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METHODS

Spray Drift Segmentation for Intelligent Spraying System Using 3D Point Cloud Deep Learning Framework

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ABSTRACT This study proposes a novel spray drift analysis method, based on 3D deep learning, managing and reducing spray drift using a mobile LiDAR method. LiDAR point clouds were trained to classify and segment spraying forms from orchards using the PointNet++ model, which is a 3D deep learning structure. The trained deep learning model represented an accuracy of 96.23%. The spray drift analysis system was demonstrated through its application in intelligent spraying systems. Three control field experiments were performed in a pear orchard to verify the effectiveness of the system. The obtained results confirm the satisfactory performance of 3D deep learning-based spray drift analysis method. It is expected that the proposed system can measure and manage spray drift.

INDEX TERMS Drift, deep leraning, moblie LiDAR, intelligent spraying system.

I. INTRODUCTION

In agriculture, spraying is essential task to improve the quality and productivity of crops. Here, it should be noted that the spray will always be accompanied by a drift. Spray drift is defined as the movement of sprayed pesticide droplets beyond the target area and may be caused by several factors, including the influence of wind. Pesticide droplets from spray drift can volatilize from plant and soil surfaces for several days after application, thereby posing a danger to non-target areas. Hence, non-target areas can be acutely exposed and suffer from adverse effects immediately after spraying, resulting in residues in crop commodities, water pollution, and adverse human exposure. Because of these life-threatening problems make reducing spray drift has been a complex and important problem in the agriculture industry [1]–[4].

However, traditional agricultural ground sprayers focuses on performance, such as pesticide residue using air-blast sprayer [5]. It is particularly difficult to reduce drift and achieve the performance while using these sprayers. Spray drift has always been a complex, challenging, and urgent issue for farmers when using agricultural ground sprayers. Therefore, to reduce spray drift, farmers have begun using other mobile platforms and intelligent control systems. Recently, unmanned aerial vehicles (UAVs) that are less affected by topography and have low labor costs have been widely used for spraying. However, because UAVs scatter pesticides in the air, wind-induced spray drift occurs more commonly, particularly because of the wind generated by the rotation of UAV wings [6].

Therefore, intelligent spraying systems that spray only on target areas have been developed as a means of reducing spray drift [7]–[12]. Spraying accurately on the target ensures that only the required amount of pesticides is used, which is effective in reducing spray drift. As the amount of pesticide decreases, the mount of pesticide that is affected by wind is reduced compared with conventional spraying. Therefore, intelligent systems that focus on the perception and control of precision spraying systems have been developed. In this aspect, while many intelligent spraying systems have been

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studied, a system that measures how effectively a control method reduces spray drift has not been thoroughly examined. Hence, to reduce spray drift, it is essential to study not only the control methods of sprayers for using less pesticides, but also the systems for measuring pesticides. Thus, in the agricultural industry, it is important to accurately measure as well as manage drift in order to effectively reduce drift.

Many methods have been studied for measuring spray drift [13]–[16]. Spray drift measurements through field tests are important for determining practical drift amounts; however, existing methods are time-consuming and heavily dependent on external factors. Wind tunnel experiments have been used to determine the relative drift amounts under various conditions. Spray quality characteristics, such as the total spray volume below a certain droplet size, have also been used to estimate the drift using predictive drift models or potentials. However, existing methods for spray drift management have spatial and temporal limitations. In summary, to compensate for the previous limitations, ground, aerial and intelligent sprayers require a system that can measure, control and manage spatial and temporal spray drift.

Therefore, the objectives of this study were: (a) to detect spray drift based on mobile 3D LiDAR in real-time for pear orchards, (b) to analyze spray drift measurement for spatial and temporal data, and (c) to conduct field tests for evaluating the system and determine whether it achieves objectives (a) and (b). The research hypothesis was that such a system can detect spatial and temporal spray drift for spray drift management if deep learning-based model with 3D LiDAR point cloud data is applied. To prove this hypothesis, this study developed a measurement system to analyze the spray drift. Spray performance was evaluated using an intelligent spraying system in our previous research [12]. In other words, this research proposes a methodology for reducing the spray drift of pesticides by proposing a system for measuring spray drift, along with control methods for nozzle control. The contributions and novelty of this study are as follows:

1) This study proposed a novel spray drift measurement method using mobile LiDAR based on 3D deep-learning.
2) The proposed spray drift measurements system is capable of analyzing both spatial and temporal data regarding spray drift.
3) This study conducted rigorous and practical field experiments with three nozzle control methods, and measured spray drift using the proposed method in actual pear orchards.

A. STRUCTURE OF PAPER

The remainder of this paper is organized as follows. In the section II, an existing the spray drift measurements methods by reviewing other papers. In the section III, present a 3D deep learning-based spray drift analysis method using LiDAR point clouds. In the section IV, present and discuss experimental setup and results regarding the verification and evaluation of the proposed intelligent spraying system performed in a pear orchard. In the section V, experimental results and challenges for future work are discussed. Finally, summarize the conclusions and provide directions for future research.

II. AN EXISTING SPRAY DRIFT MEASUREMENTS METHODS

Spray drift measurement methods aimed at reducing and managing spray drifts have been a popular research topic. Spray drift measurement methods can be classified into three types: water-sensitive paper analysis, spraying form visualization, and stationary LiDAR-based methods. In this section, review existing spray drift measurement methods.

A. WATER-SENSITIVE PAPER ANALYSIS METHOD

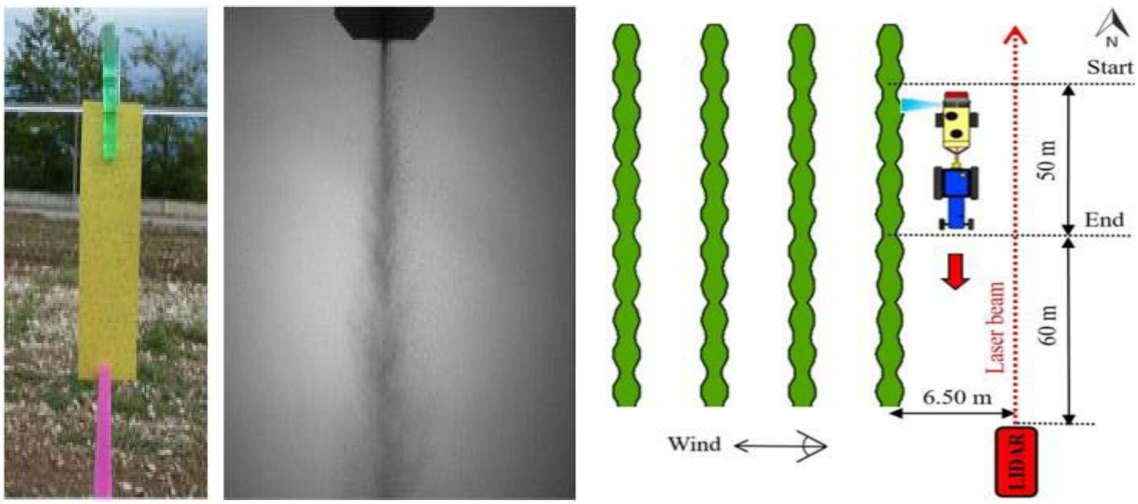
Water-sensitive paper has a specially coated yellow surface that turns blue by the influence of aqueous droplets. It can be used to measure spray drift according to the droplet density and sizing. In [17], water-sensitive paper sheets were used for spray drift measurements. As shown in Fig. 1(a), 16 water-sensitive paper sheets (26×76 *mm*) were attached to a nylon string with pegs. In [13], proposed a method for reducing spray drift by increasing the size of the droplets produced especially near cropping zones. They placed several water-sensitive papers 2.5 m away from the target area and analyzed them to confirm that their proposed model reduces spray drift. In [19] proposed a method for analyzing spray drift by placing 12 water-sensitive papers at a height of 0.30 m. The sliding covers were actuated to cover the water-sensitive papers during spraying, thus protecting them from unintended spray droplets. They were simultaneously uncovered when the spray boom had passed by actuating the actuator.

B. SPRAYING FORMS VISUALIZATION METHOD

Spray drift can also be indirectly evaluated and measured using spraying forms with visualization. Techniques for the visualization of spraying forms include Mie-Scattering Scattering [20], Shadograph [21], and Laser sheet methods [15]. In [22], a spray droplet size determination scheme was introduced using phase Doppler particle analyzers and laser light diffraction techniques under laboratory conditions (Fig. 1(b)). Existing spray drift visualization methods are not applicable in the field and can only be used to predict spray drift potential by identifying the droplet characteristics of the nozzle. Spray drift potential can also be indirectly evaluated from the droplet size distribution through visualization. It is widely known that smaller droplets exhibit a greater tendency to drift. At this time, spray droplet size is usually determined in a laboratory under controlled conditions using laser light diffraction techniques or phase Doppler particle analyzers [15]; however, only the nozzle is evaluated using these techniques.

C. STATIONARY LiDAR-BASED METHOD

The stationary LiDAR-based method measures and monitors the spray drift that occurs during driving and spraying



(a) (b) (c)

FIGURE 1. **The existing spray drift measurement methods: (a) Spraying form visualization methods, (b) Water-sensitive paper analysis method [17], (c) Stationary LiDAR-based methods [18].**

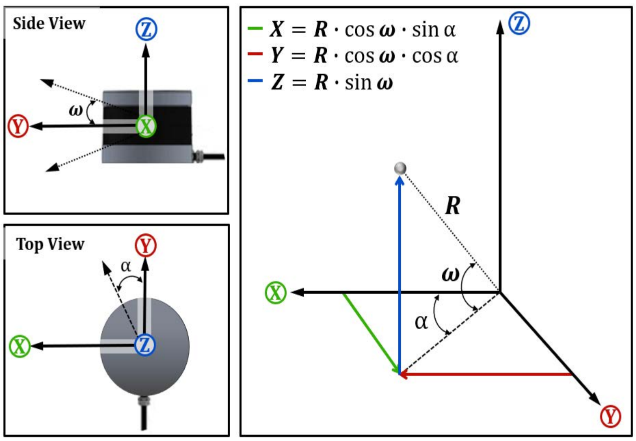


FIGURE 2. **Data from LiDAR point clouds.**

operations, with the lidar fixed at a specific location at a specific distance from the sprayer [16], [23]–[27]. In [18], a LiDAR system was introduced to evaluate the potential drift risk according to different spray nozzles (Fig. 1(c)). In field tests, their LiDAR system for measuring the spray drift was able to differentiate between standard and drift reduction nozzles under real application conditions. In [27], a stationary LiDAR-based method was introduced to measure the spray drifts for different nozzle types. They used a LiDAR system with a spatial resolution of 2.4 m, which allowed for elevation and azimuth scanning. The LiDAR system was placed parallel to the trees at 3.3 m and the spray drift was measured.

D. LIMITATIONS OF CONVENTIONAL SPRAY DRIFT MEASUREMENTS METHODS

Existing spray drift measurement methods cannot analyze spray drift in real time and only have a limited range for monitoring spray drift. Moreover, existing spray drift visualization methods are not applicable in the field and can only be used to predict spray drift potential by identifying the nozzle droplet characteristics. It is difficult to accurately predict the potential of spray drift because it depends not only on the nozzle spray characteristics but also the external environment, such as the growth status of trees in orchards and the interval between trees.

To address this problem, this study proposes a novel spray drift measurement method that monitors and analyzes spray drift in real time using LiDAR point clouds. Existing stationary LiDAR based spray drift measurement method can be used in a specific area, there it has scalability when expanded to Moblie LiDAR. It can obtain spatial and temporal data on spray drift from point clouds and identify based on 3D deep learning.

III. SPRAY DRIFT MEASUREMENTS METHODS USING LiDAR POINT CLOUDS

This study proposes a pesticide spray drift measurement method using LiDAR point clouds for the real-time measurement and visualization of spraying forms that occur during spraying.

A. LiDAR POINT CLOUDS

A point cloud is a set of data points in 3D space. The points represent a 3D shape, and each point position has a set of Cartesian coordinates (X, Y, Z). Point clouds are generally produced by 3D scanners, 3D LiDAR, RGB-D cameras, or photogrammetry software, which measures many points on the external surfaces of objects around them. Point clouds are used as the output of 3D scanning processes for many purposes, including creating 3D CAD models for manufactured parts, metrology, and quality inspection, as well as a multitude of visualization, rendering, and mass customization applications.

In this system, point clouds are acquired using a LiDAR sensor. The point cloud positions $X = R \cdot \cos\omega \cdot \sin\alpha$, $Y = R \cdot \cos\omega \cdot \cos\alpha$, and $Z = R \cdot \sin\omega$ are obtained. R is the linear distance from the obstacle measured by LiDAR and the vertical angle ω can be obtained as shown in Fig. 2. The angle ω corresponding to each laser beam was fixed. As shown in Fig. 2, α is the rotation angle measured at the first point.

B. SEGMENTATION OF SPRAYING FORM FROM ORCHARD POINT CLOUDS BASED ON 3D DEEP-LEARNING

1) NETWORK ARCHITECTURE FOR POINT CLOUD SEGMENTATION

This research proposes the segmentation of the spraying form method from orchard point cloud data based on PointNet++ [28]. PointNet++ is a deep neural network algorithm for point cloud classification and segmentation, which is an extension of PointNet [29] with an added hierarchical structure. The input data of PointNet is represented by an $n \times 3$ matrix. n is the number of points and 3 describes the position (X, Y, Z) of a point in the Cartesian coordinate system. The PointNet architecture that shares a multi-layer perceptron is a 1×1 convolution mathematically. Therefore, PointNet can be recognized using fully connected layers with branches. The transformation structures are organized by an $n \times M$ input matrix, where $M = 3$ in the case of the input transformation and $M = 64$ in the case of feature transformation.

The network architecture for point cloud classification and segmentation is shown in Fig. 3. PointNet++ creates a hierarchical grouping of points and progressively abstracts larger local regions along the hierarchy in comparison with PointNet, which uses a single max-pooling to aggregate the entire point set. The set of points was abstracted to create a new set with fewer components in each layer. The set abstraction layer consists of sampling, grouping, and PointNet layers. First, the sampling layer determines the set of points that determines the centroids of the local region. Second, the grouping layer creates local region sets by obtaining neighboring points around the centroids of the local region. Finally, the PointNet layer encodes local region patterns into feature vectors using mini-PointNet.

To extract the local features of a set of points with uneven density in different regions, PointNet++ uses density adaptive PointNet layers (Fig.3). PointNet++ proposes two types of density adaptive layers: multi-scale grouping (MSG) and multi-resolution grouping (MRG). Applying grouping layers with different scales followed by PointNets to extract each scale feature is not only simple but also an effective way to obtain multiscale patterns. PointNet++ learns an optimized approach for merging multi-scale features using a random input dropout with a randomized probability for each instance.

The MSG method operates local PointNet in large-scale neighborhoods for all centroid points; therefore it is computationally expensive. PointNet++ proposes an alternative method that avoids expensive computations based on the distributional features of points. The feature of a region is a combination of two vectors. One vector is obtained by selecting the features at each sub-region from the lower level using the set abstraction level. The other vector is a feature that uses a single PointNet and is obtained by directly processing all the raw points in the local region. The MRG method is more efficient in terms of computation because it avoids feature extraction in large-scale neighborhoods at the lowest levels.

The original point set was subsampled in the abstraction layer. For segmentation tasks, the point features for all the original points should be obtained. PointNet++ adopts a hierarchical propagation method with distance-based interpolation and cross-level skipped links. In feature propagation, PointNet++ propagates point features from $N_l \times (d + C)$ to N_l points, where N_l and N_l are the point set sizes of the input and output of the set abstraction level l, respectively. Feature propagation was achieved by interpolating the feature values f of N_l points at the coordinates of the N_l points. PointNet++ uses the inverse distance weighted average based on k nearest neighbors for interpolation. The interpolated features on N_l points are then concatenated with skip-linked point features, and the concatenated features are passed through a convolution called a unit PointNet. To update the point's feature vector, shared fully connected and ReLU layers were applied. This process is repeated until the features of the original set of points are propagated.

2) POINT CLOUD SEGMENTATION EVALUATION METRICS

Three measurement metrics were used to evaluate the point cloud segmentation. The point cloud segmentation evaluation metrics mainly focused on accuracy, precision, and recall.

Definition 1: **Accuracy** is the number of correctly predicted data points among all the data points, which is defined by

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

where TP (true positive) is an outcome where the model correctly predicts the positive class, TN (true negative) is an outcome in which the model correctly predicts the negative class, FP (false positive) is an outcome in which the model incorrectly predicts the positive class, and FN (false negative) is an outcome in which the model incorrectly predicts the negative class.

Definition 2: **Precision** is a measure of how often something labeled as positive is actually positive, which is defined by

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Definition 3: **Recall** is the measure of the percentage of positives labeled correctly, which is defined by

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

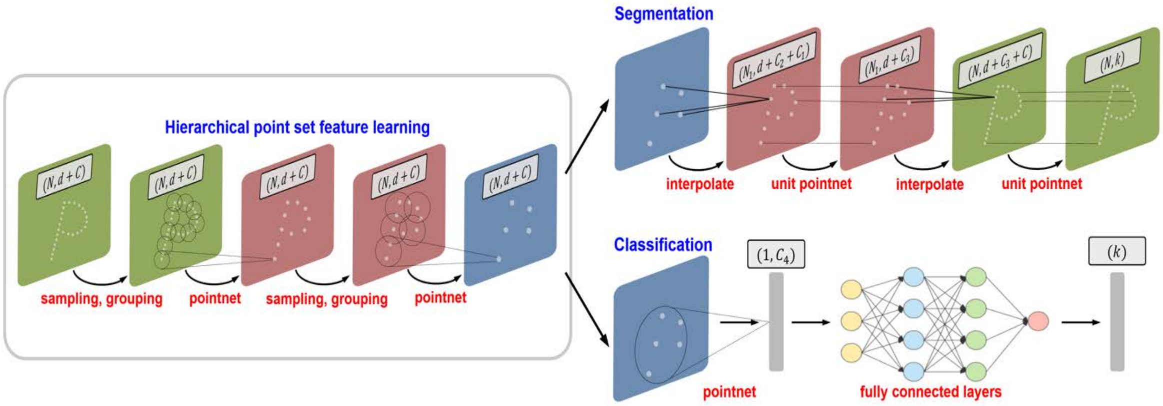


FIGURE 3. Network architecture for point cloud classification and segmentation.

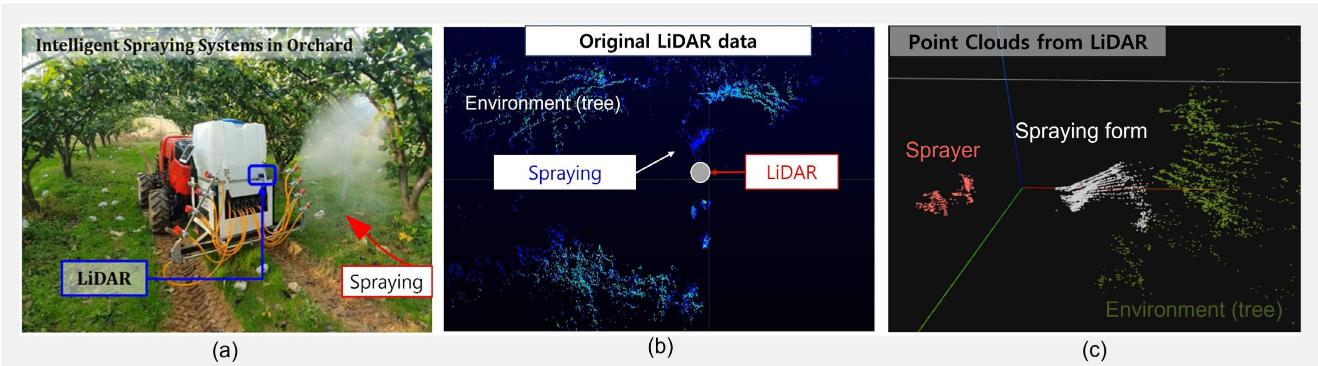


FIGURE 4. Overview of drift measure system. (a) Field experiments using an intelligent spraying system in an orchard for obtaining LiDAR data of spray. (b) Original LiDAR data before the processing. (c) System measures and visualizes spraying forms for a pesticide spray drift measurement from original data.

3) SPRAY DRIFT MEASUREMENT METRICS

Two measurement metrics were used to analyze spray drift. The spray drift measurement metrics mainly focused on the spraying distance and spraying size as the volume. By measuring these metrics, it becomes possible to confirm how many pesticides are sprayed in what form.

Definition 4: **Spraying distance** is the

$$d_{hmax} = \sqrt{(a_x - b_x)^2 + (a_z - b_z)^2} \tag{4}$$

where a_x is the point cloud of the minimum x-coordinate belonging to a class *spraying form*, b_x is the point cloud of the maximum x-coordinate belonging to a class *spraying form*, a_z is the point cloud of the minimum z-coordinate belonging to a class *spraying form*, and b_z is the point cloud of the minimum z-coordinates belonging to a class *spraying form*.

Definition 5: **Spraying volume** refers to the volume being sprayed using the number of spraying points as defined by

$$v_s = \sum p_{spraying\,form} \tag{5}$$

where $p_{spraying\,form}$ is a point cloud p belonging to the class *sprayingform*. The set of points in 3D space can represent the volume.

IV. APPLICATIONS

This study evaluated the proposed spray drift analysis system by applying it the to an intelligent spraying system developed in [12].

A. AN INTELLIGENT SPRAYING SYSTEMS

In [12], an intelligent spraying system was proposed to minimize the use of pesticides while maintaining a desirable spraying performance. The proposed drift measure of the intelligent spraying system is shown in Fig. 4. Spraying system was tightened and lifted through a three-point hitch link on a mobile platform. The mobile platform can freely be driven on unstructured roads, such as agricultural fields. Spraying systems and computing platforms receive power from 24 V batteries. The spraying systems were equipped with a 300 L capacity 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 cameras.

B. EXPERIMENTAL DESIGN

The dataset was acquired from pear orchards using experiments described in [12]. Field experiments using the variable spraying system were conducted in a pear orchard in

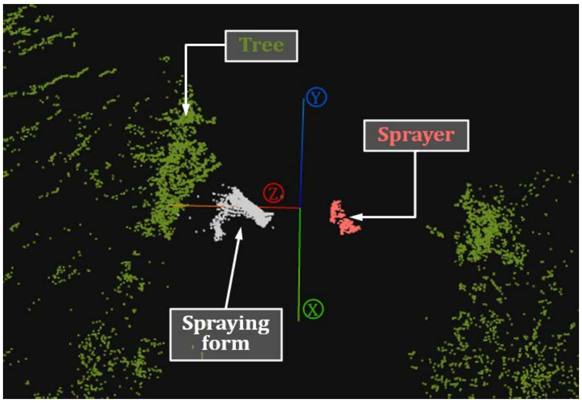


FIGURE 5. LiDAR point clouds acquisition in the pear orchard and example images of dataset. There are three classes in the dataset: spraying form, tree, and sprayer.

Bonghwang, Naju, South Korea. The variable spraying system was attached to a mobile platform as an intelligent spraying system, and the environment was configured as shown in Fig. 5. There were three target (T) and three no-target (NT) zones in the orchard. T refers to an area where there is a fruit tree that must be sprayed, and NT refers to an area with no fruit trees that does not need to be sprayed.

C. EXPERIMENTAL CONTROL METHOD

In this paper, drift is defined as the movement of sprayed pesticide droplets beyond of the target area owing to inaccurate control methods. In other words, the drift is defined as the reachability of an area that should not be sprayed. Drift reachability refers to the possibility of reaching another area (NT) from the area to be controlled. Drift reachability is significantly affected by external forces such as wind. Therefore, to reduce drift reachability, a control should be constructed by minimizing the influence of external forces. Therefore the experiment was conducted using three controls. At this time, LiDAR data were acquired at intervals of 10 Hz from the start to the end of the spraying of each control. The each control as follows:

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

*Control*1 (all nozzles open) represents the performance of the conventional spraying method, which means that control is not performed according to the environment. Hence, *Control*1 represents the representative performance of an intelligent spraying system and can be compared to other controls. Please refer to [12] for a detailed description of each control method.

1) DATASET PRE-PROCESSING

The point cloud was acquired using Velodyne LiDAR VLP-16 which was attached to the sprayer while the sprayer was driven and sprayed in the pear orchard at an acquisition speed of 10 Hz (Fig. 4). The point cloud was acquired as a PCAP, a Velodyne LiDAR data form, and was then transformed into point clouds for deep learning. There were three classes in the dataset, as acquired from the training: spraying form, orchard, and sprayer. Pre-processing was performed on the point clouds to label the data by class. Of the total 1100 pre-processed data, 980 were used for training and 120 were used for testing.

D. EXPERIMENTAL RESULT

1) POINT CLOUD SEGMENTATION RESULTS

The point cloud is segmented and classified into three classes. The overall accuracy, precision, and recall of the trained deep learning model were 96.23%, 93.11%, and 98.37%, respectively. Fig. 6 (a) shows a snapshot of the intelligent spraying system for pesticides spraying. At this time, LiDAR sensors acquire data at 10 Hz, therefore, spray form data can be monitored in 0.1 s intervals. The 0.1 s period is sufficient to confirm that the spraying form changes over time, as shown in Fig. 6 (a).

2) SPRAY DRIFT MEASUREMENT RESULTS

Figures 6 (b) and (c) show the results of the spray drift measurements using the spray drift analysis systems. In Fig. 6 (a), d_{hmax} is the lowest in *Control*3 and the highest in *Control*1, indicating the extent of pesticide spray drift. The experiment demonstrated that the method applied to *Control*3 had the lowest pesticide usage [12], with the lowest spray drift as well. This result indicates that an area should be sprayed according to the distance from the tree to the sprayer because undesired drift is caused by the wind according to the spraying volume.

Similarly, in Fig. 6 (b), v_s is the lowest in *Control*3 and the highest in *Control*1, indicating the amount of pesticide. Although the approximate amount of pesticides used was determined using the water-sensitive paper method established in previous studies, the proposed drift analysis method can be used to determine the pesticide usage and the degree of scattering more accurately. These results demonstrate that proposed system is capable of measuring spray drift in actual field environments. Furthermore, it is possible to acquire and verify the spray drift data at any point in time when pesticides are sprayed at 0.1 s intervals, as shown in Fig. 6 (a).

V. DISCUSSIONS

This study demonstrated that by applying proposed system to intelligent spraying systems, it is possible to effectively perform a spray drift analysis. In addition, the degree of spray drift was analyzed using the spraying distance and volume. However, the topic of this study remains an interesting one for future research, as there are issues that need to be further discussed and addressed. A discussion regarding future research is provided below.

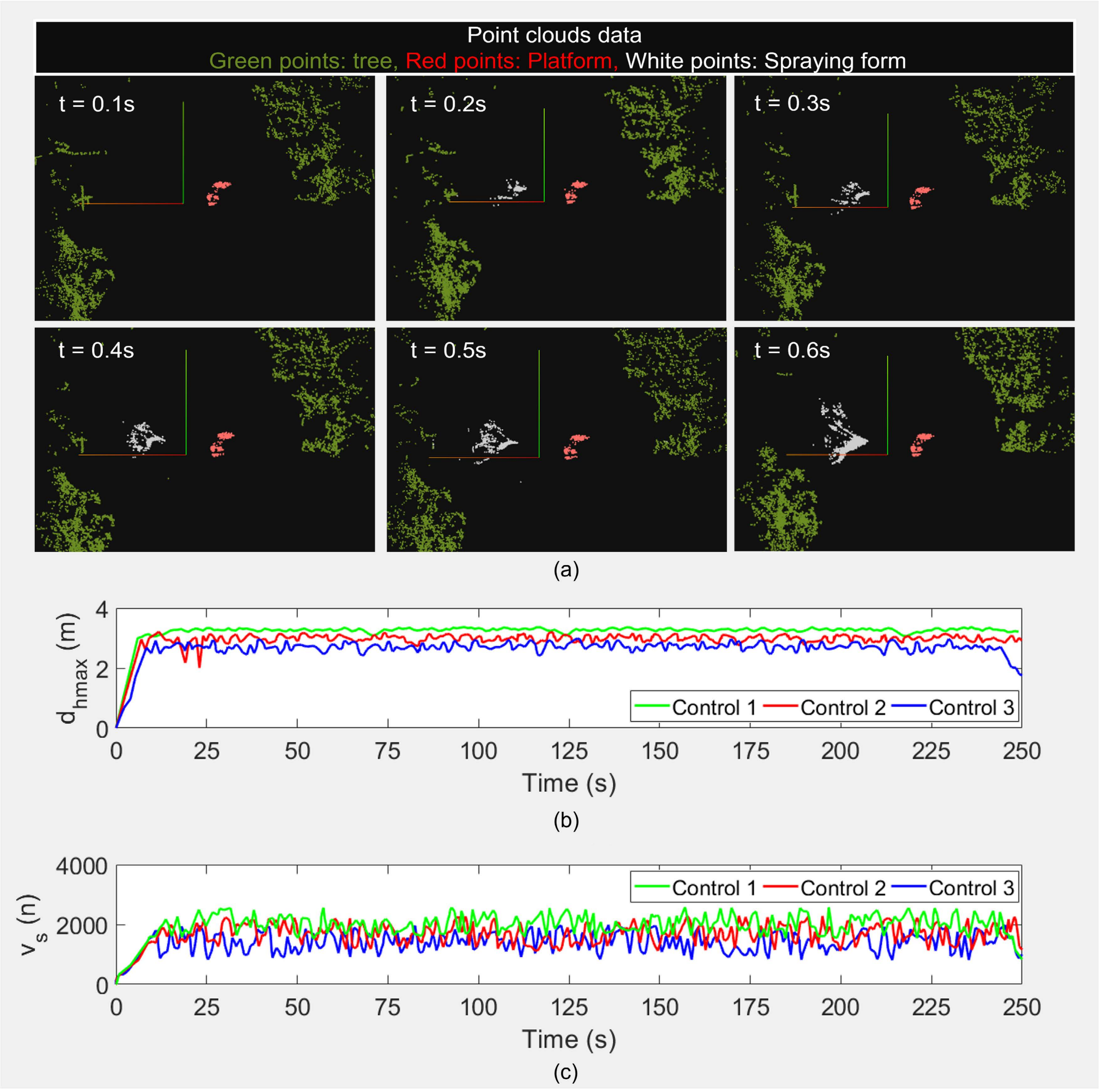


FIGURE 6. Experiment results; (a) Snapshot of spray drift segmentation results. Point cloud of spray form can be monitored in 0.1 s intervals. (b) Experimental results of spraying distance according to the control method. (c) Experimental results of spraying volume according to the control method.

A. ANALYSIS

The experimental results showed that both metrics were low in *Control*3, which used the least amount of pesticide. These results suggest that spray drift affected by wind and can be minimized with low reachability by adopting appropriate controls with respect to the orchard environment. Although, the reachability was not quantitatively measured in this research, it can be used to measure the spray drift with the proposed system and identify the dispensing characteristics. In particular, the proposed drift analysis system can obtain both spatial and temporal data for drift in real time. In addition, the amount of spray drift that changes in real time because of external factors such as wind is also determined. This means that the spray drift can be measured at any point during spraying.

Specifically, a method capable of quantitatively measuring scattering can be developed as follows. It is possible to investigate the spray properties in an area that is not affected by wind. If spraying occurs in a place according to the spray characteristics, it can be regarded as a drift and quantitatively evaluated. When the spray properties are considered, the spray drift analysis system will be without limitations in terms of practical applications and drift measurements. In addition, the system can be applied by acquiring LiDAR point cloud data for the candidate environment and training the resulting point cloud with deep learning, which makes the analysis more consistent.

Moreover, the proposed spray drift analysis system has no limitations in term of appropriate applications. It is possible to apply the system by acquiring LiDAR point cloud data for candidate environments and training the resulting point cloud with deep learning. A 16-channel LiDAR was used in this study; however, if a high-channel (32 or 64 channels) LiDAR is used, a more accurate spray drift analysis is possible.

B. LIMITATIONS

In this study, we used a 16 channel LiDAR sensor with a wavelength of 905 nm. However, the drift measurement system depends on the characteristics of the LiDAR sensor. The 905 nm LiDAR failed to scan water molecules with very small particles. Therefore, there is a limit to the precise measurement of the drift involving tiny particles. These limitations can be overcome by changing the wavelength of the LiDAR. If a high-channel LiDAR, such as 32 or 64 channels is used, a more accurate spray drift analysis is possible. For example, if a 1550 nm LiDAR is used, more detailed point clouds for pesticides will be detected, and more accurate spray drift measurements are expected.

Furthermore, to reduce drift, a drift measurement system can be applied to UAV pesticide application systems. This is more important and the limits become clearer as the wind generated by UAV flight causes significant spray drift. In addition, aerial spraying may require a higher FPS because the drone moves faster than a ground sprayer. For this, a system is required that analyzes it precisely and quickly; however, it is expected that the currently developed model will be sufficient. If the FPS is insufficient, it can be solved by applying a lighter deep learning model. Therefore, an advanced drift analysis system is expected to solve this more pressing issue by applying a spray drift analysis system to UAV pesticide spraying system.

VI. CONCLUSION

This study proposes novel methods for spray drift measurement using LiDAR point cloud data. LiDAR point clouds were trained to classify and segment the spraying forms from orchards using the PointNet++ model, which is a 3D deep learning structure. The trained deep learning model achieved an accuracy of 96.23%. A spray drift analysis system was demonstrated through its application in intelligent spraying systems. Three controls of field experiments were performed in a pear orchard to verify the effectiveness of the proposed system. Experimental results confirmed the satisfactory performance of 3D deep learning-based spray drift analysis method which can acquire both spatial and temporal data of spray drift. It is expected that the introduction of this system to spray drift measurements can accurately manage the spray drift.

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(Jaehwi Seol and Jeongeun Kim contributed equally to this work.)

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