Washington State Grape and Wine Research Program

FINAL REPORT

PRECISE MECHANICAL SOLUTION FOR VINEYARD SHOOT THINNING

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1. **Project Summary:** Canopy management is one of the major production activities in the annual lifecycle of the vineyard. Green shoot thinning is one of the many field operations used to create and maintain healthy and productive canopies, which, in another term, is a component of overall pruning activity. Shoot thinning is used to improve uniformity, spacing and direction of shoot growth. This operation can help improve light penetration and air movement through a canopy, adjust crop load (by thinning fruiting shoots to reduce the crop), and adjust the leaf-area-to-crop ratio (by thinning non-fruiting shoots). Shoots growing from the base of spurs, multiple shoots from the same node, shoots growing from non-spur positions or originating in the head region or on the trunk are all candidates for removal, unless needed to replace an old or poorly positioned spur or an old cordon. Shoot thinning is a labor-intensive task and is costly. Dean (2016) found that the cost for shoot thinning by hand is about $650 per hectare. If a mechanical shoot thinner is used, the cost could be reduced to about $25 per hectare. In addition, one machine can replace up to 25 workers (productivity 25 hrs/ha v_s 1 hr/ha; Dean, 2016). Therefore, mechanical shoot thinning is essential for the profitability and sustainability of wine grape production. In the past, a few machines have been developed and tested in vineyards for shoot thinning. Some of them only focus on removing suckers from the trunk (Clemens Vineyard Equipment Inc., Rotary Brush), while others can remove both shoots in the cordon and suckers in the trunk (Oxbo Cordon Brush: Model 62731; Vine Tech Equipment, Shoot Thinner). However, based on tractor ground speed and the thinning head speed (number of head rotations per minute), cluster removal may vary between 10% and 85% (Dokoozlian, 2013). Such variability generates an issue of either too many shoots being removed or not being removed sufficiently. In this project, we developed a technique for automated positioning and orientation of the thinning heads for precise operation of the machine, which is expected to improve usability and commercial adoption of shoot thinners. We have successfully developed the artificial intelligence-based machine vision system that can identify the location of the cordon, trunk, and shoots in the real vineyard environment. This machine vision was integrated with the 3DoF (Degrees of Freedom) prototype machine for lab and field evaluations. Based on the laboratory and field evaluations of the integrated systems, the system has potential to estimate cordon trajectories and move the thinning end-effectors to the desired position with precision in the vineyards. This study proved the proposed concept, and the developed technology is ready for being transferred to commercial entities for adoption.

2. **Annual or Final Report**: Final report

3. **Project Title**: PRECISE MECHANICAL SOLUTION FOR VINEYARD SHOOT THINNING

4. **Principal Investigator/Cooperator(s)**: Name, institutional affiliation, address, phone number and e-mail.

PRINCIPAL INVESTIGATOR(S)

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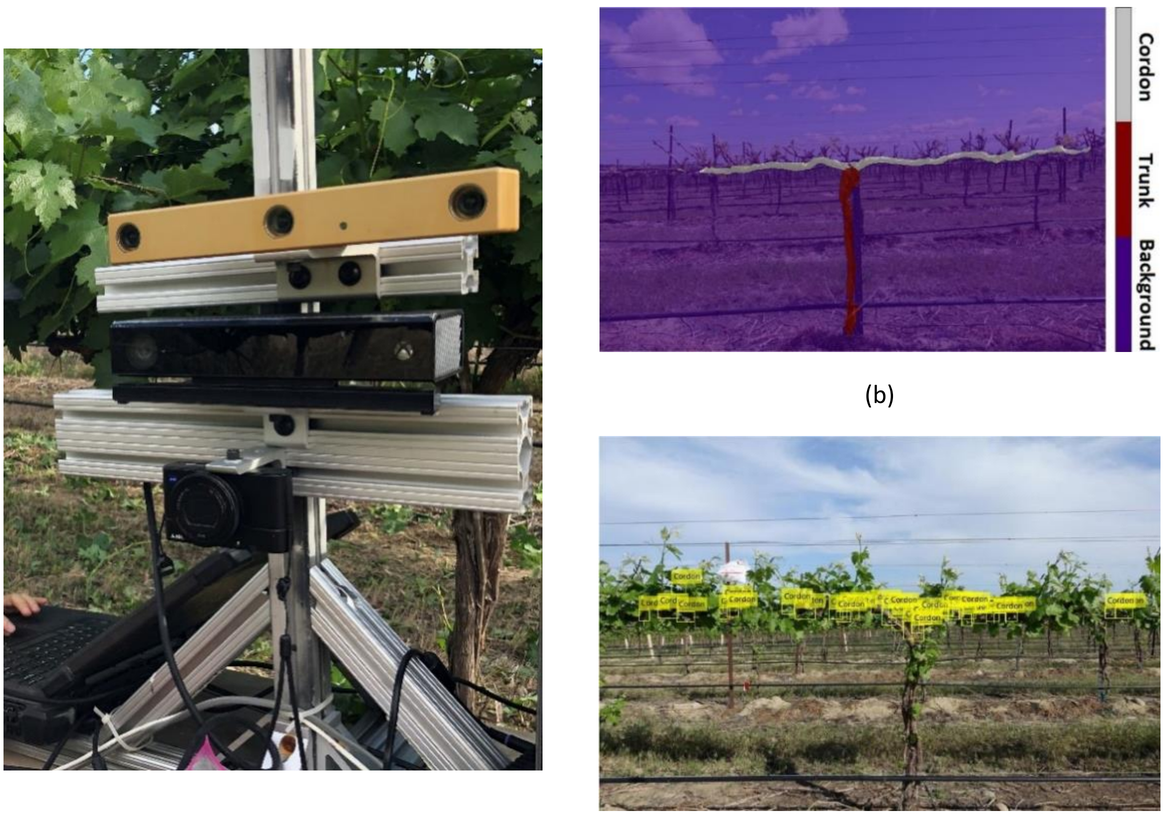
5. **Objective(s) and Experiments Conducted to Meet Stated Objective(s)**:
The **primary goal** of this study was to develop a sensing (machine vision) and actuation system for automated positioning and orientation of thinning heads (rollers) to the desired position for precision shoot thinning. Specific objectives were to:

1. **Develop a machine vision system based on the RGB images and stereo-vision technique to identify the location/trajectory of the cordon and trunk, as well as the density of the shoots along the cordon; and**
2. **Develop a prototype shoot thinning mechanism using pneumatic actuators, aiming to quickly adjust the height, orientation and speed of the rollers for precisely removing desired shoots based on the results from objective 1.**

Experiments Conducted

Experiment 1 - Obj #1 (Machine Vision System): An image acquisition system (developed at CPAAS, WSU) was used to acquire images of wine grapevines. Data were collected during the 2018 and 2019 thinning seasons. Four different cameras (a color camera, Microsoft Kinect sensor, Intel RealSense, and Bumblebee stereo camera) were used to acquire images over different growth stages (from 1st to 4th week of shoot growth) of green shoots in a commercial vineyard (Figure 1a). The images from different camera systems were used to identify trunks and cordons in the canopies. Also, the distance and height of the cameras were varied to analyze the effect of the camera positions in detecting trunk and cordons. The accuracies achieved in detecting the trunk and cordons were used for determining the optimal camera system for the machine vision system to be used in automated green shoot thinning operation.



(a) (c)

Figure 1: a) Image acquisition system consisting of Bumblebee, Kinect V2, and Sony RGB cameras (from top to bottom) used to acquire color images and 3D information of the vines; b) Resulting cordon detection in the images with the first week of shoot growth using a deep

learning technique; and c) Resulting cordon detection image with the second week of shoot growth.

After the image data collection, artificial intelligence-based algorithms were developed to identify the location/trajectory of the cordon, trunk, and shoots. The results of this objective are discussed in the summary section (section 6) of the report.

Experiment 2 – Obj #2 (Prototype Shoot Thinning Mechanism): A 3-DoF (3 Degree-of-Freedom) prototype platform was developed to evaluate the developed machine vision systems (objective 1). A series of lab experiments were conducted using this platform. The details of the platform and lab experiments results are discussed in section 6.

Experiment 3 – Integrating Obj #1 and 2 (Integration of Machine Vision System and Prototype Shoot Thinning Mechanism): A series of field experiments were conducted using the 3DoF prototype platform discussed in experiment 2 to evaluate the performance of the integrated machine vision system (objective 1) and the prototype platform (objective 2). The details of the setup used in the experiments and results are discussed in summary section 6.

Experiment 4 – Enhancement on Integrating Obj #1 and 2 (Integration of Machine Vision System and updated Prototype Shoot Thinning Mechanism): A new, improved system prototype was developed that could be mounted on a tractor or similar vehicles for shoot thinning. The performance of the integrated machine vision system and the improved prototype was investigated in the lab. The information on the prototype and results from the lab experiments are discussed in detail in section 6.

6. Summary of Major Research Accomplishments and Results by Objective:

6.1 Objective#1: Develop a machine vision system based on the RGB images and stereo-vision technique to identify the location/trajectory of the cordon and trunk, as well as the density of the shoots along the cordon

To detect and classify the trunk and cordons, two deep learning-based algorithms (i.e. SegNet - encoder-decoder convolutional neural network, and FCN - fully convolutional neural network) were applied to color images acquired in the vineyard. FCN-VGG16 (one of the deep learning techniques used) achieved better result in detecting trunk and cordon parts (Boundary-F1 score: 0.93) compared to the other techniques (SegNet-VGG16, SegNet-VGG19, and FCN-AlexNet) (Figure 1b). Based on results from the segmentation method, an algorithm (Figure 2) was developed to find the skeleton of the cordons from the segmented parts of the cordons. These skeletons were then represented using different mathematical models (Fourier, Gaussian, polynomial, and Sum of Sine).

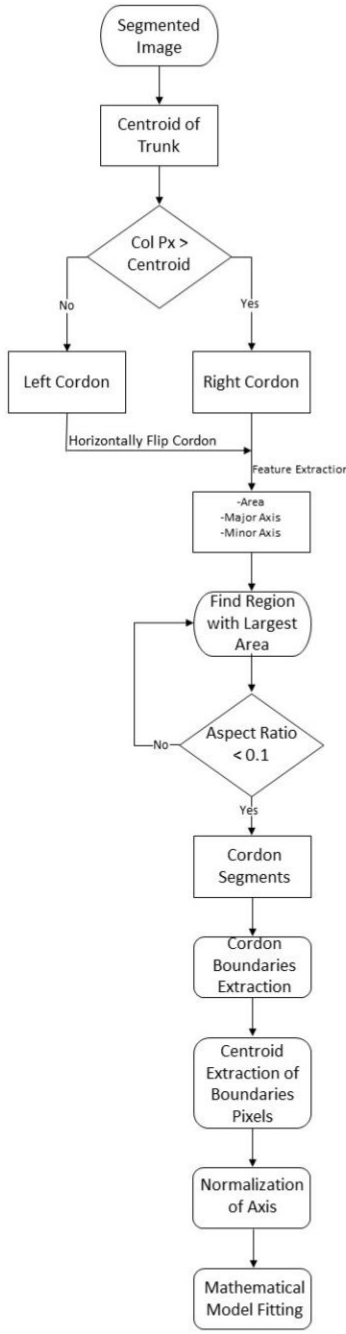
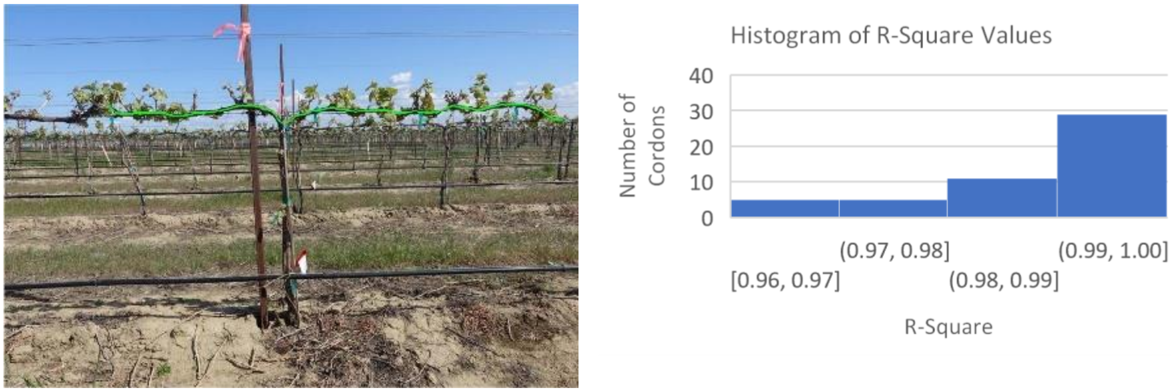


Figure 2: A flowchart for finding the mathematical model of cordon trajectories from the segmented images

Among different types of mathematical models considered, the highest average R-square value (0.99) was achieved with a polynomial model of 6th order (Gaussian: 0.97, Fourier: 0.93, and sum of sines: 0.97). The skeleton of an example cordon fitted with the 6th order polynomial model is shown in Figure 3(a). The histogram of R-square values for the polynomial (Figure 3(b)) shows that approximately 58% of the total cordons have the R-square values of 0.99 and above, while around 80% of the cordons have the R-square values of 0.98 and above.



(a) (b)

Figure 3: a) An example cordon skeleton detected (in early growth stage) and modeled using a 6th order polynomial (green line); and b) Histogram of the R-square values for the 6th order polynomial equation modeling the cordons' skeleton

In the later growth stages of the green shoots, only smaller sections of the cordons are visible. To determine the shape and location of cordons in such a situation, information from both the detected sections of the cordons and shoot locations estimated in dormant season were used. To detect the visible sections of the cordons, a deep learning technique called Faster R-CNN (region convolutional neural network) was used. As can be seen from the table, Faster R-CNN model trained with ResNet18 network showed higher average precision and F1 score with faster detection speed as compared to other tested networks (AlexNet, VGG16, and VGG19).

Table 1. Average precision, F1 score and detection speed of the Faster R-CNN models used to detect the cordon's visible parts

Network	F1 score	Average Precision (%)	Detection Speed (s)
AlexNet	0.33	26.6	0.44
VGG16	0.52	43.2	0.75
VGG19	0.50	43.2	0.88
ResNet18	0.55	45.1	0.58

Figure 4(a) and (b) show the average precision and F1 score for the data collected in 2018 and 2019 thinning seasons during different growth stages of the green shoots (weeks 2, 3 and 4). These results show that relatively more cordon and trunk parts were exposed to the camera when it is place closer to the canopies, which is expected to lead to the more accurate estimation of the cordon trajectories during the thinning season. Detection results for week 2 dataset were better as compared to the same for weeks 3 and 4 dataset. This result was expected as the length and volume of individual shoots (including leaves) was smaller in week 2 compared to the same in weeks 3 and 4, thus causing relatively limited amount of occlusion to cordons and trunks. In addition to detecting the visible parts of cordons, an algorithm was developed (Figure 5) to estimate the position and orientation of cordons using detected segments of cordons and the model information of the cordon skeleton from the dormant season.

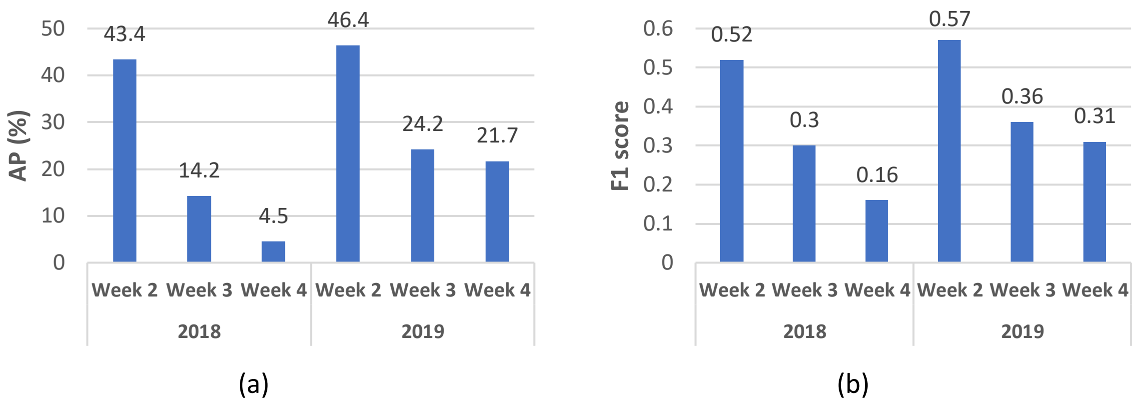


Figure 4: Average precision (a) and F1 score (b) achieved by ResNet18 implementation of Faster-RCNN model with the images collected over different growth stages of green shoots during 2018 and 2019 thinning seasons. Average Precision (AP) and F1 Score are two important measures used to describe the success in detecting cordons; measures close to 100 or 1 show high level of success.

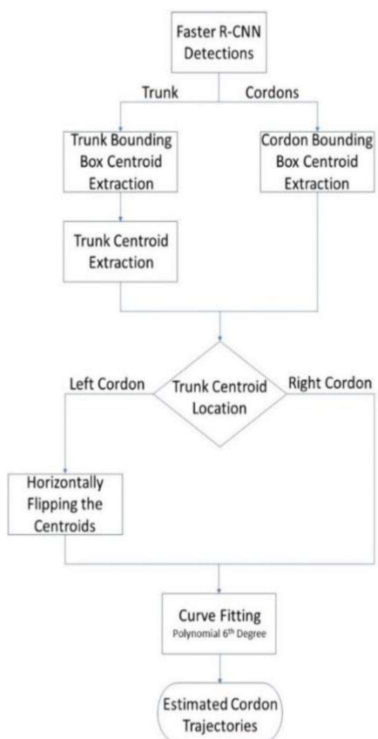
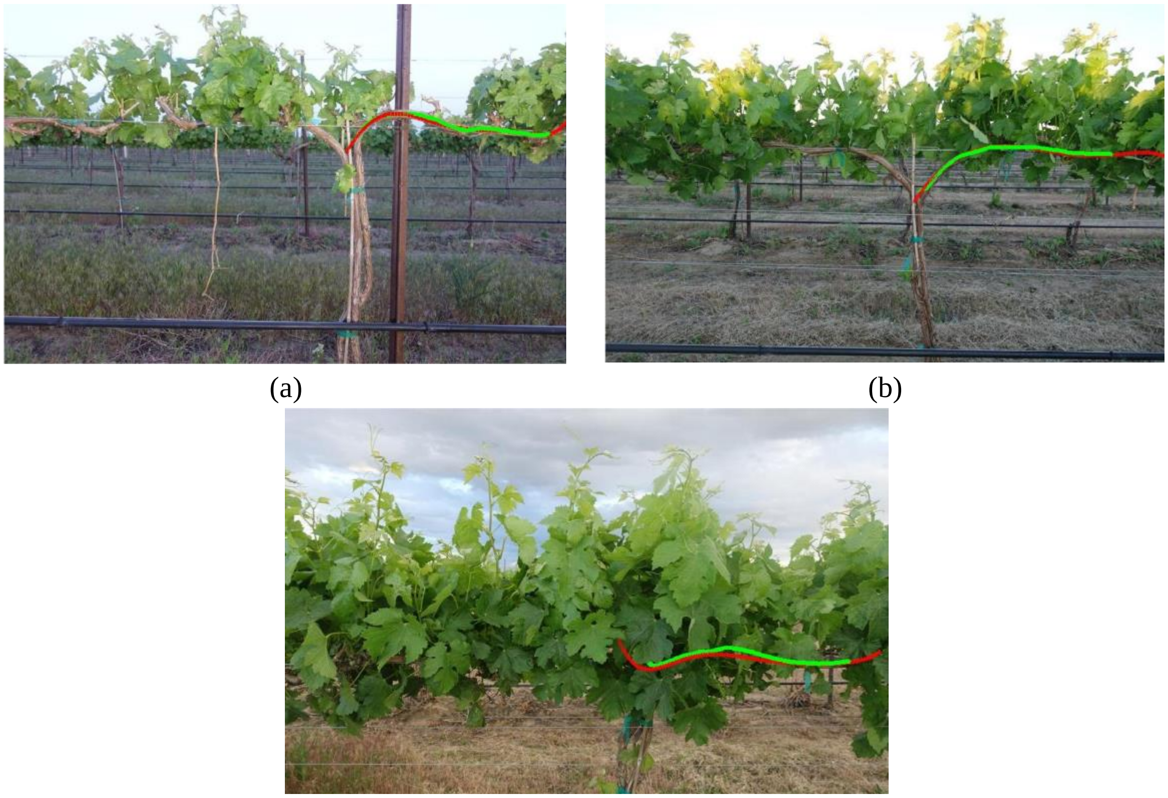


Figure 5: A flowchart for estimating the trajectories of cordons for weeks 2, 3 and 4

Figure 6 (a) to (c) shows results of the estimated trajectories during weeks 2, 3 and 4 using the developed algorithm. Table 2 shows summary results of the estimated trajectories.



(a) (b) (c)

Figure 6: (a), (b) (c) Estimated trajectories of cordons during weeks 2, 3 and 4 of the thinning season, respectively. The green lines show the ground truth trajectories while the red line shows the estimated trajectories generated using the developed algorithm.

Table 2. Correlation coefficient, error of predicted curve, and root mean square error (RMSE) of the estimated trajectories during weeks 2, 3 and 4

	Week 2	Week 3	Week 4
Correlation Coefficient	0.993	0.991	0.987
Error of Predicted Curve	8.54	12.9	18.6
RMSE	13.5	25.7	35.7

It was observed that predicting the position of cordons in occluded segments could help to improve the overall results for cordon trajectory estimation. A new algorithm (Figure 7) was developed that first predicted the position of cordons in the occluded segments using shoot density information, which was then combined with visible positions of cordons. The approach helped improve the trajectory estimation results as shown in Table 3.

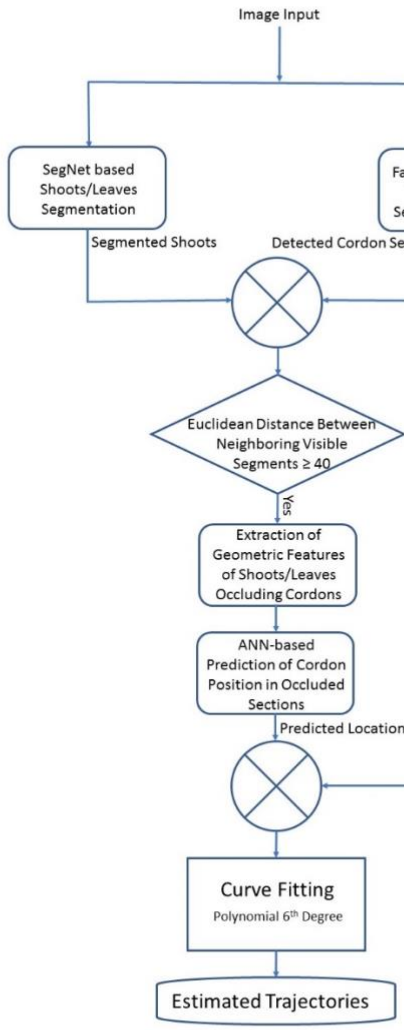


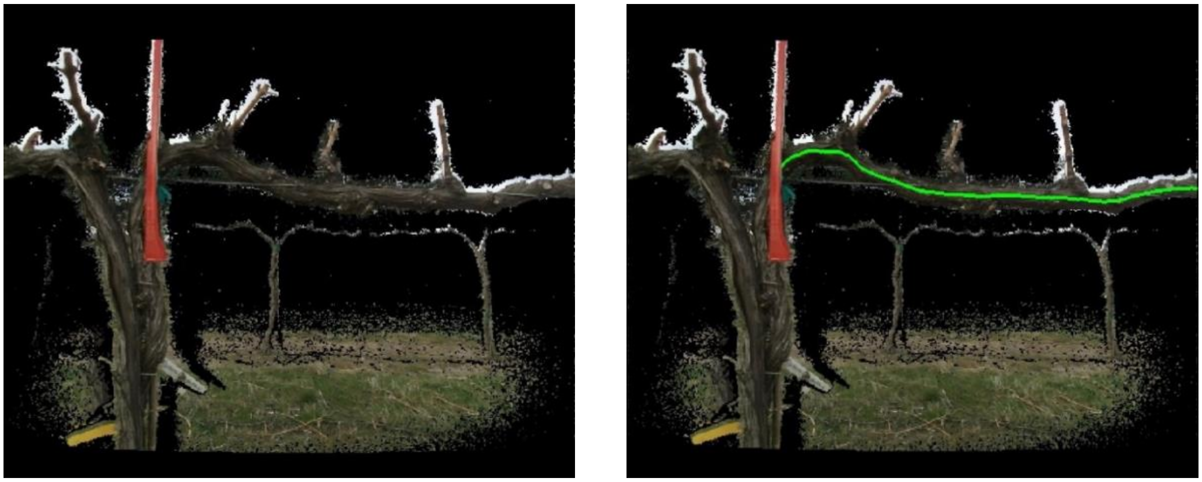
Figure 7: A flowchart for improved estimation of cordon trajectories for weeks 2, 3 and 4

Table 3: Correlation coefficient, error of predicted curve, and root mean square error (RMSE) for the improved estimated trajectories during weeks 2, 3 and 4

	Week 2	Week 3	Week 4
Correlation Coefficient	0.997	0.996	0.991
Error of Predicted Curve	7.27	10.26	16.13
RMSE	11.21	14.69	26.52

The machine vision system was tested in the field setting to evaluate its performance in localizing the position and orientation of cordons using the RGB-D (red, green, blue and depth) sensor for precise thinning of the shoots. The experiments were conducted using machine vision system integrated with prototype platform in a research vineyard with 20 cordons with dormant canopies. Kinect V2 sensor was used to capture the RGB-D information of grapevine cordons.

Then, machine vision system was used to determine the cordon position and orientation from RGB information using the FCN-VGG16-8s network. RGB and depth information were registered together to localize the actual cordon positions (world coordinates) from RGB images. Figure 8(a) and (b) show an example of test grapevine canopy and localization of cordon position and orientation (represented by green line) by the developed machine vision system, respectively.



(a) (b)

Figure 8: (a) An example of test grapevine canopy; and (b) cordon trajectory (green line) estimated by the machine vision system.

6.2 Objective#2: Develop a prototype shoot thinning mechanism using pneumatic actuators, aiming to quickly adjust the height, orientation and speed of the rollers for precisely removing desired shoots based on the results from objective 1

In the research, two versions of shoot thinning prototype were developed. The two prototypes and their performances are discussed below.

Prototype# 1: The first prototype was a research platform with 3 degrees of freedom (Figure 9). It consisted of a static base, and a stepper motor was used to move the end-effector forward along rows of the grapevines. The end-effector was moved vertically using a linear actuator. A control algorithm was developed to actuate and control the position of the end-effector. The performance of the platform and control algorithm was first tested in the lab environment. For the test, a wire laid on a white board was used to mimic the cordons in vineyards (Figure 10(a)). A Kinect V2 sensor was used for capturing images of the wire, and the world coordinates of the wire were extracted by mapping the RGB and depth information from the sensor (Figure 10(b)). The world coordinates provided estimation of several locations of the wire simulating cordon trajectories. The control algorithm was then implemented to actuate the thinning end-effector to follow the desired wire trajectory. Figure 10 shows the wire's world coordinates as desired trajectory and the coordinates of the thinning end-effector after applying the control algorithm. The platform prototype and the preliminary lab experiments conducted with the prototype served as the basis for determining appropriate actuation system and control method to be integrated for effective shoot thinning.

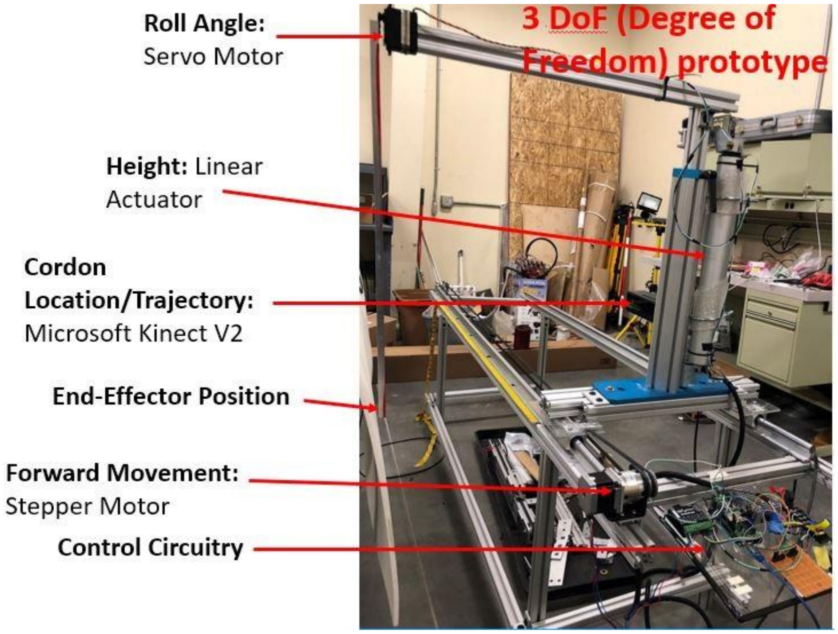
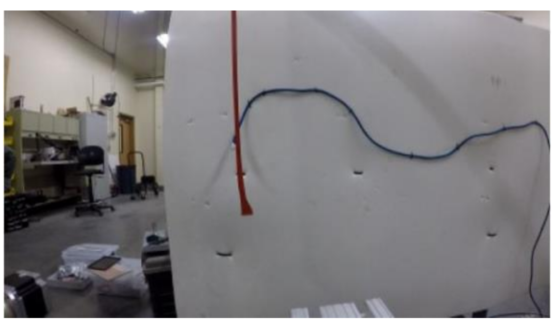
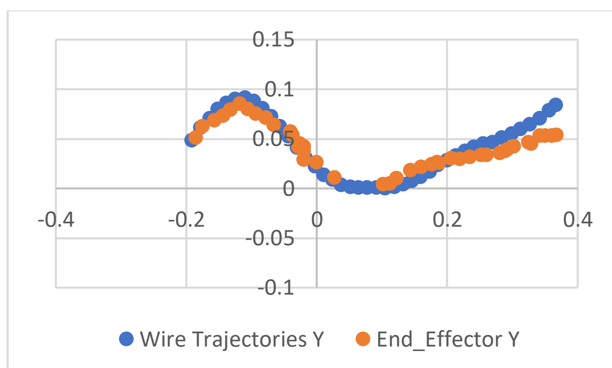


Figure 9: A research platform developed for automated control of position and orientation of thinning rollers.





(a) (b)

Figure 10: a) A wire used to mimic cordons in vineyards; and b) Blue dots show the position of the wire while brown dots show the position of the thinning end-effector as it followed the simulated cordon

As discussed in section 6.1 objective 1, the prototype research platform was integrated with the machine vision system, and the integrated system was evaluated in the field environment for dormant canopies (Figure 11). Two Kinect V2 sensors were mounted on the platform for the field tests. The first Kinect sensor was used to acquire RGB-D information of grapevine canopies for the machine vision system and the second to evaluate the performance of the control mechanism. The RGB-D information from the second sensor was acquired while the platform was moving and saved for later analysis. Then world coordinates of the cordon trajectory (Figure 8) were extracted by mapping the RGB and depth information from the Kinect V2 sensor as described in section 6.1 objective 1. Then, a control algorithm was developed (Figure 12) to automatically control the thinning end-effector position against the determined cordon positions. Figure 13 shows the overall flowchart of the integrated system to control the end-effector (robotic hand) to follow the cordon trajectories.

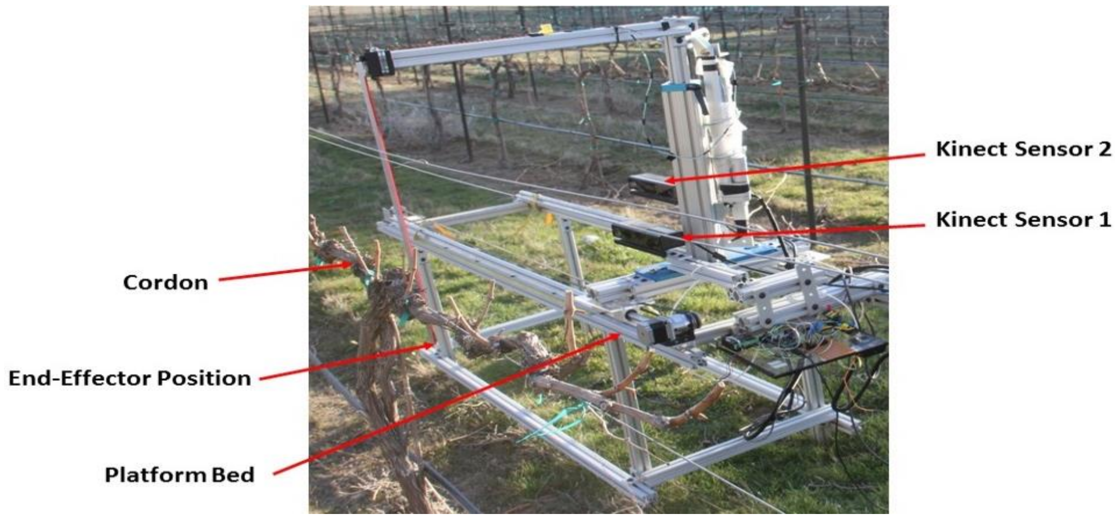


Figure 11: Integrated research platform and machine vision system in the research vineyard for evaluation of precise control of end-effector.

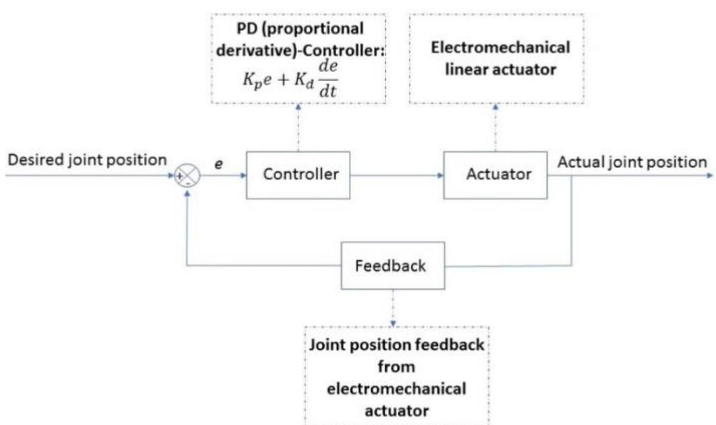


Figure 12: Closed loop control schematic to control the joint positions for research platform, PD (proportional derivative) controller was used with K_p =1 and K_d = 1.

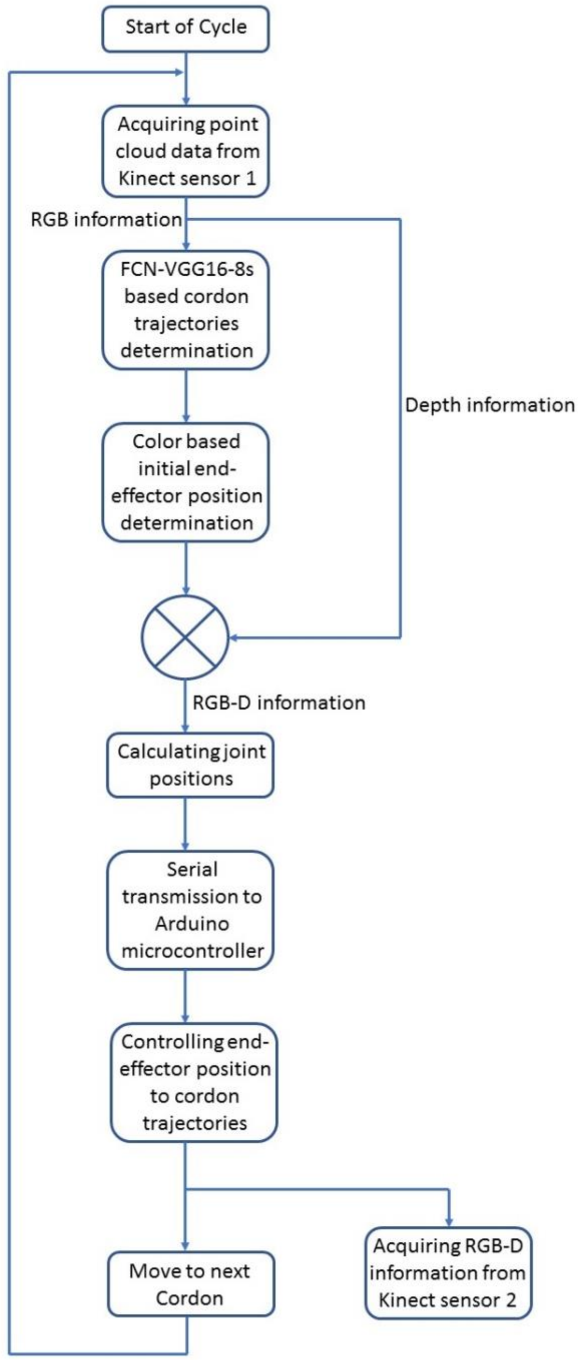


Figure 13: An overall flowchart of the general sequences of integrated system to control the end-effector to follow the cordon trajectories.

Figure 14 shows the real time positions of thinning end-effector relative to the cordon trajectories. Blue lines show the lower and upper boundaries of the cordons while green lines show the centroid trajectories of cordons, which was given as an input to automatically position the thinning end-effector. The red '+' signs in Figure 15 show the positions of end-effector extracted in each frame. Table 4 shows the RMSE (root mean square error) of the thinning end-effector position to the actual cordon trajectories at different tested forward speeds of the platform. These results show that the integrated system can automatically position the thinning end-effector within ~1.5 cm of the center position of the cordons, which proves the concept of automated green shoot thinning in vineyards.

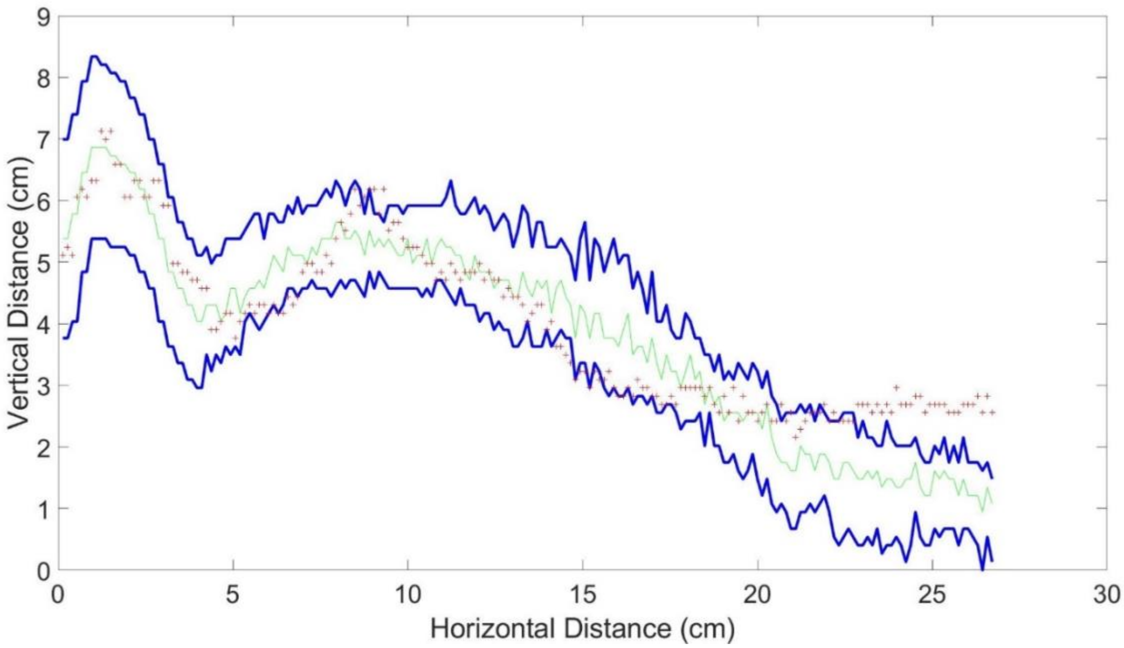


Figure 14: Accuracy of end-effector positioning on an example cordon using the integrated system. (blue lines: boundaries of cordons; green line: centroid cordon trajectory; and red '+' sign: actual positions of end-effector).

Table 4: Positioning errors of the thinning end-effector to cordon trajectories at different forward speeds of the thinning platform

	Speed ($cm \cdot s^{-1}$)	RMSE (cm)
Speed 1	3.3	1.47
Speed 2	6.6	1.47
Speed 3	10	1.51

Prototype #2: The second prototype was developed to be mounted on a vehicle (Figure 15; e.g. a gator or a tractor).This was an improved prototype that did not have to rely on a rail for forward motion and used more powerful actuators and a rolling head similar to the ones used in commercial machines. The prototype has 2 DoF (Degrees of Freedom) and consists of cylindrical rollers with flappers as thinning end-effectors (or hands). The two rollers will be placed on either side of the cordons during thinning and can be rotated by DC motor at any desired speed optimal for thinning. The two electro-mechanical linear actuators of the prototype are used for accurate positioning of the thinning end-effectors along the cordon trajectories. The cordon trajectories can vary both vertically and horizontally. The end-effector can be moved vertically using the first linear actuator (linear actuator 1) and horizontally using the second linear actuator (linear actuator 2) for tracking such variations in cordon trajectories. Moreover, the linear actuator 2 can align the end-effectors in accurate horizontal position even if the vehicle does not travel along a straight path.

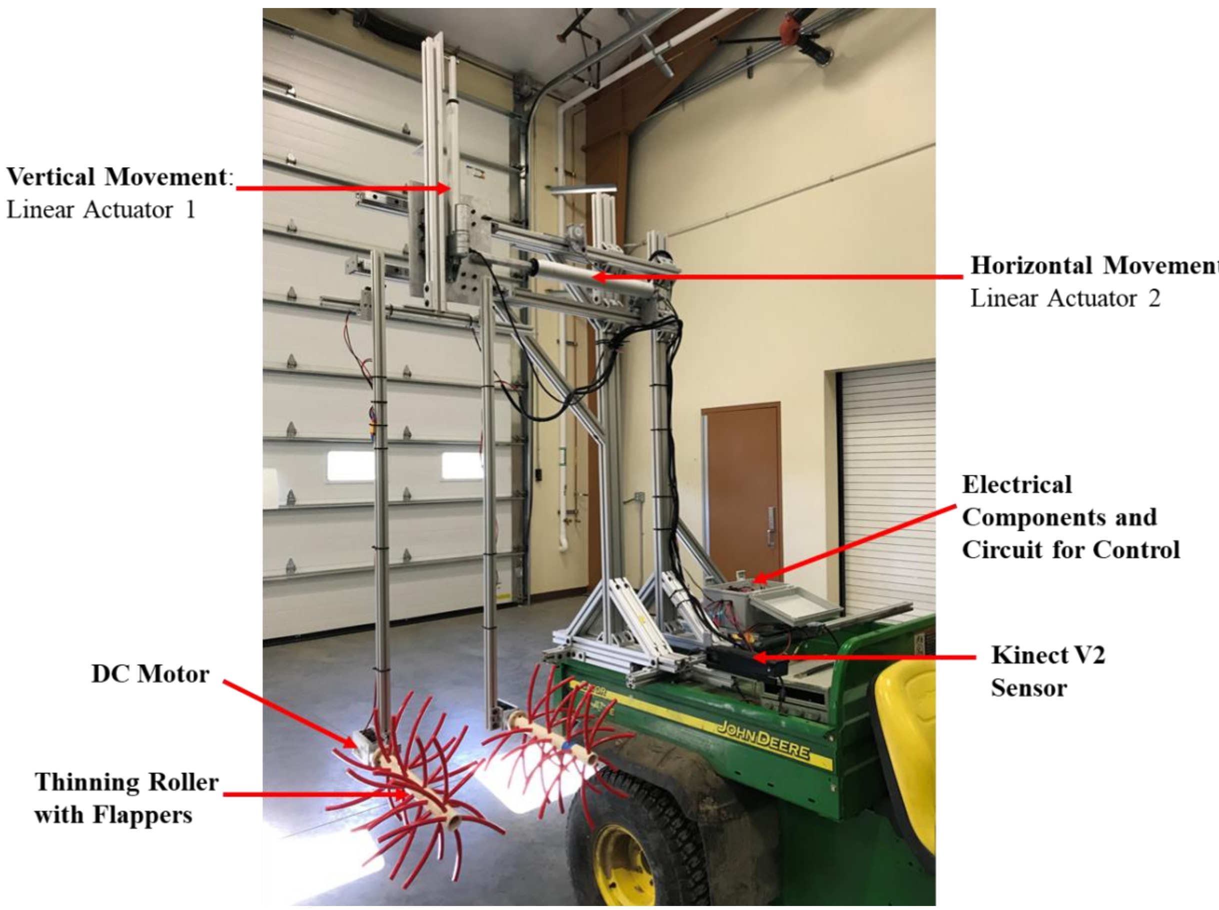


Figure 15: The second prototype of the green shoot thinning machine developed in this research project. The thinner is mounted on a vehicle consisting of thinning rollers with flappers as end-effectors. The rollers are positioned to the desired cordon trajectories by two electro-mechanical

linear actuators of the prototype. It is noted that electrical actuators were used instead of proposed pneumatic actuators in this project to prove the concept of automated thinning.

A machine vision system (discussed in objective 1) was integrated with the improved prototype and its performance in precise positioning of the thinning end-effectors was assessed in the lab. The branches of a dead tree were used to simulate cordons in this case as the field test season was passed by the time the prototype was fully integrated. A Kinect V2 camera was used for capturing images and a trajectory (Figure 16) was generated from the images for positioning the thinning end-effectors along the cordons. The world coordinates of the simulated cordons were determined next from the trajectory. Vertical and horizontal distance information extracted from the trajectory was used for moving the thinning effectors using two linear actuators.

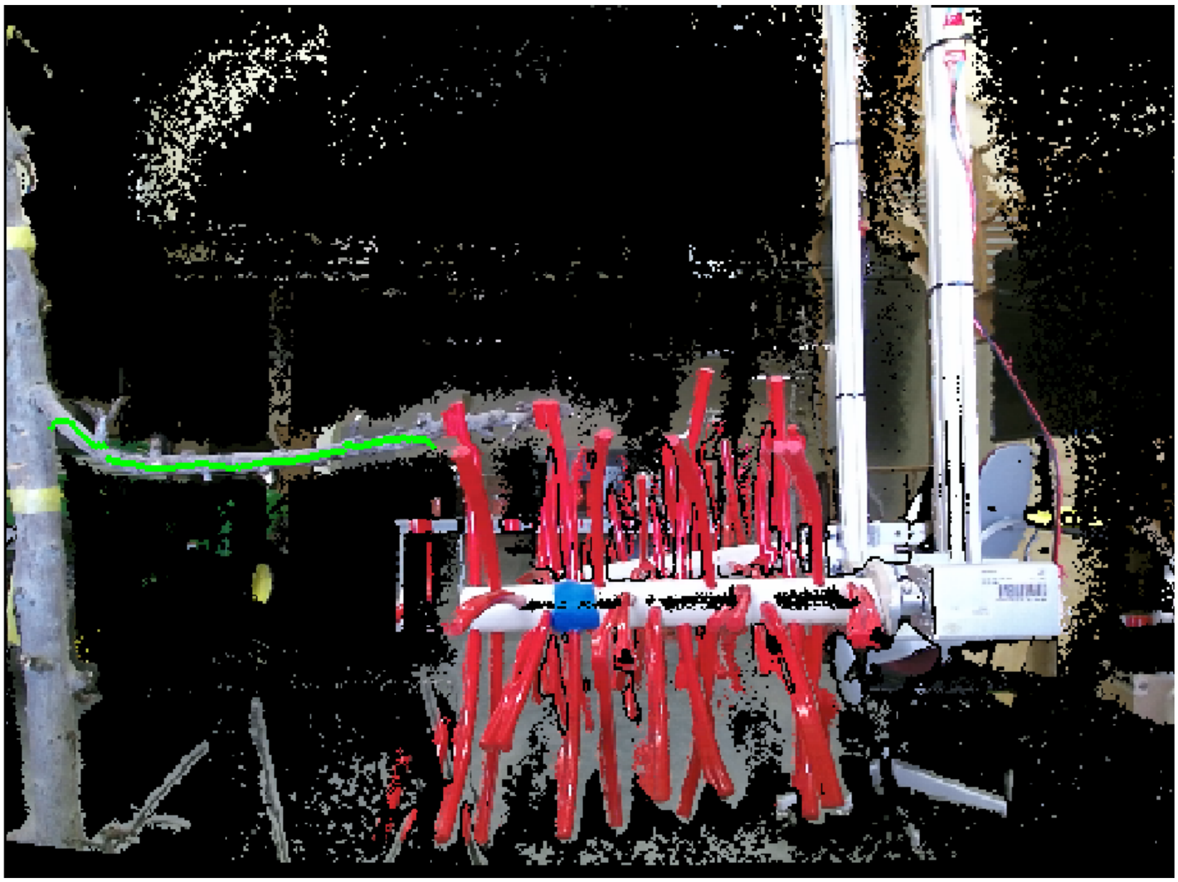


Figure 16: Branch of dead tree simulating cordon with trajectory represented by a green line generated by the machine vision algorithm. Red lines are the strings used by the thinning head.

Both the linear actuators were controlled using separate PID controllers for precise positioning of the end-effectors. A coordinate point above and between two thinning rollers was determined as a reference point to be positioned along the desired cordon trajectory. The reference point ensured the cordons lie between the rollers, and the flappers do not hit and damage the cordons during the thinning tests. The actual vertical and horizontal positions of the reference point compared to desired positions from one of the lab tests is shown in Figure 17. The desired and actual positions of the reference points in the plots represent the distances of the reference point from its initial starting position. For this lab test, the root mean square error (RMSE) for vertical distance and horizontal distance was found to be 0.15 cm and 0.21 cm, respectively. The result shows the integrated thinning prototype can be used for automating shoot thinning process with a high level of precision.

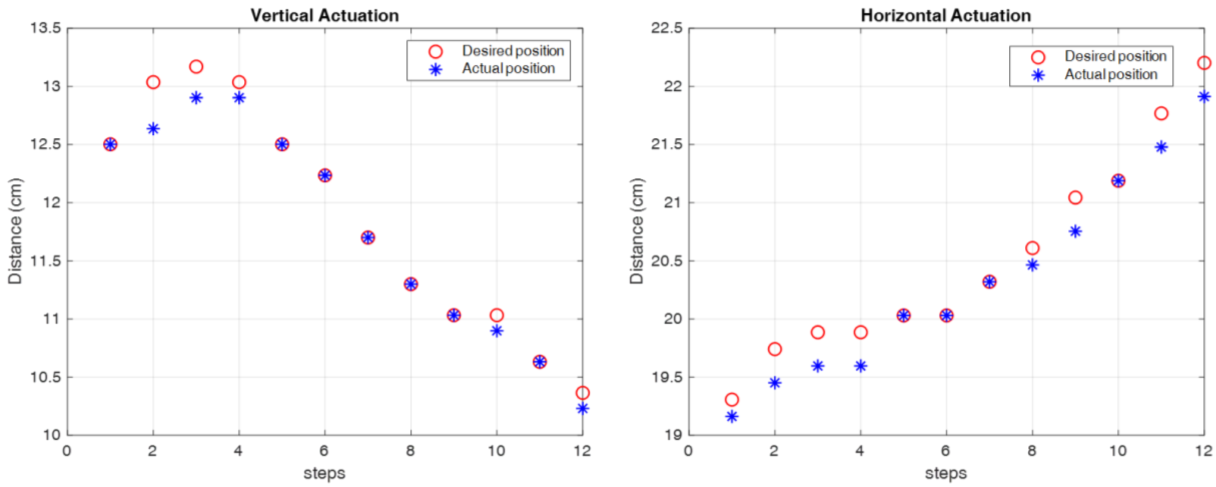


Figure 17: Desired and actual positions of reference points for vertical and horizontal actuation of the thinning end-effectors.

7. **Outreach and Education Efforts - Presentations of Research**:

List of Publications:

i. Majeed, Y., Karkee, M., Zhang, Q., Fu, L., & Whiting, M. D. (2021). Development and performance evaluation of a machine vision system and an integrated prototype for automated green shoot thinning in vineyards. *Journal of Field Robotics*. ***https://doi.org/10.1002/rob.22013***

ii. Majeed, Y., Karkee, M., & Zhang, Q. (2020). Estimating the trajectories of vine cordons in full foliage canopies for automated green shoot thinning in vineyards. Computers and Electronics in Agriculture, 176, 105671.

iii. Majeed, Y., Karkee, M., Zhang, Q., Fu, L., & Whiting, M. D. (2020). Determining grapevine cordon shape for automated green shoot thinning using semantic segmentation-based deep learning networks. *Computers and Electronics in Agriculture*, *171*, 105308.

iv. Majeed, Y. (2020). *Machine Vision System for the Automated Green Shoot Thinning in Vineyards* (Doctoral dissertation, Washington State University).

v. Majeed, Y., Karkee, M., Zhang, Q. Fu, L. and Whiting, M.D. (2019). A Study on the Detection of Visible Parts of Cordons Using Deep Learning Networks for the Automated Green Shoot Thinning in Vineyards. *IFAC-PapersOnLine*. 52(30), pp.82-86.

vi. Majeed, Y., Karkee, M., Zhang, Q. (2019). Automated Green Shoot Thinning in Vineyards. In *2019 CPAAS Ag. Tech Day, Prosser, WA.*
vii. Majeed, Y., Zhang, X., Fu, L., Karkee, M., Zhang, Q. (2019). Determining the Shape of the Cordon for Automated Green Shoot Thinning in Vineyards Using Semantic Segmentation-based Deep Learning Networks. In *2019 ASABE Annual International Meeting in Boston, MA.*
viii. Majeed, Y., Zhang, J., Zhang, X., Fu, L., Karkee, M., Zhang, Q. and Whiting, M.D. (2018). Deep Learning Based Segmentation for Automatic Apple Trees Trellis Training. In *2018 PGSA Research Expo in Prosser, WA.*

Strategy for communicating research results to end-users and stakeholders:
As listed above, we presented our results and findings in various conferences such as 2019 and 2020 American Society of Agricultural and Biological Engineers (ASABE) conference; 6th IFAC Conference on Sensing, Control and Automation Technologies for Agriculture, Sydney, Australia (December 04-06, 2019); and CPAAS Ag-Tech Day 2019, Prosser, WA (08/22/2019). We also published manuscripts in the renowned journal such as Computers and Electronics in Agriculture and Journal of Field Robotics. Moreover, we presented posters and oral presentation in 2020 and 2021 Winegrowers Conventions and a few other commodity group or professional organization meetings and conferences. Project progresses and prototypes were demonstrated to different stakeholder groups using WSU CPAAS Technology Exposition, regular visit of growers, reporters and researchers, and various field days.

8. **Research Success Statements**: In a few sentences, describe in detail how your research program benefits the viticulture industry. For example, "This research has provided vintners/growers with the essential tools to control…" ***These statements are different from the project summary in that they specifically indicate how the research benefits industry rather than summarizing progress.***
In this research project, a machine vision system was developed that could identify and locate cordons, trunks, and shoots in winegrape canopies. Cordon trajectories were also estimated even when cordons were heavily occluded by shoots and leaves. Two thinning prototypes were developed integrating the machine vision system and were evaluated in the lab and in the field. The results from the research show the manufacturers and growers can adopt the approach and findings from this study to develop a solution for automated green shoot thinning in vineyards by integrating the technology with the existing shoot thinning machines for their improved performance in the field.

9. **Funds Status**: Include a general summary of how funds were spent. (Copy of budget tables is acceptable if accurate.)

The funds were provided in the last two years. This report is a request for no cost extension.

Approved By: Karen Kneip Date: 12/7/2017	**Year 1 FY (2018-2019)**	**Year 2 FY (2019-2020)**	**Year 3 FY (2020-2021)**
	Jul 01 – Jun 30	Jul 01 – Jun 30	Jul 01-Jun 30
Item			
Salaries	14,733	15,322	0
Benefits	8,201	8,704	0
Wages			
Benefits			
Equipment			
Supplies	1,000	1,000	0
Travel	500	500	0
Miscellaneous			
Total	24,434	25,526	

Footnotes:

- Salary to hire a graduate student to carry out field experiments and analyze data
- Benefits to cover student health care and other costs
- Supplies will be used for field experiments
- WSU CPAAS has resources to provide equipment fabrication materials and facilities