozzle was selective fully open nozzle for Control 2. The circle represents a fully open nozzle

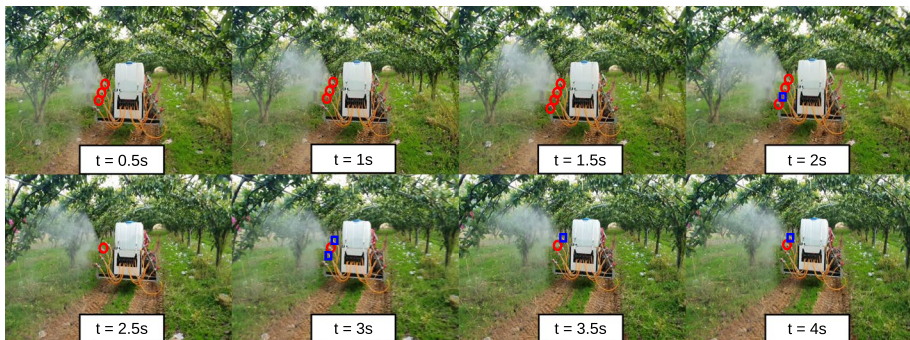
T and NT in each zone  $R_p$  are shown in Fig. 10. The experiment was performed in two trials, and 54 water-sensitive papers were used in the T and NT trials. It is assumed that this would be the same as in attempting 54 experiments with one water-sensitive paper attached. The amount of pesticide used in one row of orchards was 25 L. In the experiment, the  $R_p$  values of the T and NT, which should be controlled, were recorded as an average of 56.15% and 58.80%, respectively. These results show that  $R_p$  is the same in all areas because the spraying was performed indiscriminately.

### Control 2: on/off control

The second experiment was conducted to confirm the degree of adhesion to the water-sensitive paper when spraying was performed by on/off control. In contrast to the results of the first experiment, the performance of the intelligent spraying system was obtained through an on/off control. If the result of the first experiment is the same for T, where the fruit tree

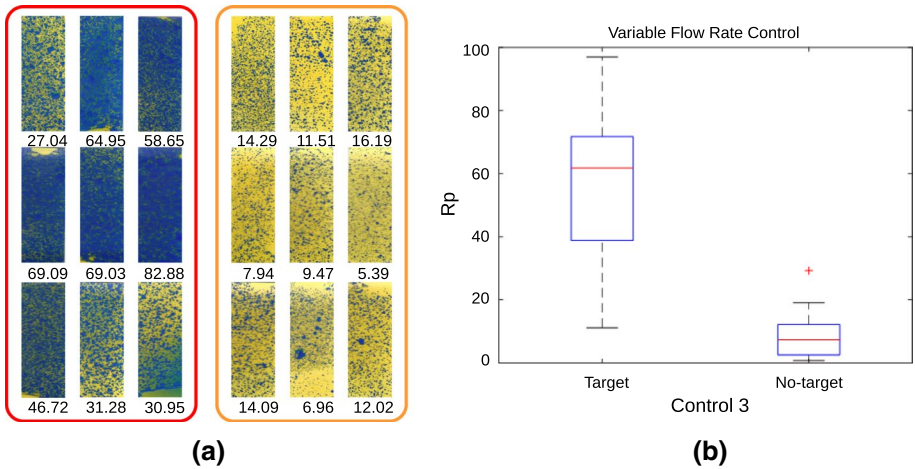


**Fig. 12** Spraying result in Control 2—on/off control. **a** Example of water-sensitive paper result: Target (left) and No-target (right), and **b** box plots display median, interquartile range, maximum, and minimum values



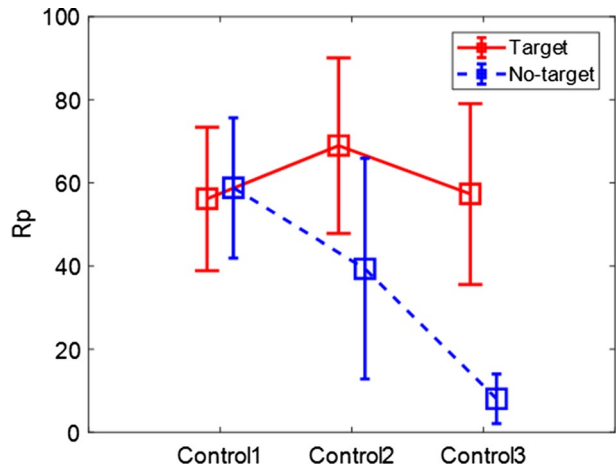
**Fig. 13** Control 3 of snapshots from 0.5 to 4 s of spraying. The flow rate of each nozzle was controlled using Control 3. The flow rate of each nozzle was determined by calculating the area and distance of the fruit tree in the area corresponding to each nozzle. The circle represents a fully open nozzle. The square indicates that the nozzle is not fully open according to the variable flow rate control

exists, the control in the desired area was performed well. In addition, if the result in the NT area, which is an area where fruit trees do not exist, was lower than that of the first experiment, fewer pesticides would exist in the area. This would indicate that the consumption of unnecessary pesticides was reduced. Figure 11 shows snapshots from 0.5 to 4 s of spraying. Each nozzle was a selective fully open nozzle for Control 2. When the fruit tree area corresponding to each nozzle was recognized, the nozzle was fully open. The red circle and blue square represent a fully open nozzle and not fully open one according to variable flow rate control, respectively. For example, when  $t = 1$  s, two nozzles were opened because the area corresponding to the top two nozzles was recognized as a fruit tree, and when  $t = 1.5$  s, the area corresponding to top three nozzles was recognized as a fruit tree and three nozzles were opened.



**Fig. 14** Spraying result in Control 3—variable flow rate control. **a** Example of water-sensitive paper result: Target (left) and No-target (right), and **b** box plots display median, interquartile range, maximum, and minimum values

**Fig. 15** Experimental results for each control. The figure is plotted as the *mean ± standard error*



The experimental results are presented in Fig. 12 and represent  $R_p$  at T and NT in each zone, respectively. The amount of pesticide used in one row of the orchard was 19.6 L. In the experiment,  $R_p$  of the T and NT, which should be controlled, averaged 68.95% and 39.36%, respectively. Compared with the first experiment,  $R_p$  increased by 12.7% in T, and  $R_p$  decreased by 18.44% in NT. Consequently,  $R_p$  did not decrease in the T, which is the area where the control needs to be performed, thus, the control performance does not deteriorate. The  $R_p$  decreases in the NT, which is the area where control does not need to be carried out, reducing unnecessary pesticide use.

### Control 3: Variable Flow Rate Control

A third experiment was conducted to confirm the degree of adhesion to water-sensitive paper when spraying was performed through variable flow rate control. This shows the performance of the intelligent spraying system in contrast to the first experiment. In addition, the highest performance is shown by comparing the results with the consumption of pesticides in the second experiment and showing the lowest consumption of pesticides.

Figure 13 depicts snapshots from 0.5 to 4 s of spraying. Each nozzle was a selective fully open nozzle for Control 2. When the fruit tree area corresponding to each nozzle was recognized, and the nozzle was fully open. The red circle represent a fully open nozzle. For example, when  $t = 1$  s, two nozzles were opened because the area corresponding to the top two nozzles was recognized as a fruit tree. When  $t = 1.5$  s, the area corresponding to the top three nozzles was recognized as a fruit tree and three nozzles were opened.

The experimental results are shown in Fig. 14 and represent  $R_p$  at T and NT in each zone. The amount of pesticide used in one row of orchard was 12.7 L. In the test, the  $R_p$  value of T and NT, which should be controlled, averaged 57.33% and 8.08%, respectively. Compared to the first experiment,  $R_p$  increased by 1.18% in T, and  $R_p$  decreased by 49.72% in NT. Consequently,  $R_p$  did not decrease in the T, which is the area where the control needs to be performed, so that the control performance did not deteriorate; and  $R_p$  decreases in the NT, the area where the control is not required. Thus, the amount of unnecessary pesticides was reduced. In addition, compared with the control 2, this experiment showed a lower  $R_p$  in the NT, and the amount of pesticide used was also low, which proved that this was the most effective control.

### Summary and discussion of results

A field experiment was conducted with three controls. Figure 15 and Table 6 summarize the results of each control. Control 1 is representative of the sprayer performance because it performs conventional spraying. Therefore, the spraying performance can be defined based on the  $R_p$  result of T in Control 1. In the T,  $R_p$  shows result of 56.15 ( $\pm 17.24$ )%, 68.95 ( $\pm 21.12$ )%, and 57.33 ( $\pm 21.73$ )% for each control. Controls 2 and 3 showed higher  $R_p$  than Control 1. These results indicate that the spraying performance did not decrease in T. Control 2 was the highest  $R_p$ , and this result could be caused from the difference in the form of pesticides attached to the sensitive paper.

Spraying performance can also be defined based on the  $R_p$  result of NT in Control 1. The NT shows results of 58.80 ( $\pm 16.83$ )%, 39.37 ( $\pm 26.54$ )%, and 8.08 ( $\pm 5.97$ )% for each control. Controls 2 and 3 showed lower  $R_p$  than Control 1. This indicated that the undesired area was not sprayed. In particular, Control 3 significantly differed from Control 1, and was lower than that of Control 2. In this result, the spraying performance of Control 3 was higher than that of Control 2 indicating the highest overall performance. Therefore, the proposed variable flow rate control-based spraying method was shown to be the most optimal control, and the flow rate modeling based on the preliminary experiments achieved optimization.

## Discussions

### Performance measure

This study proposed a deep learning-based intelligent spraying system and proved the superiority of variable flow control in real-time by comparing on/off control. To evaluate

the spraying performance, it was confirmed that the performance was improved by comparing the pesticide adhesion rates on water-sensitive paper. The performance of the water-sensitive paper, may be seen as an insufficient result because it represents only a specific area. Therefore, it is necessary to evaluate the system using a performance measure that is different from the pesticide adhesion rate.

As another example, to evaluate the performance of the water-sensitive paper, it will be possible to more accurately verify the spraying performance by analyzing the droplet size and pattern recorded on the water-sensitive paper. In this case, the water droplets formed on the leaf surface droop owing to gravity. Separation and analysis of these cases are a major issues.

### **Precision level**

Currently, a very precise level of spraying is considered not necessary in fruit trees, but as precision agriculture develops in the future, the importance of precise agriculture in open fields and orchards may be highlighted. Therefore, precision agriculture needs to consider spraying time and amount based on the leaves and fruit tree state. In addition, it is necessary to analyze how much of the pesticide has reached the trees by sensing the spraying type and droplets.

However, it is expected that it will be very difficult to control the precise level of spraying owing to the effects of drift. For precise spraying, a method to suppress drift should be researched. If a study to minimize drift by changing the structure of the nozzle and a study to analyze the degree of drift according to the pump pressure are conducted, then the control parameters can be optimized.

### **Drift analysis**

As one of the factors that significantly influence spraying performance, drift can damage other crops. However, drift is mainly caused by wind, and it is, therefore, difficult to analyze accurately. In the case of the proposed intelligent spraying platform, no air-assist device is used in other orchards; therefore, it is expected that drift will not occur over long distances. However, when drift occurs, it is difficult to control because external forces such as wind cannot be controlled. Therefore, measuring the drift and determining its effect are major challenges.

It is possible to investigate the distance and effect of drift by investigating the overlapping pesticides as an indirect measurement method; however, the exact variables that are required are not known. Additionally, if the drift can be precisely sensed through a vision sensor, the factors that affect the spray can be immediately confirmed visually. If the factors are accurately confirmed, policies to minimize the drift can be established. However, crops that exist in an open field environment or an orchard environment can act as obstacles to drift sensing.

### **Conclusions**

In this study, a deep-learning-based real-time variable flow control system was proposed with fruit tree perception. Theoretical modeling may not be accurate because pressure acts as a variable on the actual nozzle tip. Flow rate modeling was designed by a preliminary experiment that

evaluated whether the result completely covered the spraying area according to the duty cycle. The spraying distance was evaluated to determine whether the output reached the corresponding spraying area according to the duty cycle. Field experiments were conducted for three controls, and the results of each experiment confirmed that the pesticide was reduced to 56.80%, 39.37%, and 8.08% in areas where spraying should not be performed. In addition, the actual use of pesticides decreased to 25, 19.6, and 12.7 L in the experiment, confirming that the proposed variable flow rate control system is more effective than the existing control method. This paper discussed the performance measures, research directions, and drift analysis.

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## References

- Asaei, H., Jafari, A., & Loghavi, M. (2019). Site-specific orchard sprayer equipped with machine vision for chemical usage management. *Computers and Electronics in Agriculture*, *162*, 431–439. <https://doi.org/10.1016/j.compag.2019.04.040>.
- Bac, C. W., van Henten, E. J., Hemming, J., & Edan, Y. (2014). Harvesting robots for high-value crops: State-of-the-art review and challenges ahead. *Journal of Field Robotics*, *31*(6), 888. <https://doi.org/10.1002/rob.21525>.
- Berenstein, R., & Edan, Y. (2017). Automatic adjustable spraying device for site-specific agricultural application. *IEEE Transactions on Automation Science and Engineering*, *15*(2), 641. <https://doi.org/10.1109/TASE.2017.2656143>.
- Berk, P., Hocevar, M., Stajanko, D., & Belsak, A. (2016). Development of alternative plant protection product application techniques in orchards, based on measurement sensing system: A review. *Computers and Electronics in Agriculture*, *124*, 641. <https://doi.org/10.1016/j.compag.2016.04.018>.
- Butts, T. R., Butts, L. E., Luck, J. D., Fritz, B. K., Hoffmann, W. C., & Kruger, G. R. (2019). Droplet size and nozzle tip pressure from a pulse-width modulation sprayer. *Biosystems Engineering*, *178*, 52. <https://doi.org/10.1016/j.biosystemseng.2018.11.004>.
- Cai, J., Wang, X., Gao, Y., Yang, S., & Zhao, C. (2019). Design and performance evaluation of a variable-rate orchard sprayer based on a laser-scanning sensor. *International Journal of Agricultural and Biological Engineering*, *12*(6), 51. <https://doi.org/10.25165/j.ijabe.20191206.4174>.
- Chen, L., Wallhead, M., Zhu, H., & Fulcher, A. (2019). Control of insects and diseases with intelligent variable-rate sprayers in ornamental nurseries. *Journal of Environmental Horticulture*, *37*(3), 90. <https://doi.org/10.24266/0738-2898-37.3.90>.
- Chen, Y., Zhu, H., & Ozkan, H. (2012). Development of a variable-rate sprayer with laser scanning sensor to synchronize spray outputs to tree structures. *Transactions of the ASABE*, *55*(3), 773. <https://doi.org/10.13031/2013.41509>.
- Chen, Y., Zhu, H., & Ozkan, H. E. (2011). Development of lidar-guided sprayer to synchronize spray outputs with canopy structures. In *2011, Louisville, Kentucky, August 7–10, 2011* (p. 1). American Society of Agricultural and Biological Engineers. <https://doi.org/10.13031/2013.37206>.
- Cheng, Z., Qi, L., Wu, Y., Zhang, H., Xiao, Y., Yang, Z., & Li, X. (2019). Spray deposition and distribution under different canopy densities based on FCM-R. In *2019 ASABE annual international meeting* (p. 1). American Society of Agricultural and Biological Engineers. <https://doi.org/10.13031/aim.201900434>.
- Escolà, A., Rosell-Polo, J., Planas, S., Gil, E., Pomar, J., Camp, F., Llorens, J., & Solanelles, F. (2013). Variable rate sprayer. Part 1—Orchard prototype: Design, implementation and validation. *Computers and Electronics in Agriculture*, *95*, 122. <https://doi.org/10.1016/j.compag.2013.02.004>.
- Gao, G., Xiao, K., & Ma, Y. (2018). A leaf-wall-to-spray-device distance and leaf-wall-density-based automatic route-planning spray algorithm for vineyards. *Crop Protection*, *111*, 33. <https://doi.org/10.1016/j.cropro.2018.04.015>.
- Giles, D., Klassen, P., Niederholzer, F., Downey, D., et al. (2011). “Smart” sprayer technology provides environmental and economic benefits in California orchards. *California Agriculture*, *65*(2), 85. <https://doi.org/10.3733/ca.v065n02p85>.

- Guan, Y., Chen, D., He, K., Liu, Y., & Li, L. (2015). Review on research and application of variable rate spray in agriculture. In *2015 IEEE 10th conference on industrial electronics and applications (ICIEA)* (p. 1575). IEEE. <https://doi.org/10.1109/ICIEA.2015.7334360>.
- Ju, C., & Son, H. I. (2019). Modeling and control of heterogeneous agricultural field robots based on Rameda–Wonham theory. *IEEE Robotics and Automation Letters*, *5*(1), 48. <https://doi.org/10.1109/LRA.2019.2941178>.
- Jun, J., Kim, J., Seol, J., Kim, J., & Son, H. I. (2021). Towards an efficient tomato harvesting robot: 3D perception, manipulation, and end-effector. *IEEE Access*, *9*, 17631–17640. <https://doi.org/10.1109/ACCESS.2021.3052240>.
- Kim, J., & Son, H. I. (2020). A Voronoi diagram-based workspace partition for weak cooperation of multi-robot system in orchard. *IEEE Access*, *8*, 20676. <https://doi.org/10.1109/ACCESS.2020.2969449>.
- Kim, J., Kim, S., Ju, C., & Son, H. I. (2019). Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications. *IEEE Access*, *7*, 105100. <https://doi.org/10.1109/ACCESS.2019.2932119>.
- Kim, J., Seol, J., Lee, S., Hong, S. W., & Son, H. I. (2020). An intelligent spraying system with deep learning-based semantic segmentation of fruit trees in orchards. In *2020 IEEE international conference on robotics and automation (ICRA)* (p. 3923). IEEE. <https://doi.org/10.1109/ICRA40945.2020.9197556>.
- Koen, B. V. (1988). Toward a definition of the engineering method. *European Journal of Engineering Education*, *13*(3), 307–315. <https://doi.org/10.1080/03043798808939429>.
- Le, M.-Q., Pham, M.T., Moreau, R., & Redarce, T. (2010). Comparison of a PWM and a hybrid force control for a pneumatic actuator using on/off solenoid valves. In *2010 IEEE/ASME international conference on advanced intelligent mechatronics* (p. 1146). IEEE. <https://doi.org/10.1109/AIM.2010.5695894>.
- Liu, H., Zhu, H., Shen, Y., Chen, Y., & Ozkan, H. E. (2014). Development of digital flow control system for multi-channel variable-rate sprayers. *Transactions of the ASABE*, *57*(1), 273. <https://doi.org/10.13031/trans.57.10216>.
- Mahmud, M. S., Zahid, A., He, L., & Martin, P. (2021). Opportunities and possibilities of developing an advanced precision spraying system for tree fruits. *Sensors*, *21*(9), 3262. <https://doi.org/10.3390/s21093262>.
- Manandhar, A., Zhu, H., Ozkan, E., & Shah, A. (2020). Techno-economic impacts of using a laser-guided variable-rate spraying system to retrofit conventional constant-rate sprayers. *Precision Agriculture*, *21*, 1–16. <https://doi.org/10.1007/s11119-020-09712-8>.
- Osterman, A., Goděsa, T., Hočevar, M., Širok, B., & Stopar, M. (2013). Real-time positioning algorithm for variable-geometry air-assisted orchard sprayer. *Computers and Electronics in Agriculture*, *98*, 175. <https://doi.org/10.1016/j.compag.2013.08.013>.
- Salcedo, R., Zhu, H., Zhang, Z., Wei, Z., Chen, L., Ozkan, E., & Falchieri, D. (2020). Foliar deposition and coverage on young apple trees with PWM-controlled spray systems. *Computers and Electronics in Agriculture*, *178*, 105794. <https://doi.org/10.1016/j.compag.2020.105794>.
- Shen, Y., Zhu, H., Liu, H., Chen, Y., & Ozkan, H. (2013). Delay times of a lidar-guided precision sprayer control system. In *ASABE annual international meeting. Paper*. <https://doi.org/10.13031/aim.20131594649>.
- Shen, Y., Zhu, H., Liu, H., Chen, Y., & Ozkan, E. (2017). Development of a laser-guided, embedded-computer-controlled, air-assisted precision sprayer. *Transactions of the ASABE*, *60*(6), 1827. <https://doi.org/10.13031/trans.12455>.
- Wei, Q., Sanqin, Z., Weimin, D., Chengda, S., Jiang, L., Yinian, L., & Jiabing, G. (2016). Effects of fan speed on spray deposition and drift for targeting air-assisted sprayer in pear orchard. *International Journal of Agricultural and Biological Engineering*, *9*(4), 53. <https://doi.org/10.3965/j.ijabe.20160904.1938>.
- Xiao, K., Ma, Y., & Gao, G. (2017). An intelligent precision orchard pesticide spray technique based on the depth-of-field extraction algorithm. *Computers and Electronics in Agriculture*, *133*, 30. <https://doi.org/10.1016/j.compag.2016.12.002>.
- Zeng, L., Feng, J., & He, L. (2020). Semantic segmentation of sparse 3D point cloud based on geometrical features for trellis-structured apple orchard. *Biosystems Engineering*, *196*, 46–55. <https://doi.org/10.1016/j.biosystemseng.2020.05.015>.
- Zhou, M., Jiang, H., Shi, W., & Knoll, A. (2018). Design and optimization of the target spray platform. In *2018 IEEE international conference on robotics and automation (ICRA)-workshop on robotic vision and action in agriculture*.

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