An Advanced Robotic System for Precision Chemical Thinning of Apple Blossoms

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Highlights

- A cartesian robotic spraying system was developed for precision apple blossom thinning.
- Flower clusters were detected and localized with deep learning model for target spraying.
- A communication algorithm was developed for positioning the spray end-effector to the target flowers.
- The cartesian robotic system greatly reduced chemical usage while maintaining thinning effectiveness in the final green fruit set.

Abstract. *Crop thinning, including blossom thinning, is one of the critical management strategies that determines the annual profitability of apple orchards. Challenges still remain for applying appropriate amounts of chemical thinner; if thinning is inadequate and too many fruits remain on the tree, fruit size will be small, fruit quality will be poor, and flower bud initiation for the following year's crop may be either reduced or eliminated. Over-thinning also carries economic perils since yield and crop value in the year of application will be reduced. In addition, chemical thinning with excessive spray volume may cause leaf damage and fruit russeting. Thus, a robotic apple blossom thinning system was proposed, aiming to reduce the usage of chemical thinner while maintaining good thinning performance. The robotic system consisted of three major components: (1) a machine vision system that can identify and localize the apple flower clusters in tree canopies, (2) a cartesian robotic system with the guidance of a machine vision system to reach target flower clusters, and (3) a flat-shaped spraying nozzle connected with a solenoid valve as a spraying end-effector to deposit chemical thinner to the targeted flower clusters. A set of field tests was conducted to evaluate the performance of the robotic thinning system by comparing it to conventional air-blast and boom-type sprayers. In the test, the flower cluster detection reached a precision of 93.82%. The integrated robotic system used 2.3 L of chemical thinner to finish the chemical thinning for 18 apple trees, followed by the boom sprayer and air blast sprayer with 4.2 and 6.8 L usage, respectively. The robotic system also obtained an average fruit set of 2.4 per cluster after thinning, which was comparable to that of the air blast sprayer. The results showed that the robotic thinning system saved 66.7% and 45.5% of chemicals compared to the air-blast sprayer and boom-typed sprayers, respectively, while achieving a similar fruit set per cluster. The outcomes of the study provided guidance for developing a full-scale robotic chemical thinning system for modern apple orchards.*

Keywords. *Apple orchard, Blossom thinning, Cartesian robot, Chemical thinning, Machine vision.*

In tree fruit production, thinning refers to the removal of a fraction of the trees' flowers or fruit such that the growth of the remaining fruit is improved. The link between thinning and fruit quality has been well established (Forshey, 1986; Link, 2000). During the blossom period, apple trees generally produce a large number of flowers, which can later be pollinated to set fruit. Each flower requires resource allocation from the tree to grow properly and turns into an apple fruit. However, when the number of flowers is too high, an abundance of small, low-quality apples can result in things that may be unworthy for sale. On the other hand, a low number of flowers in a tree produces a small number of apples, leading to a decreased profit for apple growers. To obtain the optimal number of apples specific to a given cultivar, growing site, and market price structure, apple trees must undergo the thinning process, including blossom thinning and green fruit thinning. In addition to maintaining the optimal number of fruits on the tree, the result of proper thinning also ensures stable crops for years to come, thus avoiding a phenomenon known as 'biennial bearing', indicating excessive fruit number in one year while a small number or even no fruit in the next year. This biennial

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bearing can directly impact fruit size and quality, and possibly introduce a long-term effect.

Crop load management is a necessary step to produce marketable apples, which can be accomplished through flower and fruit thinning (Aggelopoulou et al., 2010). Thinning during blooming is the first step towards removing excess crop load and, at the same time, helping to break the biennial bearing habit (Williams, 1979). The most common practice in the U.S. apple industry is for farmers to manually count the number of flowers in randomly sampled trees within the orchard and use their experience to decide what level of thinning is needed for the whole orchard, which is very time-consuming, labor-intensive, and inaccurate. Many growers hand thin flowers or fruits, which is very labor-intensive and costly.

Several studies over the last decade have reported on the effects of mechanical thinning in peaches (Reighard and Henderson, 2012), apples (Schupp and Kon, 2014 ; McClure and Cline, 2015; Mika et al., 2016), pears (Lei et al., 2021) and nectarines (Steyn et al., 2016). The results of mechanical thinning depend largely on the machine configuration and may significantly reduce labor costs (Blanke and Damerow, 2008; Seehuber et al., 2014), but different types of specialty crops require a variety of designs for the mechanical thinning systems to be effective (Theron et al., 2016). Some studies showed that mechanical thinning alone in apples did not meet the expected level of thinning, and therefore chemical or manual thinning is used in addition to the mechanical thinning (Hampson and Bedford, 2011; Kon et al., 2013). In addition, mechanical thinning has a relatively large potential to damage young leaf shoots, which can significantly reduce photosynthesis or, in some cases, increase the incidence of bacterial fire blight (Greene and Costa, 2012; Ngugi and Schupp, 2009).

Chemical thinning has proven to be one of the most effective methods to improve apple quality, size, and color (Yoder et al., 2013). It can achieve large scale blossom thinning at a fast speed and minimize damage to fruit trees during the thinning process compared to mechanical thinning. However, excessive use of chemical thinner not only harms fruit trees, leading to leaf damage and fruit russeting, but also pollutes the environment (Bisht and Chauhan, 2020). Therefore, improved chemical thinning processes are desired (Bound, 2018). Precision chemical thinning targeting flower clusters would be a potential solution. Precision spraying approaches have been studied in recent years to overcome the problems of excessive usage of chemicals in various usages such as leaf disease control and pesticide application (Mahmud et al., 2022). No similar study has been reported on precision spraying technologies for apple blossom thinning.

A precision spraying system for apple blossom thinning requires automatically detecting apple flower clusters and spraying chemical thinner only where it is needed. The development of the vision system is an important step in accurately estimating the locations of flower clusters. There are numerous studies related to the problem of object detection in an agricultural environment, with the aim of automating agricultural tasks that are highly labor intensive (Gongal et al., 2015). A few studies have focused on flower or flower cluster detection in the orchard environment. Dias et al. (2018) introduced a CNN-based algorithm for apple flower detection to classify apple flowers. Farjon et al. (2020) used Faster-RCNN to count apple flower clusters in individual tree canopies. Wang et al. (2018) proposed a machine learning protocol consisting of Speeded Up Robust Features (SURF) and Support Vector Machine (SVM) classification for mango flower segmentation. The Mask R-CNN network has been proven to be a promising solution to blossom detection. It was observed that a Mask R-CNN based deep learning algorithm was able to detect apple flower blossoms with mean average precision (mAP) of 0.86 (Bhattarai et al., 2020).

Our previous study also addressed king flower detection in an orchard tree canopy (Mu et al., 2023), but the integration of the vision system with a robot manipulator to accurately applying chemical thinner to these flower clusters remained to be developed. To address the challenges of precision chemical spraying, a cartesian target sprayer was developed to achieve precision apple blossom thinning. The objectives were to: (1) build an automated vision system for flower cluster detection and localization, (2) integrate the vision system with a cartesian robot manipulator to position a sprayer nozzle to the detected flower clusters, and (3) evaluate the sprayer system on the effectiveness of thinning and the usage of chemical thinner through field tests.

Materials and Methods

Overall Experiment System

A cartesian robotic system was designed for precision apple blossom thinning consisting of three major components: (1) a color stereo camera (ZED2, Stereolabs Inc., San Francisco, CA) based machine vision system, (2) a cartesian system-based manipulator, and (3) a spraying end-effector with a solenoid valve (55295-1-12, TeeJet Technologies, Glendale Heights, IL) and flat-shaped nozzle (AIXR11003, TeeJet Technologies, Glendale Heights, IL), as shown in figure 1. The entire system was placed on a utility cart that could be moved manually along the tree rows. A four-gallon battery-powered backpack sprayer (Chapin 63985, Chapin International Inc., Batavia, NY) filled with chemical thinner (Lime Sulfur) was also placed on the cart. The solenoid valve and nozzle were mounted at the end of the cartesian manipulator and connected to the sprayer with a chemical-resistant soft plastic tube.

The general flowchart of the robotic system operation is presented in figure 2. The first step in the robotic chemical thinning process is to acquire an image of the flower clusters in the target tree. The image was captured using the ZED2 camera with 2208×1242 resolution, which was then processed with the flower cluster detection model implemented in a laptop (refer to the “Control System with Decision-Making Algorithm” section for details). The detection model identified the locations of target flower clusters within the image and sent the coordinates to the control system (refer to the “Cartesian Robotic System and End-Effector" section for details) for further decision making. A sequence of target coordinates was communicated between the control system

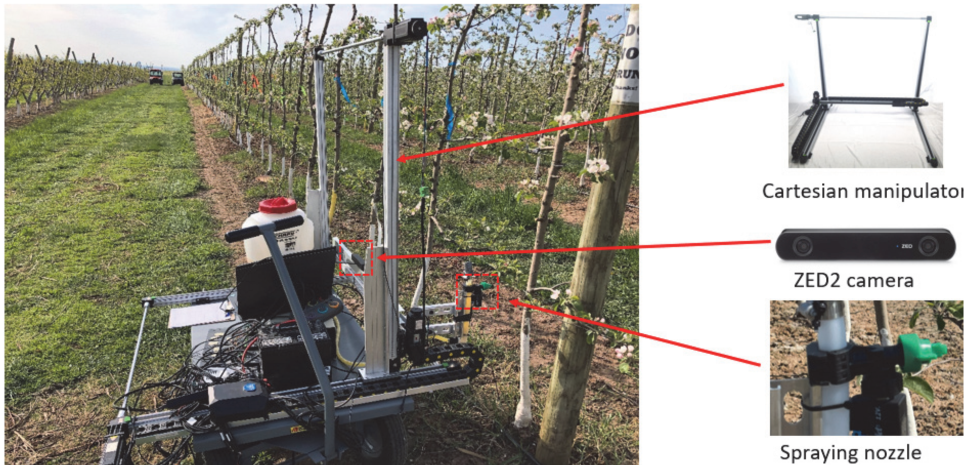


Figure 1. Overall description of the cartesian robotic sprayer and its three major components.

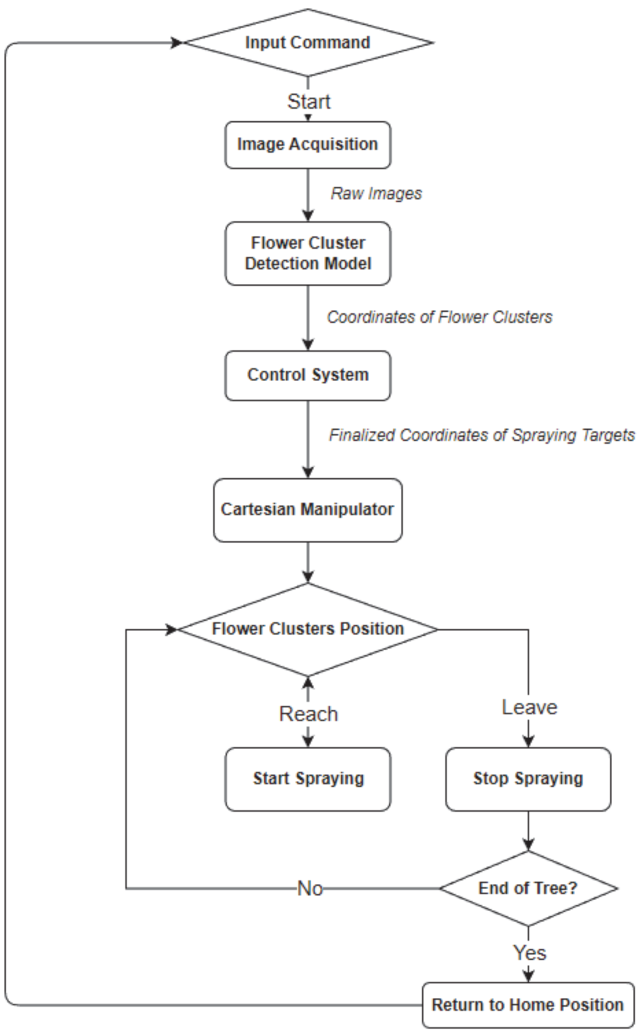


Figure 2. General flowchart of the cartesian target spraying system.

and the cartesian manipulator so that the manipulator would move to the specific positions of the detected flower clusters and open the solenoid valve to start spraying. The spraying stopped when a flower cluster was fully covered. Once all the flower clusters within the camera field of view were sprayed with the thinner, the manipulator moved the nozzle back to the home position.

Flower Cluster Detection Model

Image Data Collection for Model Training

A set of images was acquired from a commercial apple orchard located in Biglerville, PA, U.S., in Spring 2021, trained to tall spindle architecture with a tree spacing of ~1.5 m and row spacing of ~3.5 m (fig. 3). One hundred Gala and Honeycrisp variety trees were selected. Datasets were collected after the first bloom. Daytime images were taken with two ZED2 RGB-D cameras for one side of the row on the same day to verify the consistency of flower density. Images of 2208x1242 pixel resolution were captured under natural illumination. The two ZED 2 cameras were mounted on the side frame of a Kubota utility vehicle, for image acquisition (fig. 3a). The vehicle traveled forward at approximately 0.67 m/s (1.5 mph) with cameras facing to the left to capture images. A total of 800 images were collected for the flower cluster detection model training and testing dataset.

Deep Learning-Based Flower Cluster Detection

The core of the machine vision system was the Mask R-CNN-based apple flower cluster detection model, which served to automatically localize the location of spraying targets. The implementation of the Mask R-CNN was based on the Feature Pyramid Network (FPN) with ResNet101 as the backbone. Before training the flower detection model, a pre-trained model based on the COCO data set (Lin et al., 2014) was used to address the problem of a small training set. COCO is a huge dataset for object detection and image segmentation with 328k images including 91 categories. The pre-trained model extracted the general features of all categories from COCO. The starting weights were taken from the pre-trained network with COCO. The apple flower detection model was then fine-tuned using the specific dataset collected for this application.

Among the 800 images captured, 400 were randomly selected and labeled with makesense.io annotator without any pre-processing or background manipulation. Each image was annotated at the pixel level with multiple polygonal masks indicating clusters of apple flowers (fig. 4a). These annotated images were further augmented by scaling,

(a) (b)

Figure 3. (a) Image acquisition system mounted on a Kubota utility vehicle; (b) example of acquired images in a trellis-trained tall spindle apple orchard.

(a) (b)

Figure 4. (a) Example of labeled apple flower clusters; and (b) an example of flower cluster detection result (flower cluster inside blue and red polygons indicate ground truth and detection results, respectively).

flipping, cropping, and rotation, which led to 2,000 training images (400 raw images + 1600 augmented images). The rest of the 400 original images were reserved as the testing set so that the training-testing split ratio was 2000:400 (5:1).

The instance segmentation algorithm outputs a binary mask indicating if the region of interest belongs to the "flower cluster" or "background" class. The manually labeled masks of flower clusters were assigned as ground truth, which were compared against the detection results (fig. 4b). With the intersection and union of ground truth (blue mask) and predicted result (red mask), four types of zones were defined: (a) the true positive (TP) represented the predicted pixels of the flower cluster that belonged to actual flowers; (b) the false positive (FP) represented the pixels that the model detected as part of flower clusters where none existed; (c) the false negative (FN) represented the actual flower pixels that were failed to be predicted by the detection model; (d) the true negative (TN) was the region that both the model and the ground truth considered as background.

Four evaluation metrics were applied to assess the performance of the detection model: precision, recall, F1 score, and intersection over union (IoU). These parameters were estimated using equations 1 to 4.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{1}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{2}$$

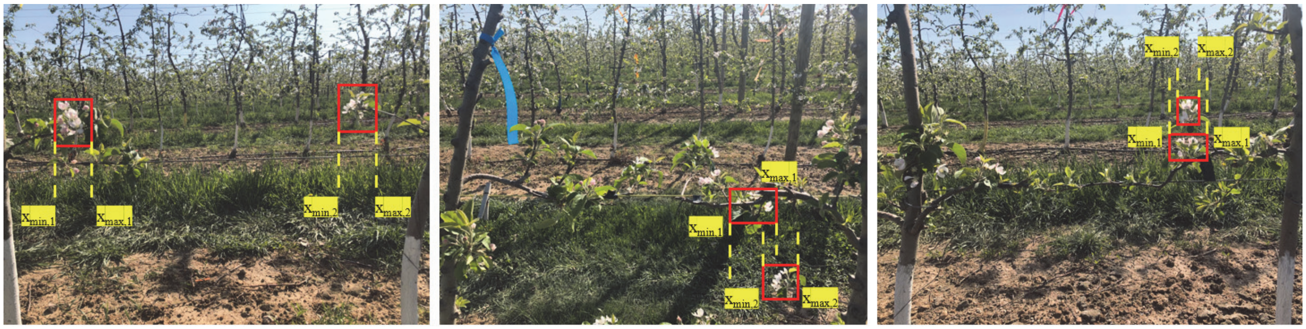
$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

$$IoU = \frac{True\ Positive}{True\ Positive + False\ Positive + False\ Negative} \tag{4}$$

Control System with Decision-Making Algorithm

The output of the detection model was pixel-level masks of flower clusters with a bounding box (fig. 5). The x-coordinates of each bounding box were extracted to represent the location of each flower cluster in the horizontal direction. The position of flower clusters within each window of the trellis wire was treated as a sequence of paired x-coordinates (xmin,i, xmax,i), where xmin,i was the starting position of the flower cluster, xmax,i represented the ending position, and i indicated the number of flower clusters that were detected in an image. Before the sequence of x-coordinates were sent to the cartesian manipulator, a decision-making algorithm was used to address two special situations regarding the flower clusters position: overlapping and inclusion.

The cartesian manipulator would function effectively and efficiently if all the flower clusters were separated clearly as shown in figure 5a. However, in the real orchard



(a) Separation **(b) Overlapping** **(c) Inclusion**

Figure 5. Illustration of relative position between clusters. From left to right: non-overlapping clusters, overlapping clusters, and occluded clusters.

environment, if flower clusters are too close together, overlapping and/or inclusion in position might occur (figs. 5b and 5c). Such situations can cause the cartesian manipulator to move back and forth if each single cluster is considered separately. To maximize efficiency, an algorithm was developed to address these two situations by merging multiple overlapped or included flower clusters into one "super flower cluster," as shown in figure 6. This algorithm processed two overlapping flower clusters as one large flower cluster and generated the coordinates of this "super flower cluster" instead of the coordinates of the individual clusters. For the two included flower clusters, the coordinates of the larger flower cluster were used for spraying the thinning agent.

Cartesian Robotic System And End-Effector

The final coordinates were sent to the cartesian robotic system as the target for moving the manipulator after localizing all flower clusters (and superclusters) in an image. The cartesian robotic system was capable of moving in three orthogonal axes, X, Y, and Z, with three individual linear actuators mounted along each direction. A chemical spraying system, including a solenoid valve and a flat-shaped spraying nozzle tip, was mounted at the front arm of the cartesian robotic system as the end-effector. The AIXR TeeJet flat spray nozzle offers a spray angle of 110 degrees, providing a fan-shaped coverage width of 30 centimeters at a distance of one meter from the target surface. The size of the droplet is in the level of Coarse (C) with a diameter of 340 micrometers.

Using the output coordinates from the vision system introduced in the section titled "Deep Learning-Based Flower Cluster Detection", the cartesian robotic system moved the end-effector to the targeted flower clusters within a range of 90 cm. Since the trees in the test field were trained to have horizontal branches with trellis wire support, most of the flower clusters were located within 15 centimeters along the wires. However, the distance between the robotic system and the apple tree trunks was kept constant at ~60 cm. Therefore, the robotic system was moved with fixed positions in the Y (vertical) and Z (distance to the tree trunk) directions, and the movement of the nozzles was only in the X direction during spray, which was along the trellis wires.

Experimental Design

The vision system and the end-effector were integrated with the cartesian spraying system. The system was tested on the trellis-trained Fuji apple trees in Biglerville, PA. The robotic spraying system was compared with two conventional spraying approaches to verify and assess the performance for precision apple blossom thinning: boom-type sprayer and air-blast sprayer (fig. 7). The boom-type sprayer consisted of a six-foot-long plastic pole with seven nozzles. The nozzles were manually controlled using the Arduino MEGA microcontroller as a switch. The boom-type sprayer was mounted at the back of a utility vehicle (Polaris Range EV, Polaris Inc., Medina, MN) driven at 1.3 m/s during spraying. The air-blast sprayer is an intelligent sprayer equipped with a 150-gallon tank and a LiDAR sensor-based smart spraying kit (Smart Apply, Inc., Indianapolis, IN). The

Algorithm 1 Merging Flower Clusters

Require: Input coordinates $(x_{min,i}, x_{max,i})$
$i = 1$
while $n = i$ **do**
Start checking if there is overlapping or inclusion;
if $(x_{min,n} < x_{min,n+1})$ & $(x_{max,n} > x_{min,n+1})$ & $(x_{max,n} < x_{max,n+1})$ **then**
Overlapping occurred;
Output $(x_{min,n}, x_{max,n+1})$;
else if $(x_{min,n} < x_{min,n+1})$ & $(x_{max,n} > x_{max,n+1})$ **then**
Inclusion occurred;
Output$(x_{min,n}, x_{max,n})$ and ignore $(x_{min,n+1}, x_{max,n+1})$;
end if
end while

Figure 6. Algorithm for merging flower clusters under overlapping and inclusion conditions scripted in Python.

Figure 7. Spraying systems used in the test. Left: Cartesian target sprayer (CTS); middle: boom-type sprayer (BTS); right: air-blast sprayer (ABS).

distance between the trellis wire and the ZED2 camera remained at 60 cm to satisfy the preset parameters in the robotic sprayer vision system throughout the experiment.

Three different treatments, the cartesian target sprayer (CTS), boom-type sprayer (BTS), and air-blast sprayer (ABS), were tested on the same day for precision apple blossom thinning. In total, 90 trees were used for the experiment, including 54 experiment samples and 36 buffer trees. Three consecutive trees were selected as one experiment unit, and six replicates were used for each treatment (fig. 8). Two additional buffer trees were included at the beginning and end of each experiment unit to prevent chemical deposition from other treatments. All other trees within the same row were left as an un-thinned control (UTC) to compare the effectiveness of thinning. Due to the height limitation of the cartesian manipulator, the CTS only covered the bottom two sections (limbs) of apple trees, starting from the bottom, while both BTS and ABS were capable of covering the entire canopy.

Three metrics were recorded during the experiment to assess the performance of the spraying approaches: time spent spraying each tree (or two limb sections in the case of the CTS), chemical usage in total, and green fruit set before June drop. Since the ABS tractor was driven at a constant speed, the time used for one tree was calculated with the following equation:

$$Time_{ABS} = \frac{Average\ width\ of\ apple\ trees\ in\ the\ same\ row}{Speed\ of\ tractor} \quad (5)$$

For the CTS, the start of each spray was triggered manually, then the nozzle was moved horizontally along the tree branches (two horizontal branches in most cases) to target the detected flower clusters to cover one section at a time. Finally, the nozzle returned to the initial position after all the clusters were sprayed. The start and end of the BTS and ABS sprays were controlled manually using a switch button for three trees at a time. The spray time for the CTS and BTS was directly recorded using a stopwatch. For CTS, the spray time was recorded for each section, and then the average spray time for one section was calculated for all tested sections. At last, the average spray time for one tree was calculated by timing four, due to having four sections for these trees. Chemical usage was calculated after all six replicates were finished. The total chemical usage of the CTS was recorded by doubling the real usage because it only covered two sections, which was half of an entire apple tree. The chemical usage for both the BTS and ABS were measured from the sprayer tanks. Two weeks after the treatments, the number of green fruit set was counted for every limb of each experimental unit. The number of green fruits per cluster was also recorded to determine the effectiveness of chemical thinning within each cluster.

Statistical Analysis

One-way Analysis of Variance (ANOVA) along with Tukey's test at a 0.05 confidence level was used to determine the significant difference among the number of green fruit set in the four thinning approaches (CTS, ABS, BTS, and UTC) using Minitab 19 statistical software (Minitab Inc., State College, PA, USA).

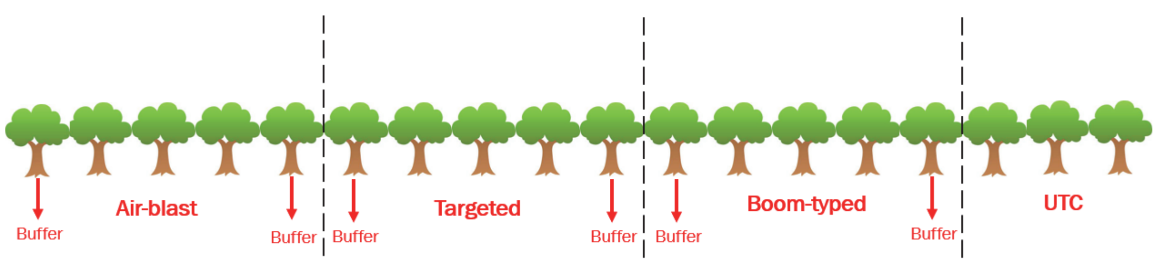


Figure 8. Illustration of three different thinning treatments (six replicates for each) and the un-thinned control.

RESULTS AND DISCUSSION

FLOWER CLUSTER DETECTION

Training included 2000 labeled apple flower cluster images, with the image input batch size given as 32 for better generalization results. The learning rate was 0.001 and was adjusted per 1,000 training iterations with an adjustment factor of 0.95. The model output included bounding boxes and masks of apple flower clusters for each input image. The training time for 100,000 iterations was approximately 16 hours, and the model loss function achieved a convergence state. Figure 9a shows an example image of the detection results obtained with the Mask R-CNN-based instance, segmentation and table 1 lists the quantitative results. The model output included pixel-level masks together with bounding boxes around the flower clusters detected (fig. 9a). The pair of x-coordinates needed for robotic thinning was extracted from the bounding box. The visualization code was modified so that it only showed the bounding box in output images, as shown in figure 9b.

As shown in table 1, the model achieved a Precision, Recall, and F1 score of 93.8%, 91.2%, and 92.5% with an IoU of 86.1%. These results showed that out of all the positive predictions made by the model (i.e., the instances identified as flower clusters), 93.8% were correct, implying that the model is effectively distinguishing flower clusters from other objects (i.e., leaves, branches, etc.) or background. Some inherent variabilities in the orchard environment prevented the detection model from achieving perfect precision: (1) since the vision system only took images from one side of the canopy, some of the flower clusters may be occluded by obstacles including leaves, branches, or tags; (2) with natural illumination, the lighting conditions were affected by variations of shadow, leading to false or even no prediction of the instances. Overall, the detection model met the expectation, but some improvements can be expected for future work: (1) fine-tune the model on a larger and more diverse dataset specifically focused on apple flower clusters, and (2) ensure the input image set is properly preprocessing with the adjustment of brightness, contrast, saturation, sharpness, and white balance.

Table 1. The performance of the flower cluster detection model on the experimental trees, with Precision, Recall, and F1-score.

Evaluation Parameters	Precision Rate (%)	Recall Rate (%)	F1 Score (%)	IoU (%)
Flower Cluster	*93.8*	*91.2*	*92.5*	*86.1*

BLOSSOM THINNING EXPERIMENT

The CTS was compared with the ABS and BTS in thinning apple blossoms. Three measurements were recorded during the field test: time used for spraying, usage of chemical (lime-sulfur), and the number of fruit sets before the June drop. CTS took an average of 4.7 s to finish spraying one out of four sections of each apple tree, from image taking and processing to moving spray nozzles for spraying and returning to the home position. To simplify comparison, the recorded time for the CTS was multiplied by four to estimate the total time it would take to complete the spraying for a whole tree. Table 2 shows that the processing time was not an advantage of the CTS spraying system. The cartesian target sprayer was six to nine times slower than boom-type sprayer and air-blast sprayer. The main reason for the slowness was because the speed of the linear actuators on the cartesian manipulator was set to 0.45 m/s, while the driving speed of the boom-type sprayer and air-blast sprayer was around 0.89 m/s. Another important reason was the processing route: after finishing spraying one limb, the cartesian manipulator was required to return to its home position before it could start working on the next target limb (fig. 2), which doubled the distance the manipulator needed to travel. It is also noted that there was only one flat-shaped nozzle used as the end-effector (refer to the "Overall Experiment System" section for details) to spray one quarter (one tier limb) of a tree at each step, which was also one of the causes of the longer spraying time.

Despite the longer spraying time per tree, the CTS reduced the quantity of chemical thinner applied. As shown in table 2, the amount of chemical usage with the CTS was 2.3 L, which was a reduction of 66.7% and 45.5% compared to the ABS and BTS, respectively. Since the CTS only covered two out of four layers of the tree at the lower portion

(a) (b)

Figure 9. Mask R-CNN based instance segmentation of apple flower clusters, (a) original output with predicted masks and bounding boxes included, (b) bounding boxes were extracted.

Table 2. Comparison among three different sprayers for spraying time and chemical usage.

Spraying System	Average Spray Time per Tree (s)	Total Chemical Usage (L)
Cartesian Target Sprayer	18.6	2.3
Air-blast Sprayer	2.4	6.8
Boom-typed Sprayer	3.3	4.2

during testing, the projected amount of CTS chemical usage was calculated by multiplying the measured usage by two.

Another major metric used to assess the effectiveness of chemical thinning was the number of green fruits set before the June drop. As shown in figure 10, the average number of fruits per cluster was 2.4, 2.6, 3.9, and 5.5 for the CTS, ABS, BTS, and UTC, respectively. Compared to the UTC, all three spraying systems showed significantly better thinning effectiveness, as indicated by the lower number of fruit sets. From the ANOVA analysis, there was no significant difference in the number of green fruits between the CTS and ABS, while both obtained a significantly lower fruit set compared to the BTS and UTC. The results indicated that the CTS was able to achieve higher thinning effectiveness while greatly reducing the usage of chemical thinner.

The CTS thinning approach resulted in an average of 2.4 flowers in each cluster developing into green fruits, which met the expectations of this experiment to leave two green fruits on average for each fruiting cluster. Although the average number of fruits per cluster was only 2.4, a few clusters contained five green fruits, which suggested that thinning was missed on these clusters. Further investigation revealed that these un-thinned clusters were located at the back of the trellis wire, and the cartesian target sprayer was not able to either detect the flower clusters that were hidden or reach those locations with the current design.

Overall Discussion

The cartesian target sprayer was designed to help achieve optimal apple blossom thinning. The ideal effective blossom thinning removes all the lateral flowers so that the king flowers absorb most of the nutrients to produce higher quality fruits. The experimental results indicated that applying thinning by the cartesian target sprayer achieved good thinning performance with an average of 2.4 fruits per cluster after chemical thinning. A few limitations were also observed with the current CTS system, so it is important to make improvements to achieve better efficiency and performance.

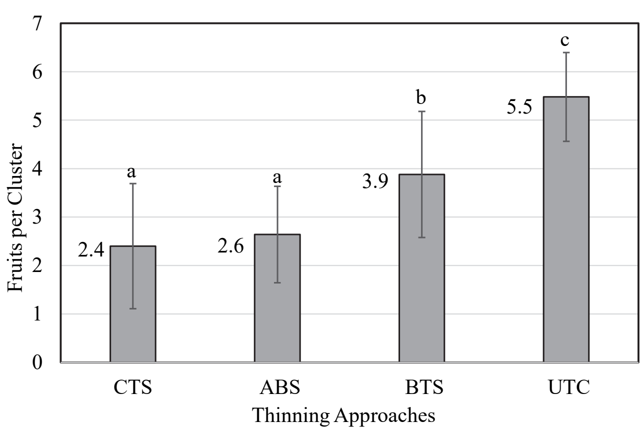


Figure 10. Comparison of average fruits per cluster under three thinning spraying systems (CTS, ABS, and TBS) and the un-thinned control (UTC). The numbers at each bar are average fruit numbers per cluster, and letters were used to indicate the significance among these thinning methods.

The cartesian target sprayer took longer to finish the thinning work due to the low speed of positioning the spray nozzle. The flowering stage usually takes one week from first pink to full bloom for most of the cultivars, so the overall spraying efficiency of the CTS needs to be improved to ensure the timely completion of the thinning in orchards. Another limitation of this prototype is that the cartesian target sprayer could only spray one section at a time since there was only one nozzle included in the end-effector. This can be addressed by implementing multiple nozzles with individual solenoid valve control in the vertical direction to cover the whole tree at once. The CTS system was mounted on a utility cart that was pulled manually in the orchard. To achieve fully automated apple blossom thinning, the CTS will be mounted on an unmanned ground vehicle (UGV). The UGV speed can then be increased in coordination with the processing speed of flower cluster detection and nozzle control to achieve the best spray efficiency with the robotic solution.

The cartesian target sprayer was only applicable for trellis-trained apple canopies. The trellis-trained structure creates a two-dimensional canopy surface that presents the majority of the flower clusters to be accessible with a linear approach. The primary limbs were tied to the wires, which potentially reduced the collisions between the manipulator and tree canopy. Some other tree structures, such as tall spindles, are more complicated and may present challenges for detection and spray application. For example, in tall spindle apple trees, flower clusters can be more occluded by tree branches and leaves compared to the canopy architecture used in this study. An end-effector with more degrees of freedom may be needed to achieve similar performance in this complicated workspace.

Conclusions

A cartesian robotic system was developed to apply a chemical thinning agent to target apple blossoms. The system consisted of a machine vision system to automatically detect flower clusters using Mask R-CNN-based instance segmentation, a cartesian robotic system for positioning a spraying nozzle to the targeted flower clusters, and a nozzle control to execute the chemical thinning. A high precision score of 93.8% was obtained for the flower cluster detection, which is a very important step for the effectiveness of the entire robotic system. The cartesian target spraying system reduced the chemical thinner usage, compared to two conventional spraying technologies (boom-type sprayer and air-blast spray), which reduced production costs while minimizing environmental impact. Due to the high accuracy of flower cluster detection and targeted spraying of these detected flowers, the robotic thinning system achieved an average green fruit set of 2.4 fruits per cluster, which is comparable to the conventional method using the air blast sprayer.

Even though the initial focus of this study was on robotic blossom thinning in apples, the technology is expected to be applicable, with minimal modification, to other tree fruit crops, thus benefiting a large number of additional specialty crop producers. In particular, the machine vision system for flower cluster detection and localization, and the manipulation technology for a targeted spraying end-effector, may be applicable to a range of other robotic applications in production agriculture (e.g., robotic flower pollination), and can be extended to many other cropping systems. The outcomes of this study provided a basis for developing an automatic precision spraying system for apple blossom thinning, which could benefit the apple industry economically and environmentally.

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