FINAL PROJECT REPORT

Project Title: Towards automated canopy and crop-load management in tree fruit

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Cooperators: Dave Allan, Allan Brothers Fruits; Karen Lewis, Washington State University; Joseph Davidson, Oregon State University.

Total Project Request: **Year 1:** $115,904 **Year 2:** $80,740 **Year 3: 0** **Year 4: 0**

Percentage time per crop: Apple: 80% Pear: Cherry: 20% Stone Fruit:
(Whole % only)

WTFRC Collaborative expenses: None

Budget 1
Organization Name: Washington State University **Contract Administrator:** Katy Roberts
Telephone: (509) 335-4564 **Email address:** katy.roberts@wsu.edu

Item	2018	2019	2020
Salaries[1]	$27,653	$28,759	
Benefits[1]	$ 2,303	$ 2,395	
Wages	$13,500	$14,040	
Benefits	$2,448	$2,546	
Equipment			
Supplies[2]	$3,000	$3,000	
Travel[3]	$1,000	$1,000	
Miscellaneous			
Plot Fees			
Total	$49,904	$51,740	$0 (no cost extension)

Footnotes:
[1]Salary and benefit for a PhD student
[2]Cost to purchase sensors, metals, and other supplies for lab and field tests
[3]Travel cost for field data collection, and testing; and travel cost for cooperative meetings

Budget 2
Organization Name: Carnegie Mellon University **Contract Administrator:** Patricia Clark
Telephone: 412-268-3483 **Email address:** pclark@andrew.cmu.edu

Item	2018	2019	2020

Salaries[1]	$0.00	$5,000.00	
Benefits[1]	$0.00	$1,170.00	
Wages	$0.00	$0.00	
Benefits	$0.00	$0.00	
Equipment	$66,000.00	$18,454.11	
Supplies[2]	$0.00	$1,300.00	
Travel[3]	$0.00	$3,000.00	
Miscellaneous	$0.00	$75.89	
Plot Fees	$0.00	$0.00	
Total	$66,000	$29,000.00	

Footnotes:

[1]A part of salary and benefit for a project scientist

[2]Cost to purchase sensors, metals, and other supplies for lab and field tests

[3]Travel cost for field data collection, and testing; and travel cost of cooperators

1. OBJECTIVES

1. Formulate objective pruning rules by integrating pruning strategy desirable for robotic/automated harvesting and the strategy currently used by growers in fruiting wall apple (e.g. formally trained) and cherry (e.g. UFO) orchards;
2. Develop a machine vision system to locate pruning branches in those two crop architectures.
3. Integrate and evaluate a robotic pruning machine.

Originally Proposed Timeline of Project Activities

Objectives#	Research Activities	Time (Calendar Years and Quarters)							
		2018		2019				2020	
		Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2
1	Develop pruning rules								
	Identify pruning branches								
2	Acquire canopy images and create 3D structure of trees								
3	Evaluate integrated pruning robot								

2. SIGNIFICANT FINDINGS

1. Professional pruners/managers consider formal guidelines when identifying pruning branches in dormant apple canopies. In practice, however, the branches pruned by professional pruners were inconsistent with stated guidelines and demonstrated substantial amounts of variability.
2. Deep learning techniques are capable of analyzing canopy images to estimate various parameters such as size and location of branches.
3. Our integrated pruning system is capable of reconstructing trees in 3D, identifying cutting points, safely navigating to cutting points, and executing pruning. Future efforts will focus on making our system more robust in complex orchard environments.

3. METHODS

3.1 Objective #1: Pruning Rules and Pruning Branch Identification (Carnegie Mellon – Lead; WSU - Participant; OSU - Collaborator)

In the past it was found that, for the tall spindle tree architecture, the pruning process can be captured by four basic rules (Karkee et al., 2014); *i) remove diseased or dead wood/branches; ii) remove branches longer than a specified length; iii) remove branches larger than a specified diameter; and iv) remove branches to maintain a specified spacing.* Lehnert (2015) proposed eight rules for pruning tall spindle apple trees, some of which were similar to four different rules proposed by Karkee and Adhikari (2014). It was also claimed that two major rules; i) remove two to four largest limbs, and; ii) remove all vertically growing limbs (40 degree or less); will cover more than 90% of pruning job in tall spindle apple orchards. These previously developed rules are essential for the automated pruning of tall spindle apple orchards.

However, more work was necessary to develop and apply pruning rules to identify pruning branches in other tree architectures including formally trained apple architectures. Engineers, horticulturists and growers have been working together to explore pruning methods for the proposed canopy architectures. Special consideration was given to the desired limb and fruit distribution for robotic apple harvesting that include the need of presenting fruit individually and without any obstruction by the branches, trunks, or trellis system.

Similar to Karkee et al. (2014), the pruning rule formulation process included observation and analysis of the work of experienced pruners and supervisors. Experienced pruners were selected from commercial orchard crews. They were asked to individually tag pruning branches on randomly selected fruit trees using unique color tags. To keep tagging independent between workers, tags were removed from the tree before another worker was asked to tag the pruning points on the same tree. Video and color images of each tagged tree were captured.

Pruning branches identified by workers as well as the total number of branches were located and counted for each tree. Videos and still images were analyzed to look for the pruning patterns and process each worker follows. A set of objective pruning rules are being defined using; i) expert's knowledge captured from engineering team based on their need for robotic harvesting; ii) horticulturists and growers based on their understanding of training practices, tree architectures, and physiology; and iii) from experienced workers based on pruning processes they follow. We visited with different collaborators to get their input on the pruning strategies to support the process of pruning rule identification.

After objective pruning rules are defined, the 3D tree structure created in Objective 2 and pruning rules can be used to identify branches for pruning. For this task, novel deep learning-based methods were used to distinguish trunk, main branches and sub-branches or laterals of a tree. Geometric parameters of tree canopies including branch size (diameter), branch length, and branch spacing can be estimated using 3D measurements and corresponding color images. Once all the topological and geometric parameters of trunks and branches are estimated, decisions can be made using pruning rules to determine which branches need to be pruned.

3.2. Objective #2: Machine Vision System (WSU and Carnegie Mellon – Co-Lead; OSU - Collaborator)

Under this objective, we focused on creating 3D structures of apple and cherry trees trained in modern fruiting wall architecture (e.g. formal training for apples, UFO architecture for cherries). Images were acquired using a novel stereovision system developed by Co-PI Silwal. This stereovision system features a synchronized camera flash and shutter (called active lighting) to improve point cloud generation from stereo image pairs. Six stereo image pairs were collected with each triggering, and point clouds from each stereo-pair are fused to create a dense point cloud.

A complementary vision system (called Coordinated Depth Cameras) has also been developed that generates 3D point clouds directly using multiple coordinated time-of-flight cameras. The system is mounted on the end of the UR5e robot and can function alone or in tandem with the stereovision system. The Coordinated Depth Cameras concept relies on a global camera, a local camera, and a position tracking camera. An initial image of the entire tree is taken with the global camera. The global camera could be Co-PI Silwal's stereovision system or a dedicated global time-of-flight or stereo camera. This initial image serves as a framework of points for the local camera. The UR5e then begins to "scan" the tree at close range with the local camera along a planned trajectory. The local camera generates a series of high-resolution point clouds that are mapped to the global point cloud as the tree is scanned. This mapping of local points to the global framework is made possible through the tracking camera. The tracking camera continuously estimates the relative position of the local camera to the global camera. Finally, the iterative closest point algorithm is used to complete the mapping of local points to the global framework. Once the scanning is complete, we are left with a very detailed 3D point cloud of the tree structure that can be analyzed to make autonomous pruning decisions.

After image acquisition and 3D point cloud generation, a state-of-the-art object detection algorithm (Faster R-CNN) proposed by Ren S., et al. (2015) was used to identity branching points from color images. These branching points are strong visual ques that detect branch occlusion necessary to segregate individual branches. The link between the detected branching points was associated using the skeleton image generated by the Generative Adversarial Network (GAN). The output of the GAN is a binary image with an array of connected binary pixels that traced the mid-section of branches in the color images. A multi-channel GAN was used to generate a skeleton image for branches and main trunk. Once the skeleton was identified, the curvature of the branches and trunk was warped using the depth information obtained in the previous steps to reconstruct the 3D models. Using this info, the length and size (diameter) of each branch can be estimated. Length can be estimated using the starting and end points of the branches. To estimate diameter, the skeleton of the tree can be overlaid on top of the color images taken from the same perspective. Then, the number of pixels in the orthogonal direction of the branch skeleton can be counted at the base of the branch (2 to 5 cm from the branch-trunk junction). The resulting 3D skeleton and geometric parameters can be used in identifying pruning branches as discussed in Objective 1.

A complementary machine learning approach has also been developed that generates a 3D tree skeleton directly from point cloud data (as compared to first using images). A point cloud from Co-PI Silwal's stereovision system or the Coordinated Depth Cameras system is processed to create a graph of "superpoints" and "edges." Each edge in the graph is processed by a neural network to determine its validity. Valid edges are used to determine the tips and trunk of the tree. The tips and trunk of the tree are input into an evolutionary algorithm that "grows" the tree structure between the trunk and the tips. The output of the evolutionary algorithm is a tree skeleton with trunk, support, and leader labels. Secondary branches can be identified using the leader labels. This tree skeleton can then be used for autonomous cutting point selection.

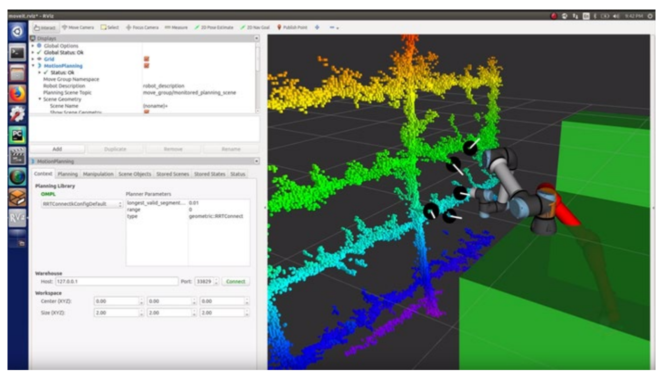

Fig. 1. Simulation of branch pruning in Gazebo. A 3D OctoMap of an apple tree has been created from a 3D point cloud. Five cutting points were selected randomly. The UR-5e traces a collision free path.

3.3. Objective #3: Integrated Robotic System Evaluation (WSU–Lead; CMU Participant; OSU Collaborator)

In the proposed work, two pruning shear end-effectors were developed and integrated with a robotic manipulator to carry out pruning tasks. The machine vision system was integrated with the hardware system for complete system evaluation in the lab and field environments.

A UR-5e robot arm from Universal Robots was used for developing an automated fruit tree pruning system. This manipulator demonstrated good speed, reach and maneuverability, and was acquired at both Collaborator Davidson's and PI Karkee's labs in addition to the similar system available at CMU. This facilitated collaborative system development, integration, and evaluation. Developing an

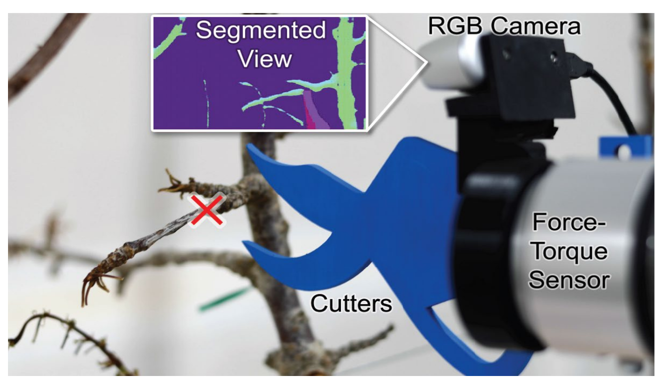

Fig. 2. To complete the final approach to a cutting point, the UR-5e uses a hybrid image/force controller instead of 3D point cloud data.

integrated software stack for robot control is key for a successful pruning system. Our approach included the following:

1) Create a 3D point cloud of the orchard environment
2) Generate collision free paths to the identified cutting points using FREDS-MP (Fig. 1)
3) Execute a controlled approach to the cutting point using inverse kinematics
4) Cut the identified branch

The planning framework we utilize is called FREDS-MP, which aims to increase the planning speed and overall throughput of the robotic system. FREDS-MP works by precomputing a database of optimistic trajectories offline, utilizing these trajectories during the online phase as effective priors, and ordering the cutting points more effectively. Additional controls have been developed to increase the accuracy of the UR-5e's approach to the cutting point while minimizing risk to the robot and the environment. Oftentimes, the 3D point cloud of the tree is not a perfect reconstruction due to a variety of environmental or technical factors. These inaccuracies could cause unintended collisions during the UR-5e's approach that cause damage to the tree, the UR-5e, or both. As such, a hybrid controller has been developed to increase the accuracy of the UR-5e's final approach (15-30 cm) to cutting points using images and force data instead of 3D point cloud data (Fig. 2). Segmented images of pruning branches and the end effector were generated using another GAN to enable robust vision-based control. The vision-based controller navigates the end effector to the pruning branch until contact is made. Once contact is made, a force-feedback controller was developed using the UR-5e's force torque sensors to navigate the end effector to the pivot point in the shears without creating high forces. This hybrid controller was trained in simulation using proximal policy optimization.

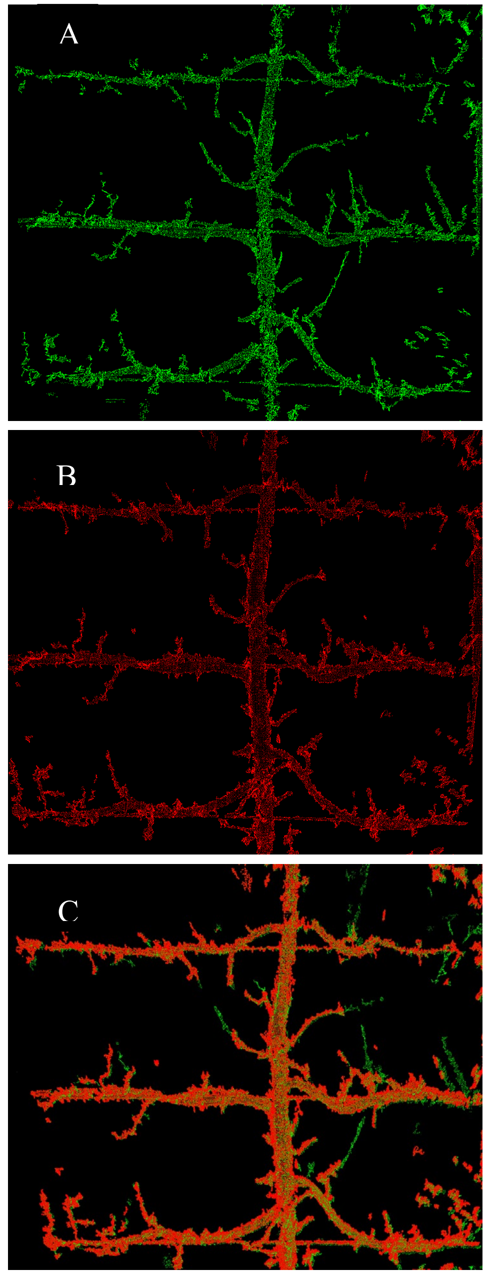

Fig. 3. Pre/post pruned point cloud overlay. (A) pre pruned point cloud. (B) post pruned point cloud. (C) overlaid point cloud. The intersections of green and orange points indicate cutting points.

4. RESULTS & DISCUSSION

4.1 Objective #1: Pruning Rules and Pruning Branch Identification

Our hypothesis for automated pruning rule generation was that the observation of commercial pruning operation and analysis of images/3D models captured before and after pruning could lead to objective pruning rules. To test this theory, we assigned professional pruners to follow commercially adopted pruning rules and prune forty dormant apple trees. For these canopies, the camera system was placed in a stationary location approximately one meter in front of the canopy and we collected before and after pruning wide angled stereo images. Later, point clouds from the two pre/post pruning datasets were overlaid to identify individual cutting points. Figure 3 shows this underlying concept.

A summary of the critical components of the ideal pruning rule for dormant apple trees are listed below for discussion. A detailed description of the pruning rule practiced by professional pruners is included in our 2018 annual report (submitted on Jan 16, 2019).

- Use of a BCA tool to optimally determine the appropriate number of fruiting location per unit length of the lateral branches.
- Fruit spacing was considered an important parameter. Minimum fruiting zone spacing was approximately 4 inches as anything closer might lead to clusters of fruit during harvest season.
- Length of fruiting laterals was another important factor. Laterals longer than 8 inches were trimmed.
- Considerations were also made to remove vertical fruiting sites and those right over or under the horizontal branches.
- Selectively remove smaller buds from a cluster. Remove buds too close to the trellis wire, shoots under the branches, and vertical fruiting zones.
- Remove dead and diseased branches and tie shoots closer to the edge of the branch to fill gaps if lateral branches are short.

The analysis of the pre/post pruning data revealed inconsistency in following the strict guidelines for pruning apple canopies. In practice, branch diameters were assessed visually and intuitively without the use of the BCA tool. This led to suboptimal selection of number of fruiting location per unit length of the lateral branches. Additionally, the minimum gap between fruiting locations were estimated using the width of the palm as a unit of measurement which varied from one pruner to another. These differences between the ideal and practiced manual pruning created large amounts of variation in the data for training a machine learning agent. As such, these revelations led us to focus on synthesizing a pruning rule by just utilizing the geometric measurements and topological parameters. We realized the most important aspect of pruning is the uniform distribution of fruit, therefore we implemented the following simplified pruning rule that prioritizes fruit distribution.

1. Estimate diameter and length of lateral branches and use the BCA equation to determine optimal number of fruiting locations per unit length of the lateral branches.
2. Count and measure the length of secondary branches and only keep secondary branches with minimum of 4 inches gap.

Fig. 4. A multi-view stereo camera system imaging dormant apple canopies. Camera system includes a linear slide.

Fig. 5. A 3D point cloud of the tree structure generated by the Coordinated Depth Cameras system.

In UFO cherries, pruning rule was highly simplified (based on the experts knowledge) to ‘remove all lateral branches on upright fruiting offshoots'.

4.2 Objective #2: Machine Vision System

Secondary branches protruding towards and directly away from the camera are missing in the 3D tree structure when only one viewpoint is used. To mitigate this limitation, Co-PI Silwal from CMU designed a new camera system that images the canopy with two stereo cameras systems (Fig 4).

The new camera system has two stereo pairs, one at a lower height for front view of the canopy and another at a higher and angled position for the top view. Both the top and bottom cameras travel along the linear slide to three different locations and provide a total of six different views of the canopy. The fused point clouds from six different locations provided a more detailed 3D structure of the canopy. In addition to multi-view stereo, like its predecessor, this new camera system is also equipped with active lighting that generates consistent image quality regardless of ambient lighting condition. Additionally, our Coordinated Depth Cameras system can operate alone or further improve the quality of the point clouds obtained by Co-PI Silwal's stereovision system. A sample point cloud obtained by the Coordinated Depth Cameras can be observed in Figure 5.

To implement any pruning rule, the vision system should be able to estimate key aspects of tree canopies such as branch and trunk shapes and sizes. Currently, we have implemented a variation of a deep learning technique called Generative Adversarial Network (GANs) that directly outputs a 2D skeleton image of just the secondary branches. This is advantageous over conventional computer vision algorithm as it bypasses several intermediate processing steps such as pre-processing, multi-class segmentation, and post-processing steps that could potentially add more inaccuracies.

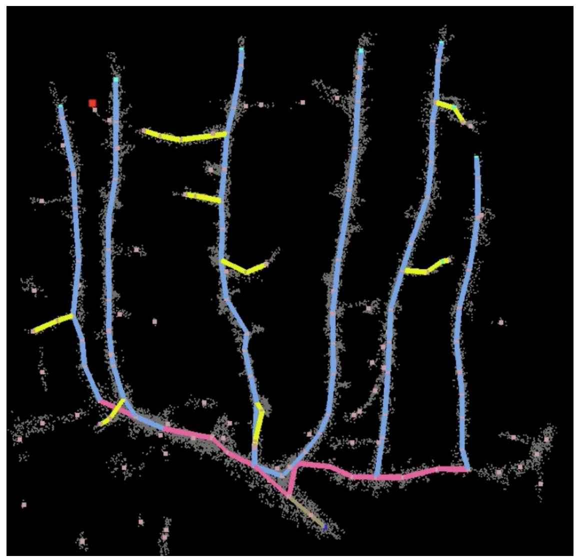

Fig. 6. Labeled tree skeleton output from the skeletonization algorithm.

Our complementary skeletonization algorithm has demonstrated the ability to label point clouds directly and generate a 3D tree structure identifying tree trunk, supports, leaders, and secondary branches. The output of this algorithm can be observed in Figure 6. This tree skeleton can then be used to autonomously determine cutting points for pruning. Further work is going on to estimate desired geometric and other parameters of trees.

4.3 Objective #3: Integrated Robotic System Evaluation

In 2019, we developed an integrated pruning system and evaluated its planning and execution performance in a lab environment. The pruning system is shown in Figure 7, consisting of the UR-5e equipped with an end-effector and an in-hand Intel RealSense D435 camera. The end effector consisted of a pneumatically actuated four-bar linkage with custom-ground blades. Initial tests showed the

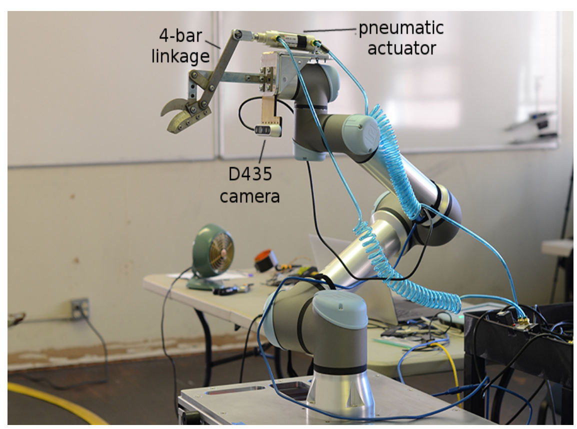

Fig. 7. Our initial pruning robot setup, consisting of a UR-5e robot arm, an Intel RealSense D435 camera, and a custom pneumatic pruning end effector.

end-effector could consistently cut branches up to 10mm in diameter near the pivot point of the blades. Cutting points could be manually selected on a 3D point cloud, and the UR5 could successfully navigate the end effector to manually selected cutting points.

In 2020, our pruning robot was further optimized. A battery-powered, electrically actuated pruning end effector was modified to interface with the UR-5e and support remote actuation. This new pruning end-effector is capable of pruning branches up to 25mm and has no need for compressed air. The UR-5e was mounted on the linear slide with Co-PI Silwal’s stereovision system to add an additional degree of freedom for FREDS-MP. Additionally, the Coordinated Depth Cameras system was mounted on the end of the UR-5e with the improved end effector. The refined prototype was further evaluated in labs using actual trees collected from commercial orchards.

In 2021, we integrated all the components of an autonomous pruning robot (Fig 8). The Coordinated Depth Cameras system was capable of creating detailed 3D point clouds, and our machine learning skeletonization algorithm was capable of autonomously selecting cutting points. FREDS-MP was capable of navigating our pruning end effector to the autonomously selected cutting point, and our end-effector was capable of autonomous actuation to cut the pruning branch. The system was brought to field evaluation in a commercial UFO cherry orchard. However, only limited test cuts were performed because of new challenges faced in the complex orchard environment and practical issues on robot operation caused severely cold weather. We outlined the steps we needed to take to have a successful demonstration and have been working towards these goals. Our Coordinated Depth Camera has been optimized since the attempted demonstration, and our vision-based controller GAN is being further trained for robustness in complex orchard environments. We have identified a more efficient mounting orientation for the UR-5e, and we are optimistic our next demonstration will be a success. We will continue to evaluate the system through additional funding provided by USDA to our team.

Fig. 8. The final pruning robot used for our 2021 evaluation, consisting of the UR-5e robot arm, the stereovision system, the Coordinated Depth Cameras system, and a custom electric pruning end effector.

EXECUTIVE SUMMARY

Project Title: Towards automated canopy and crop-load management in tree fruit

Key words: Pruning robot, automated pruning, deep learning, machine vision, robotics

Abstract: The widespread adoption of robotic harvesting systems requires deliberate canopy management to grow fruit in easily accessible locations. Therefore, it is necessary to automate canopy management in tree fruit so that labor use can be minimized throughout the entire production process. Specifically, this project focused on the automated pruning of fruit trees. The objectives of this project were to: i) Formulate objective pruning rules by integrating pruning strategy desirable for robotic/automated harvesting and the strategy currently used by growers in fruiting wall apple (e.g. formally trained) and cherry (e.g. UFO) orchards; ii) Develop a machine vision system to locate pruning branches in those two crop architectures; and iii) Integrate and evaluate a robotic pruning machine. To develop objective pruning rules, 3D point clouds were collected of 40 dormant apple trees before and after pruning by professional pruners. We found that, although professional pruners consider formal guidelines, in practice the branches pruned were inconsistent with the stated guidelines and demonstrated substantial amounts of variability between pruners. As such, we adopted two simple rules that prioritize the uniform distribution of fruit. Two complementary machine vision systems were developed to capture 3D tree structure. An active lighting stereovision system was developed consisting of two stereo pairs that utilized a linear slide. The stereo pairs would take images from three positions along the linear slide to provide a total of six perspectives of the tree to minimize branch occlusion in the resulting 3D point clouds. Additionally, we developed a Coordinated Depth Cameras system that directly generates 3D point clouds without taking images using multiple time-of-flight cameras. The Coordinated Depth Cameras system could be used alone or in tandem with the stereovision system. These machine vision systems produced highly detailed 3D point clouds that were used to make autonomous pruning decisions. Again, two complementary approaches were developed to autonomously identify cutting points. One approach utilized a deep learning technique called a Generalized Adversarial Network to output 2D skeleton images of secondary branches that could subsequently be used to measure branch length and diameter. A complementary approach utilized an evolutionary machine learning algorithm to operate directly on 3D point clouds instead of images. The evolutionary algorithm produced a 3D tree skeleton with labels for the tree trunk, support, leaders, and secondary branches. The information from these tree skeletons could be used to autonomously identify pruning branches and cutting points. A motion planning algorithm called FREDS-MP was used to navigate our UR-5e robotic manipulator and our custom pruning end-effector to the desired cutting point. A hybrid vision-based/force-feedback controller was developed to increase the accuracy of the final approach to cutting points without causing damage to the robot or the environment. The pruning branch could then be automatically cut by our pruning end-effector. In 2021 winter, a fully integrated pruning robot was evaluated at a limited scale in the field, but the orchard environment posed new challenges that our team is currently addressing. An improved and more robust robotic system will be evaluated in the orchard environment in recent future using additional funding our team (led by collaborator Joseph Davidson) have secured from USDA.