Detection of Pesticide Mist Distribution to Avoid Spray Drift

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***Abstract*—Agriculture has made great progress due to technological advances. Spraying pesticides plays an important role in protecting crops from insects and pests. Large mechanical sprayers have made it easier for farmers to spray large areas in a short time. However, there is a risk of pesticides being sprayed in unintended areas, causing damage to nearby fields and bodies of water. In this study, we propose an approach to detect pesticide mist distribution using the U-Net-based semantic segmentation technique. To train the semantic segmentation model, images of mist from sprinklers and gardening mist sprayers were used as training data. Our results show that the semantic segmentation technique could infer the distribution of pesticide mist. The extracted mist areas were found to exclude areas, such as workers, gardening poles, and clouds. Furthermore, we were able to estimate the Three-Dimensional (3D) distribution of mist over the field based on the mist distribution in the continuous frame images. For the current attempt, we did not define the density of mist in the training data, however, we would like to consider estimating the density of mist in the future.**

Keywords-pesticide-mist; semantic segmentation; convolution neural network; agriculture; computer vision.

I. INTRODUCTION

Recently, agriculture has taken leaps in production due to advances in engineering technology and its application in various key areas of agriculture. Pesticides are sprayed on agricultural fields to protect the crops from pests [**1].** There are advanced sprayers, which can cover vast agricultural fields, such as low-pressure sprayers, high-pressure sprayers, foggers, air-carrier sprayers, and hand-operated sprayers. Low-pressure sprayers are commonly mounted on a vehicle. The type of sprayer is chosen according to the size of the agricultural field. High-pressure sprayers can reach high trees and thick bushes. Foggers, also called mist blowers, convert liquid pesticides in the tank into vapor and spray them for intensive plant care. Air carrier sprayers use high-speed air to spray pesticides. Hand-operated sprayers, on the other hand, are used to spray small amounts of pesticides to affected areas and do not spray widely.

The fine mist allows for uniform spraying of plants. The spread of the spray is affected by the environment [2]. As a result, adjacent fields and water bodies can become contaminated with pesticides. This problem is known as spray drift [3]. Research has been carried out before to mitigate this problem by adjusting the nozzle strength and mechanical tuning of the machine. However, these approaches cannot optimize the spraying up to a satisfactory degree because each time a sample must be taken from a specific distance and analyzed in the lab for sedimentation of the pesticide. This process is very time and resource-consuming.

Artificial Intelligence and Computer Vision technology have been used in many fields in recent years, such as in the medical and automotive industries. Incorporating a Computer Vision approach to spray drift detection can provide highly accurate detection while saving time and resources. As video of pesticide spraying in the field is collected, tracking the position of the vehicle's movement from each of the video frames can be performed. By integrating the vehicle's position and spray distribution in all frames, the distribution of the spray in the field can be visualized in three dimensions.

This study attempts to extract the distribution of pesticide mist in the video footage to create a Three-Dimensional Mist Model (3D-MM). The extraction is done by applying semantic segmentation to the video of pesticide spraying. To train the segmentation model, we collect public mist image data and manually annotate the regions of mist in the images. Finally, we will discuss the 3D-MM created by combining mist distributions extracted from all frames of the video.

The rest of this paper is organized as follows. Section II discusses the related works of finding out an optimum method to mitigate the spray drift. Section III describes our proposed method to detect the mist distribution from an image. In Section IV, we summarize our results. Finally, Section V concludes our study and discusses future perspectives.

II. RELATED WORKS

Various studies have been conducted to prevent pesticide sprays from spreading outside the target field. The main factor in spreading is the size of the droplets. Droplet size depends on several factors, including nozzle pressure, liquid flow rate, air temperature, and humidity [1][4]. Small droplets are carried farther by the wind and thus remain suspended in the air for a longer period. Therefore, as droplet size decreases, the likelihood of spray drift increases. Most studies target spray drift for droplets less than 100 µm in diameter, while others recommend droplet thresholds of 50 µm, 150 µm, and 200 µm in diameter [5][6]. Droplets from higher nozzles are more likely to be carried further by the wind before reaching the plant [7].

Attempts were made to reduce the possibility of spray drift by improving the air induction nozzles. However, no significant differences in droplet size, spray pattern width, or

(a) Paddy field (big droplets)

(b) Vegetable field (small droplets)

Figure 1. Pesticide spraying: (a) paddy and (b) vegetable fields.

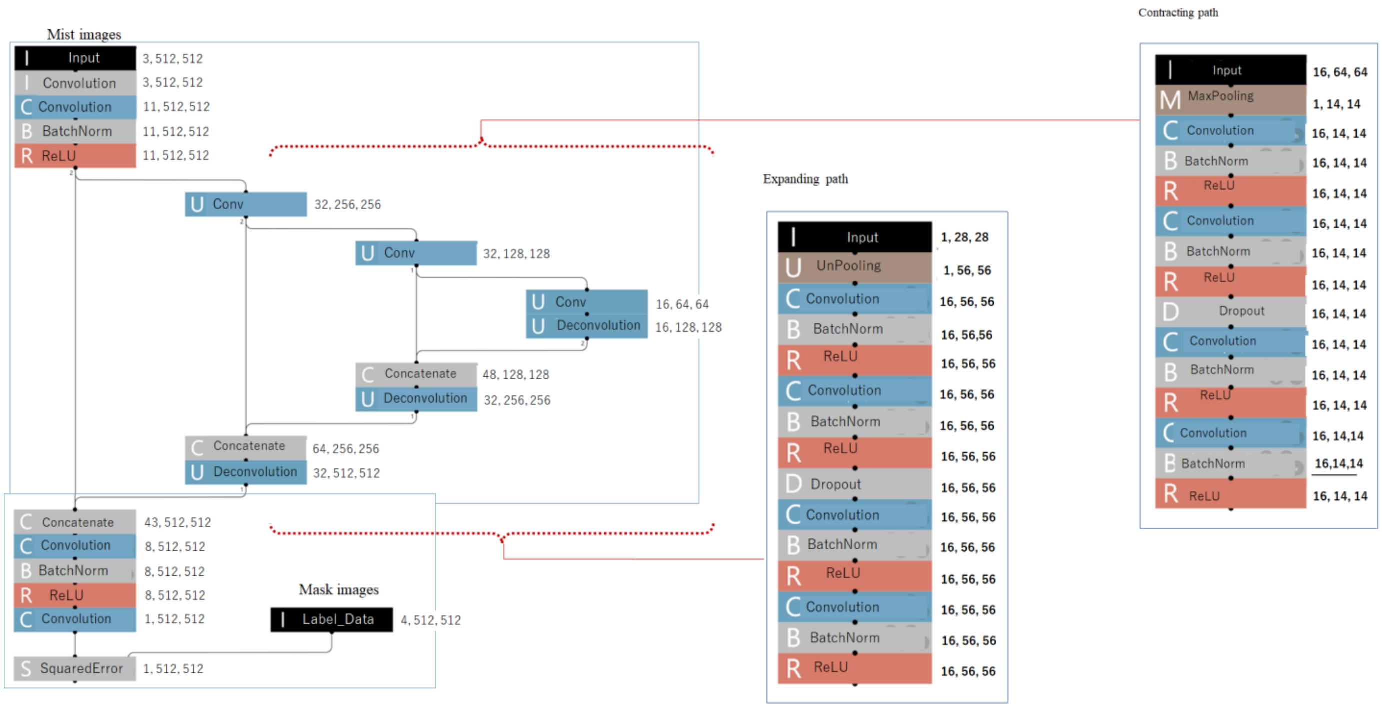

Figure 2. U-Net architecture used in this study.

spray coverage were found [8]. Nozzles installed at 0.7 m and 0.9 m with angles of 80° and 65°, respectively, would minimize spray drift. Similar results can also be obtained at 0.5 m with an angle of 100°. Installing nozzles at lower positions is preferred to avoid spray drift [9]. A single nozzle type may not give satisfactory results in all scenarios.

The combination of drift reduction methods consisting of sprayers with reflective shields and the application of coarse droplets may be an effective way to reduce spray drift [10]. Trees lined up along the wind direction in front of water bodies inside agricultural fields can significantly reduce spray drift [11].

There have been numerous advances in the field of deep neural networks for object detection and classification. Semantic segmentation based on Convolutional Neural Networks (CNNs) can classify objects at the pixel level [12] and learning an image of mist may be used to infer the distribution of pesticide mist.

III. MATERIALS AND METHODS

The task of semantic segmentation is to classify image classes at the pixel level. This method inherently requires the extraction of meaningful features in the input image, but this task can now be done automatically with CNNs. This study utilized semantic segmentation to identify the distribution of sprayed pesticides. Figure 1 shows how the pesticides were applied in our fields. The mist coming out of the nozzle appears white in the image, but the low-density portions are

(a) Paddy field (b) Garden (c) Vegetable field

Figure 3. Collected mist images (top) and their corresponding masks (bottom) to train our network.

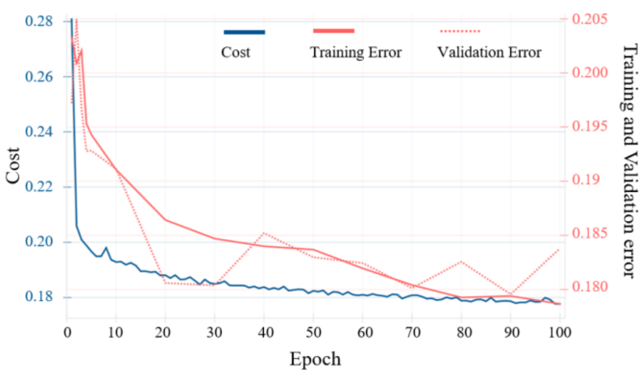

Figure 4. Training and validation learning curves of our network.

translucent. The distribution of small droplets tends to spread in more directions because they spend more time suspended in the air than larger droplets.

A. Network Architecture

Our network architecture is based on U-Net [12], as shown in Figure 2. This network was built using the Neural Network Console [13], an engineer-oriented deep learning framework developed by Sony Group Inc. It consists of two major parts: the contracting path, which is constituted by convolution layers and the expanding path by deconvolution (up-convolution) layers. Each convolution is followed by a batch normalization and a Rectified Linear Unit (ReLU). In total, the network has 11 convolutional layers. The size of the input image data and the resulting segmented image data is 512x512 pixels. The Mean Squared Error (MSE) is used as the loss function for the network optimization process.

B. Training

Approximately 500 mist images were used to train the network. All images are resized to 512 x 512 pixels. About 80% of these images were used for training, and the remaining 20% were used for validation. Figure 3 shows several of collected mist images and their corresponding masks to train our network. Despite the variation in mist concentration, a single mask was used to represent the area where the mist is distributed, rather than generating masks by concentration. LabelMe, a labeling and annotation tool, was used for annotation [14].

C. Building the 3D-MM

The 3D-MM was generated from video footage of pesticide spraying in a field by integrating the segmentation of the mist distribution in each frame image in the depth direction. These bundled image data were once converted to point cloud data to generate volumetric data. With the 3D-MM turned into volumetric data, the data can be sliced in any of the three axes allowing the distribution of mist at any point in the field to be viewed.

IV. Results

Training and validation learning curves are as shown in Figure 4. The learning time required to reach 100 epochs was approximately one hour with a NVIDIA RTX3080 (8 GB) graphics accelerator. The learning and validation losses are smallest around the ninetieth epoch, and the difference between them is small. The weights of the network at this

 ISBN: 978-1-61208-982-9

(a) Paddy field (b) Vegetable field (c) Vegetable field

Figure 5. Extracted mist distributions from mist images in this study.

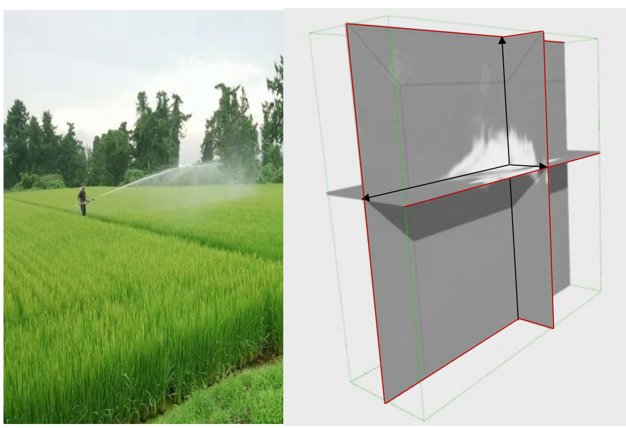

Figure 6. Visualization of 3D-MM as volumetric data. Mist distribution at any location can be visualized.

point were used as the final weights in this study, and the learned model was generated.

The resulting mist distributions extracted from each image are as shown in Figure 5. In the paddy field image, mist was successfully distinguished from clouds that were similar in color. In the vegetable field, despite the presence of people and gardening poles between the mist and the camera, we were able to successfully extract the mist area (Figure 5(b)). On the contrary, the extracted mist area will include the person behind the mist (Figure 5(c)). Overall, the results show that the network in this study was able to extract mist distributions well, although it adopted a fairly standard U-Net network.

Figure 6 shows an Open3D visualization of the mist distribution at an arbitrary location from the reconstructed 3D-MM. Our visualization method opens a new way to analyze mist distribution, whereas it has been difficult to confirm its distribution from different angles. By adding wind direction and speed data to this data, it may be possible to understand the relationship between the mist distribution and the wind.

V. CONCLUSIONS AND FUTURE WORK

In this study, we attempt to extract the distribution of pesticide mist in the video footage and create a 3D mist model. Extraction was performed by applying a U-Net based semantic segmentation to images of pesticide spraying. Despite the small number of images used to train the neural network, we were able to accurately extract the mist distribution regions in the images. The 3D mist model reconstructed in this study would provide further insight into pesticide mists and would provide an opportunity for a detailed analysis. As the present extraction of mist distribution relies on information solely from a single camera, better results could be obtained by adding multiple cameras or by considering the orientation information of the sprayer.

ACKNOWLEDGMENT

This work was done in collaboration with YAMABIKO Corporation and the Faculty of Software and Information Science, Iwate Prefectural University.

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