Chapter 6
Advanced Technologies for Crop-Load Management

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Abstract This chapter will discuss the opportunities and challenges of robotic solutions for tree fruit production with modern planar tree canopy management, including the importance of modern tree canopy system, robot-canopy interaction, robotic system control, in-field sensing for object detection, and three-dimensional (3D) reconstruction, and a case study on the robotic branch pruning for apples with modern tree canopies. In the end, the conclusion and future directions were investigated.

6.1 Introduction

Crop-load management is one of the most important tree fruit crop production operations. Fruit trees generally bloom more flowers and set more fruit than they could support to grow the desired yield of high-quality fruit (e.g., size, color, and internal characteristics such as sugar content and acidity). Precise crop-load management practices aim at optimizing the yield and these quality parameters by adequately reducing the number of fruit set and grown in a given tree. Overall crop-load management of fruit crops is commonly achieved through a strategic combination of training, pruning, thinning (flower and fruit), and/or pollination to control the number of fruit grown in individual trees.

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6.1.1 Tree Training

Tree training is an operation that creates desired tree canopy architectures with different heights, shapes, and structures. In modern orchards, trees are generally trained to a trellis system (consisting of trellis posts and trellis wires) right after planting so that the trunk of the trees grows to a specific shape and direction. Once the trunks are securely trained to a specific shape and grow to a certain height, newly growing branches are also trained to form canopy shapes. Modern training systems are designed to create narrow canopies in vertical or angled structures, often called SNAP (simple, narrow, accessible, productive) orchards. Figure 6.1 shows an upright fruiting off-shoot (UFO) cherry architecture where the main trunks are trained to create a permanent horizontal structure and branches are grown and trained vertically above the base.

Two other commonly used training systems in modern orchards are presented in Fig. 6.2. Figure 6.2b depicts a formally trained apple orchard in a V-trellis system where tree trunks are trained upright at a certain angle and branches are trained horizontally along the trellis wires creating canopies with layers of fruiting zones.

These training systems are designed to improve air movement and light distribution and make fruits and branches more visible. The trees are friendlier to both manual and automated field operations. Consequently, modern, narrow canopy architectures help maximize both the yield and quality of fruit crops compared to conventional three-dimensional trees (Fig. 6.3). More details on tree pruning concepts and their roles in fruit crop production were presented in Chap. 2.

6.1.2 Tree Pruning

Tree pruning is an operation to help grow trees into a desired shape and size, which is essential to improve the penetration of both sunlight and spray materials to all canopy parts, supporting more effective orchard operations. Pruning is also used to

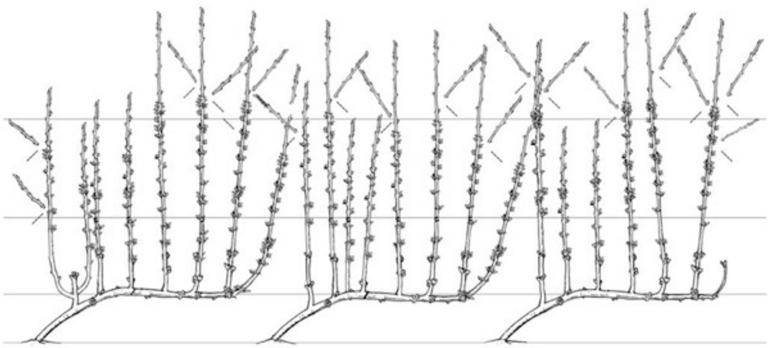

Fig. 6.1 Illustration of UFO cherry tree training and pruning. (Diagram courtesy of Dr. Mathew Whiting, Washington State University)

Fig. 6.2 A well-pruned vertical trellis (**a**) and V-trellis (**b**) system commercial apple orchard in the state of Washington which produces a high yield of good size and high-quality apples. (Photo by Qin Zhang)

Fig. 6.3 Traditional low-density sweet cherry orchard. (Pictures from Zhang 2017)

remove old and diseased branches. Otherwise, unproductive branches initiate new growth and improve flower bud development (Durner, 2013) so that the overall tree health and productivity remain at an optimal level. In modern orchards, pruning operation can also regulate fruit-bearing sites so that light interception to fruit can be enhanced and uniformity of fruit distribution over the canopy surfaces is improved, which leads to improved yield and quality of fruit crops. Pruning is typically done annually by selectively cutting and removing parts/branches of trees following certain guidelines developed by horticultural research and farmers' long experience. Therefore, achieving desired pruning results requires experienced workers with adequate knowledge and skills in pruning strategies. Figure 6.4 shows a well-pruned apple orchard in the state of Washington.

Fruit tree pruning could be conducted in the winter (dormant season) and the summer. Dormant pruning is performed from late fall to winter when the trees are not actively growing. This is the annual pruning process's major part of maintaining

Fig. 6.4 A well-pruned commercial apple orchard in the state of Washington which produces a high yield of good size and high-quality apples. (Photo by Qin Zhang)

Fig. 6.5 A graphical illustration of a few commonly used hand pruning tool samples – (**a**) a hand pruner, (**b**) a long-handled lopping shear, and (**c**) a pruning saw – and powered pruning tool samples: (**d**) an electric-powered pruner, (**e**) a pneumatic-powered pruner, and (**f**) a hydraulic-powered pruner

the desired canopy shape and size. Some farming operations also perform summer pruning, focusing primarily on removing excessively growing shoots or branches to optimize fruit exposure to sunlight. Fruit tree pruning is mainly done manually by skilled field workers using hand tools, such as hand pruners, long-handled lopping shears, or pruning saws (Fig. 6.5a–c). As hand pruning is highly labor-intensive (the second-highest labor-intensive job after harvesting) and accounts for ~20% of the total production cost (He & Schupp, 2018), some power-pruning tools, such as electric-, pneumatic-, or even hydraulic-power pruners (Fig. 6.5d–f), are increasingly being used for reducing the force required to cut branches and thus to reduce the workers' fatigue and improve their productivity. Personal communication of authors with growers in Washington has suggested that it could achieve about a 50% labor-saving in orchard pruning by simply switching from using hand tools to the use of power-pruning tools.

6.1.3 Blossom and Fruit Thinning

In general, even after strategic pruning, most fruit trees bloom many more flowers than needed for an optimal fruit set. If all flowers are left for pollination, it could result in too many fruits being set, leading to harvested fruits with small/suboptimal size and often with poor quality. Experts estimated that for some varieties of tree fruit crops such as apples if just 5% of all those spring flowers set fruit, it could be enough to provide the desired crop yield. Thus, many fruit growers have adopted flower and/or fruit thinning as a good farming practice to remove either a portion of the blooms or young fruits (or both) on the trees for growing fruit with good size and high quality.

Blossom thinning can be performed using either chemical approaches to reduce the number of flowers capable of setting fruits or physical means to remove a portion of flowers from the trees during and shortly after the bloom period. An additional green fruit thinning could also be performed later in the season (anywhere from a couple of weeks to a few months after fruit set) to remove excess and poor-quality fruit and/or those growing in suboptimal canopy areas and growing too close together, to ensure good size and quality of fruits at harvest. Chemical thinning is a less labor- and skill-intensive operation than pruning, but physical/manual thinning could be very tedious and time-consuming, which thus could be as or even more expensive field operation compared to pruning.

Chemical thinning is mechanically performed by spraying some plant growth-regulating chemicals on the trees shortly after bloom; this is a highly productive operation. However, despite many years of study and practice, chemical thinning remains unpredictable in efficacy. Its results could vary significantly from orchard to orchard or year to year due to a wide variation of field and/or weather conditions. Thus, it is still more an empirical method requiring growers to weigh many factors in planning a thinning operation to obtain a desirable response from chemical thinning.

Physical blossom thinning can be done mechanically using machines or manually using tools or even hands (from left to right in Fig. 6.6). In general, hand thinning is the most labor-intensive and laborious approach with very high labor costs, even though it could achieve the most precise control over the thinning efficacy. Using some kinds of hand tools could help solve the low productivity and high labor cost challenge, with a price of less controllability in thinning precision. Mechanical thinning is highly productive but has the least controllability in thinning precision.

Fig. 6.6 Examples of blossom thinning using a machine (left), a hand tool (middle), or hands (right) in commercial cherry orchards in the state of Washington. (Photos by Qin Zhang)

6.1.4 Crop Pollination

As fruits can be set only after the flowers are pollinated and fertilized, pollination plays a critical role in transferring pollen from male to female parts of flowers to set the fruit. Thus, crop pollination and its efficient control become one of the most important field operations for achieving desired crop load in fruit trees. In general, there are two types of pollination approaches in fruit trees: self-fruiting/self-pollinating crops and externally pollinating crops (cross-pollination). Pollination in self-pollinating crops occurs by transferring pollen from the anther to the stigma in the same flower and between different flowers in the same tree or between flowers in different trees of the same cultivar. Because pollination in self-pollinating crops can occur within the same flower, it is difficult to realize crop-load management by controlling the amount of pollination.

There are other fruit crop cultivars where self-pollination (setting fruit using the pollen from the same flower or tree) is not possible. In such crops, cross-pollination between different fruit cultivars is required for the fruit set. Cross-pollination in commercial orchards is achieved by planting pollinating trees at a certain density so that pollens from the pollinating trees are transferred to the flowers in the crop trees. Transferring of pollens from pollinator trees to crop trees is achieved by some pollinating agents, such as bees, insects, birds, water, and/or wind. Such a pollination process requiring external agents for pollen transfer offers a possibility of managing crop load using a controlled amount of pollination.

Conventionally, tree fruit growers worldwide have relied on natural means, such as insect pollinators or wind, to complete the pollination process. Due to some ecological and disease control reasons, such as a persistent decline in bee populations (e.g., colony collapse disorder), insects' sensitivity to environmental conditions, and the potential for viral disease distribution, tree fruit growers are looking for alternatives to the natural pollination process. More discussion on mechanical and robotic pollination is presented in Sect. 6.4.

6.2 Advancement in Training and Pruning Technologies

6.2.1 Introduction

Using manual labor, fruit trees are trained and pruned to the desired shape and size. These are highly labor-intensive operations requiring a large semi-skilled labor force on a seasonable basis. With decreasing availability and increasing labor costs, it has been increasingly challenging for tree fruit growers to complete these annual operations to the desired level. To improve the sustainability of the fruit crop industry, it is essential to develop automated or robotic solutions for these labor-intensive field operations (Hertz & Zahniser, 2013).

As discussed before, fruit trees are pruned to improve the fruit quality and yield by removing unproductive branches and branches in undesirable locations. Pruning helps create the desired size and shape of the trees and set the desired structure for optimal crop load. Manual pruning involves the selective removal of branches by skilled labor. Mechanically or with automated machines, pruning can be carried out in non-selective (hedging/mass removal) or selective fashion. Moore (1958), Gautz et al. (2002), and Forshey (2014) worked on mass pruning systems in which a cutting tool was run over tree canopies to keep a predetermined distance from the center of tree canopies.

Similarly, Morris (2007) developed a mechanical solution for the non-selective removal of shoots at a certain height above the cordons (permanent horizontal vine) in vineyards. These machines achieved a good performance in cutting branches in mass at a certain canopy depth and hedging at a certain height (Forshey, 2018). However, manual cleaning after a mass pruning operation is essential to achieve the desired pruning outcomes in terms of uniform distribution of fruiting sites, renewal of unproductive branches, and better exposure of fruit to sunlight.

While these machines are easy to operate, this process does not allow for selective pruning or renewal of tree branches, which is essential to achieve canopy shapes that maximize yields of premium quality fruit. Therefore, a robotic solution would be essential to selectively remove tree branches using a manipulator and end-effector system to achieve the best pruning results. The latest research and development in selective pruning of fruit trees and grapevines will be discussed in the following subsection.

6.2.2 Machine Vision for Selective/Robotic Pruning

Robotic pruning of trees consists of four main steps: (i) perceiving the visual information and creating the 3D structure of target fruit trees using a vision system; (ii) determining the branches to be pruned (pruning decision) using various pruning strategies and 3D structure of the trees; (iii) path planning and navigation of the manipulator to target branches; and (iv) selectively removing branches using an end-effector. Accurate estimation of 3D tree structures and precise execution of all these steps of the robotic pruning process are vital to achieving the desired pruning results in an orchard environment.

In the first step, machine vision techniques are applied to obtain images, remove background, detect various canopy parts (e.g., trunk and branches), and reconstruct the tree structure. In this process, various object features, including color, shape, texture, and location (e.g., distance to a branch from the sensor), are extracted explicitly or implicitly (e.g., in a deep learning model) and used to accomplish object detection and classification as needed. At this stage, errors and/or inaccuracies affect all downstream operations and, therefore, the performance of the overall robotic pruning system.

As a sensing/vision system is the fundamental component of a robotic pruning system, many researchers worldwide focus on developing an accurate and robust vision system for robotic pruning. Naugle et al. (1989) investigated the use of machine vision to guide an automated pruning device. RGB cameras were used by McFarlane et al. (1997) and Gao and Lu (2006) to capture images of grapevine canopies in vineyards. Then, simple image processing techniques (i.e., color thresholding and Hough transform) were applied to segment the grapevines in the images.

Similarly, two RGB cameras mounted on a robotic manipulator were used to acquire images of dormant apple trees by Tabb and Medeiros (2017). They used a silhouette-based algorithm for extracting the skeleton of apple trees. They then estimated different geometric and topological characteristics of trees, including diameter, length, and angle of branches, that could help determine pruning points for the robotic pruning systems. You et al. (2021) produced labeled skeleton of upright fruiting off-shoot (UFO) cherry trees in color images using the topological and geometric priors associated with these labels. A median accuracy of 70% regarding a human-evaluated gold standard was achieved by creating a skeleton of cherry trees using this algorithm.

Color and 3D or just 3D sensing systems have also been widely investigated to reconstruct fruit trees and estimate desired geometric color and topological parameters desired to make pruning decisions. Livny et al. (2010) proposed a branch structure graph (BSG) to create and represent skeletons of trees in the dormant season. Tabb (2013) developed 3D models of apple trees using the principle of shape from Silhouette. Chuang et al. (2000) used shape information called potential field to extract the skeleton of 3D objects. Palagyi et al. (2006) proposed an end-point rechecking method to avoid spurious side branches generating the skeletons. These algorithms have shown good accuracy in indoor applications. Elfiky et al. (2015) proposed a new 3D reconstruction method for apple trees trained in a tall spindle architecture. They used the Microsoft Kinect 2 sensor, which showed the potential for a low-cost sensor for orchard machine vision applications. Akbar et al. (2016) and Chattopadhyay et al. (2016) developed and evaluated a method to model tree trunks and branches using semicircles in a 3D space represented by a single depth image. A stereo vision camera was used to acquire 3D point cloud data of sweet cherry trees by You et al. (2021) for the robotic pruning. Then, a

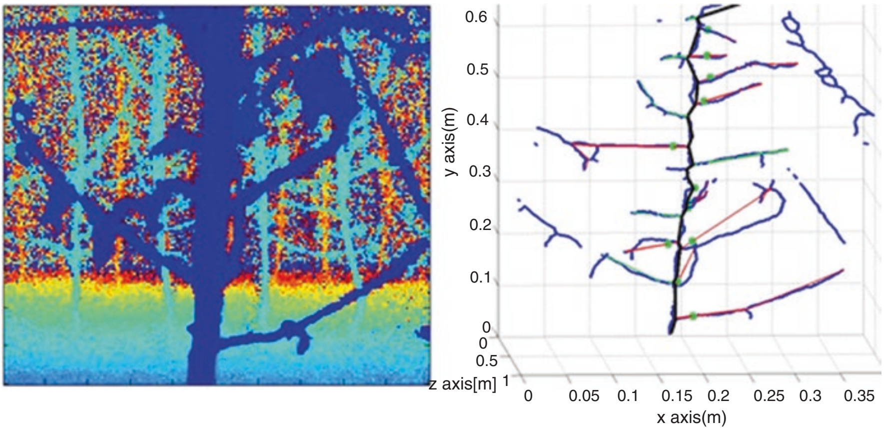

Fig. 6.7 Apple tree captured by a 3D camera (left) and identified pruning points in the tree skeleton (right)

population-based search algorithm was applied to skeletonize the cherry tree, and a CNN (convolutional neural network) was used to validate the correct edges of the skeleton.

In addition to consumer 3D cameras, a laser scanner was employed by Medeiros et al. (2017) from various perspectives to collect 3D information on dormant apple trees. A split-and-merge algorithm was applied to separate the trunk, branch, and joint segments. Once the trunk and branches were delineated, diameters of the trunk and branches were estimated, which is considered an important parameter to determine the target branches for pruning. The technique was tested in tall spindle apples and other relatively older tree architectures. A 3D camera (mounted on a pan-and-tilt system) based on the time-of-flight of light principle was used by Karkee et al. (2014) to capture image frames of apple trees for dormant robotic pruning. The skeletons of apple trees were reconstructed by adopting the medial-axis-thinning algorithm. Skeletonized trees were used to identify pruning branches following two simple rules, i.e., maintaining a specific distance between branches and maintaining a specific branch length (Fig. 6.7).

In recent years, low-cost, consumer RGB-D sensors have also been investigated widely to create the 3D structure of fruit trees. Wang and Zhang (2013) used Kinect sensors mounted orthogonally to the canopies for collecting 3D information and used a simple transformation matrix to reconstruct the skeleton of cherry trees from 3D point cloud data. Elfiky et al. (2015) employed a Kinect sensor to acquire a 3D point cloud of dormant apple trees from the front and backside. Then, they used a skeleton-based geometric-feature algorithm for the 3D reconstruction of the trees. The study also proposed a circle-based layer-aware algorithm to locate the pruning points on target branches of apple trees.

Similarly, Akbar et al. (2016) acquired the depth images of dormant apple trees using a Kinect sensor. A 3D reconstruction of the apple tree was carried out using the semicircle fitting scheme. The study then proposed empirical models to estimate the diameter of primary branches, which could help identify branches for robotic pruning.

In summary, the 3D reconstruction approaches discussed above primarily used the following steps leading to a tree skeleton that can be used for implementing pruning strategies: (i) 3D scan the tree using LiDAR (3D point cloud) or images (3D point cloud reconstructed from stereo images, structure-from-motion or optical flow); (ii) separate the 3D points into tree branches, ground, and leaves based on imaging properties and/or user intervention; (iii) reconstruct the main tree branches using a mix of a priori knowledge (branches/trunk that are essentially cylinders that get smaller and branching points) and user input (marking branching points or sketching branches); and (iv) "fill in" missing parts of the scan (particularly smaller branches and missing geometry) using the estimated density of the leaves and expected shape of the branches.

Similar to many other areas of image processing, deep learning-based techniques have also been introduced in processing tree canopy images to detect objects and classify image regions. For example, semantic segmentation and deep-learning based techniques, in general, have shown increased accuracy and robustness in analyzing orchard images and have helped reduce the impact of uncertain and variable lighting and environmental conditions.

6.2.3 Pruning Strategies and Rules

After image segmentation and 3D reconstruction/skeletonization of fruit trees, the next important step is to use experts' (e.g., horticulturists and experienced growers) knowledge and their pruning strategies to create rules to algorithmically identify and locate target branches for pruning. Some of the major goals of pruning include distributing fruiting sites as uniformly as possible, renewing fruiting branches, and removing unproductive branches.

In general, growers prune tree branches in the dormant season using "renewal cuts," "pruning cuts," and "trimming" cuts (Table 6.1). Renewal cuts are for those branches that are too big or unproductive, which are cut at the base (e.g., right next

Table 6.1 Sample pruning/hedging rules

R1	If a neighbor branch is closer than X, then it is a "close" branch
R2	If a branch is longer than Y, then it is a "long" branch
R3	If a branch has long section w/o buds, then it is a "blind" branch
R4	If a branch is dead, then it is a "non-productive" branch
R5	If a branch diameter is larger than Z, then it is a "large" branch
R6	If a branch is "close," then it is a "pruning" branch
R7	If a branch is "long," and *not* "close," then it is a "pruning" branch
R8	If a branch is "large," and *not* "close," then it is a "renewal" branch
R9	If a branch is "long," *not* "large," and *not* "close," then it is a "hedging" branch

to the trunk). Long branches are cut back to a certain length for trimming cuts based on the tree canopy design. Pruning cuts are used to keep variable branch lengths to optimize fruiting sites or uniformity and improve fruit quality. Though the goals are common, almost every grower has a strategy to identify pruning branches in a tree, which often involves substantial subjective judgment. A set of relatively complex rules will be necessary to represent such subjectivity and achieve desired pruning outcomes. To convert such human expert knowledge precisely and consistently to rules that can be implemented by the machine, a "soft-words" computation model such as the one proposed by Zadeh (1999) can be used. For example, basic rules (e.g., R1 in Table 6.1) will be used to deduce more complex rules (e.g., R9) necessary to achieve various pruning goals.

Manual pruning is performed by skilled laborers trained to follow specific strategies provided by farmers or managers. The desired number of fruiting sites can be maintained in each tree. However, as mentioned before, pruning guidelines vary substantially between tree architectures, fruit cultivars, and even individual growers and operations. Therefore, any developed solution for robotic pruning must consider canopy architectures and crop cultivars. To some extent, current manual pruning practices are also based on individual experiences and art in addition to research-driven strategies. Therefore, they lead to substantial variability and inconsistency between different workers pruning the same tree and the same worker pruning different trees. Putting these human judgment-based strategies and practices into objective rules for the robotic system to implement (similar to Table 6.1) is challenging. There are certain quantitative guidelines that farmers would like to follow, including measurement of branch diameter and pruning side branches such that the right amount of fruiting sites could be left for each branch based on its fruit-bearing capacity. However, in practice, such quantitative guidelines are rarely practiced, reducing workers' productivity substantially. Even in such a situation where it is easier and faster for a vision system to estimate branch diameters, it is challenging to implement such a strategy by machines because we lack sensing systems that can accurately and reliably estimate the number of fruiting sites (vegetative buds and flowering buds look similar to even untrained human eyes) and identify diseased branches during the dormant season.

Only a few studies have placed some effort in creating simplified objective rules that machines can implement for the robotic pruning of fruit trees. Further studies on developing effective and reliable sensing systems for flower bud detection and diseased and dead branch identification, as well as developing objective pruning strategies for consistent and robust robotic pruning, would be essential.

As discussed earlier, Karkee et al. (2014) conducted interviews with expert horticulturists to understand their decision-making process for pruning apple trees in large commercial orchards in Washington State. This study found that there are four basic rules for pruning in SNAP or fruiting wall architectures; these are to remove (i) diseased branches, (ii) long branches, (iii) large branches, and (iv) closely spaced branches. Although these rules appear simple, this study also revealed various challenges, including (1) difficulty detecting the required targets, such as dead branches, and (2) identifying pruning points and steps in complicated canopies that often require judgment and potentially complex pruning rules. Therefore, in their study, they used two simple rules that machines could implement: (i) remove long branches (when length > user-defined threshold) and (ii) remove one of the two closely spaced branches (when spacing < user-defined threshold). Based on the analysis of 20 reconstructed tree models, the algorithm achieved 77% accuracy in identifying tree branches. On average, the algorithm suggested the removal of 19.5% of branches, whereas, in the same situation, human workers suggested 22% removal.

Similarly, Dr. James Schupp (Penn State University) worked with engineers to identify rules for automated pruning of tall spindle apple trees (Lehnert et al., 2015). He proposed eight pruning rules for fruiting wall apple orchards, including "Maintain a narrow cone shape by thinning outshoots that are more than 30 inches long in the top," "Remove any secondary limb when its diameter becomes more than half the diameter of the leader," and "Remove all damaged or diseased limbs." Four of these rules were the same as Karkee et al. (2014) proposed. On the other hand, Liu et al. (2019) attempted to develop the back propagation (BP)-based neural model to make pruning decisions for the robotic pruning of apple trees. Similarly, Saxton et al. (2014) and Corbett-Davies et al. (2012) presented preliminary work on developing an expert system for understanding the pruning process from human experts and used the system to establish the best practice for robotic pruning in vineyards.

6.2.4 Integrated Pruning Systems

The vision and pruning decision systems need to be integrated with a robotic manipulator and an appropriate end-effector (hand) to perform robotic pruning in fruit trees. Even though modern SNAP fruit canopies offer simpler tree structures than traditional fruit trees, fruit trees still include a lot of branches growing randomly in all possible directions and often crossing each other in different parts of the canopies. In addition, tree canopies include trunks, trellis posts, and trellis wires. Such a canopy environment presents many obstacles to robotic manipulators and end-effectors. As the system approaches target branches for selective pruning, obstacles can cause collisions with the robot, which severely affects the performance of the robotic pruning system and can cause damage to the manipulator and end-effector. Therefore, there is a critical need for efficient and effective path planning and navigation to find the optimized path to reach the target branches avoiding collision with branches and/or other obstacles.

As described earlier, most of the work related to robotic pruning was carried out by focusing on its components, particularly the vision system. Only a few studies-focused on the overall system integration and path planning in fruit crops. However, there are a few more studies conducted in grapevines as well. You et al. (2020) and ongoing work at author Karkee's lab have developed an integrated robotic system using a UR5 (a six-DoF manipulator by Universal Robots, Odense, Denmark) manipulator and a scissor cutter-type end-effector (Fig. 6.8). The system uses

Fig. 6.8 Integrated robotic system for selective pruning of apple and cherry trees developed by researchers at Washington State University and Oregon State University. (Photo by Manoj Karkee)

consumer RGB-D cameras (e.g., Zed 2, Stereolabs Inc.) to collect color and depth information and create the 3D structure of trees. They presented an algorithmic framework for this robot's path planning. The system first moves the end-effector to the approach pose and then follows the linear approach to reach the targeted position. Motion planning was implemented using Fast-Reliable-and-Efficient-Database-Search-Motion-Planner (FREDS-MP) framework, which computes the optimistic trajectories (Sukkar, 2017). A robotic system, including the path planning method, has been evaluated in the lab environment, and further development and field evaluations are continuing.

Zahid et al. (2020) also used the UR5 manipulator for the collision-free path planning to prune apple trees. They employed the Rapidly-exploring-Random-Tree (RRT) algorithm to find the collision-free path. A nonlinear optimization technique was used to find the optimized path among the various alternatives to reach the target position. Magalhães et al. (2019) benchmarked different path planning algorithms from Open Motion Planning Library (OMPL) using a 6-DoF manipulator for grapevine pruning.

Lee et al. (1994) reported work in the electro-hydraulic control of a vine pruning robot. Kondo et al. (1993, 1994) developed a manipulator and vision system for a multipurpose vineyard robot. Similarly, Botterill et al. (2017) developed a complete pruning robot for pruning grapevine canopies and tested it in a commercial vineyard. This system consists of an enclosed mobile platform (Fig. 6.9), which can completely cover the grapevine canopies (to block the sunlight and background canopies) and houses high-intensity LEDs (light-emitting diodes), a trinocular stereo camera system, a robotic arm (6-DoF UR5) mounted with a drill bit (to prune canes), a generator, and a desktop PC. A trinocular stereo camera system was used to capture the images of grapevine canopies under constant lighting conditions

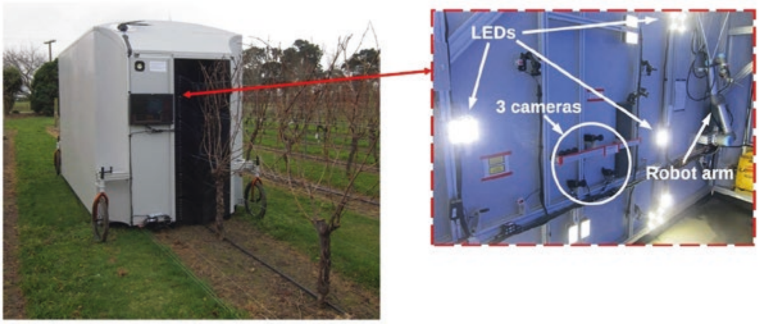

Fig. 6.9 A mobile platform for pruning grapevines that houses the high-intensity LEDs (light-emitting diodes), a trinocular stereo camera system, a robotic arm mounted with a drill bit (to prune canes), a generator, and a desktop PC. (Pictures from Botterill et al. 2017)

using LEDs. Then, a triangular-feature-matching algorithm was used for the 3D reconstruction of grapevine canopies. An AI-based algorithm was then developed to make pruning decisions. An RRT-based path planner was used for path planning and navigation with collision-free trajectories. They state that the main bottleneck in their work was the time required for online planning and motion execution. This robot system can estimate the trajectories at the rate of 0.25 m s^{-1} and takes about 1.5 s for each vine to calculate the collision-free trajectory for the manipulator. The robot took ~2 min to prune each grapevine canopy.

These studies showed that end-effector design selections strongly influence pruning performance. For example, reducing the bounding volume of the design increases the likelihood of finding a collision-free goal configuration and path. For pruning grapevine canes, Botterill et al. (2017) developed a manipulation method whereby the robot swept through the pruning zone using a rotating end mill cutter. One issue they reported was the tendency for the cutter to push the cane away from the pruning zone, leading to pruning failures. Zahid et al. (2019) developed a prototype end-effector that used scissors/shears to cut small-diameter apple tree branches.

A similar robotic pruner was developed by Katyara et al. (2020) and was tested in laboratory conditions. This robotic system consisted of a 7-DoF manipulator (Franka Emika, München, Germany), two Intel RealSense cameras (D435i, Santa Clara, California, USA), and a shear pruner attached at the end-effector of the manipulator. Intel RealSense camera was used to capture the images of grapevines. Then a Faster R-CNN (faster region-based convolutional neural network) (Ren et al., 2015)-based model was used to detect spurs/shoots. Once the spurs were detected, a statistical-pattern-recognition algorithm was used to determine the pruning points. This pruning robot dealt with only a single cordon (one side) of grapevine canopy at a time and took ~49 s to prune 5 shoots compared to ~8.4 shoots on average (due to focus on the complete vine) per vine in Botterill et al. (2017) taking ~2 min.

Although there have been several studies on developing robotic pruning systems for tree fruit crops and vineyards around the world, there has been no commercial success so far in adopting those technologies. Lack of commercial success is primarily caused by (i) limitation of perception techniques in representing the 3D structure of trees in the presence of variable and uncertain outdoor environments and self-occlusion of branches accurately; (ii) challenges in representing the pruning process with objective pruning rules that a machine can implement; and (iii) high cost and slow speed of the overall robotic system. Recent studies, such as the projects currently carried out by WSU and Oregon State University team (You et al., 2020, 2021), focus on some of these challenges, including learning from human knowledge and creating objective pruning rules. It is anticipated that future work is necessary and will be focused on developing simpler and faster 3D reconstruction methods for fruit trees in modern fruiting wall architectures such as formal apples and upright fruiting offshoot (UFO) cherries (Fig. 6.1), which are the most suitable architectures for robotic operations like pruning. In addition, new sensing studies on floral bud detection and detection of diseased and dead branches would be essential in the future. Further studies in developing objective pruning strategies for consistent and robust robotic pruning would also be critical. More discussion on general challenges and future opportunities will be discussed in Sect. 6.5.

6.3 Precision Thinning

6.3.1 Introduction

As discussed in Sect. 6.1, the production of high-value trees and fruit crops such as apples and cherries requires a large, semi-skilled workforce for short, intensive periods during the year. One of the most labor-intensive orchard activities is bloom and green fruit thinning. Bloom thinning involves selectively removing closely spaced flower clusters and/or several individual flowers from within a cluster. Only a desired number of flowers are left for pollination (typically only one). Green fruit or fruitlet thinning is similar to removing closely spaced and clustered fruit so that only a desired number of fruits are left to grow. Flower and green fruit thinning are two critical perennial operations necessary to balance fruit quantity and quality to achieve the target yield and returns for premium fruit.

Growers can deploy chemical bloom thinners or tractor-driven mechanical string thinners as an alternative to manual flower thinning. Nearly a century of research has yielded chemical thinning programs that are marginally effective and inconsistent. Washington's tree fruit research commission has investigated chemical bloom thinning programs for decades and found that the best program was effectively less than half the time (T. Schmidt, personal communication, 2021). In addition, there are handheld and tractor-mounted mechanical flower thinning machines available commercially.

A handheld mechanical device was also tested on the cherry trees for blossom thinning based on the same string thinner concept (Wang et al., 2013). Rosa et al. (2008) presented an electro-mechanical device that shakes the limbs for the fruit thinning of different fruit trees, i.e., nectarine, peach, prune, etc. Though these mechanical solutions helped reduce labor usage, they still lack precision because of their non-selective nature and high variability in their efficiencies. However, these “mass” thinning systems do not allow for selective removal of flowers/flower clusters and lack desired precision. There is no practical alternative currently available to manual thinning when it comes to green fruit thinning. In recent years, recognizing these challenges, researchers worldwide have been working on developing automated flower and green fruit thinning solutions.

6.3.2 *Flower and Green Fruit (Fruitlet) Thinning*

An automated/robotic flower or green fruit thinning system consists of a vision system to detect and precisely locate flowers and flower clusters in tree canopies, a manipulator to approach the target locations, and an end-effector to effectively remove the desired proportion of flowers or green fruit from target locations. Contrary to the dormant pruning of fruit trees discussed in Sect. 6.2, thinning is carried out in the growing season when canopies include shoots, leaves, flowers, and/or fruits in addition to trunks, branches, and trellis wires (Fig. 6.10). Such complex canopies pose greater challenges for a robotic/automated system to accurately detect and position the target objects (because of a heavy occlusion of target objects by other canopy parts) and access them for precision thinning. It is also essential that flower detection models have a high computational speed for real-time, in-field operation.

Fig. 6.10 Trellised canopies

Researchers have developed conventional and deep learning-based models to detect flower clusters in apple and cherry orchards (e.g., Aggelopoulou et al., 2011; Dias et al., 2018a, b; Farjon et al., 2020) that can provide a foundation for flower thinning as well as robotic pollination (Sect. 6.4). These efforts mostly relied on color (RGB) images captured from close distances (0.5–1.5 m) with varying pixel resolutions. Aggelopoulou et al. (2011) used the RGB cameras to collect the images and map the flower distribution of blossomed apple trees to adjust chemical thinning rates for precision application. Similarly, Hočevar et al. (2014) also used an RGB camera to capture the images of apple trees during bloom to estimate the number of flowers, which could assist in precision blossom thinning. Dias et al. (2018a) used the commercially available RGB camera to collect the images of apple trees for the blossom thinning task. Then, the CNN (convolutional neural network) and SVM (support vector machine) algorithms were used to detect the flowers from RGB images. In another study by Dias et al. (2018b), semantic segmentation was carried out for detecting flowers in apple, peach, and pear trees using a residual CNN-based technique. Tian et al. (2020) proposed an improvement over the Mask R-CNN model for segmenting out apple flowers using RGB images of apple trees collected during different bloom stages. Once flowers are detected, their 3D location would be essential for robotic thinning and pollination (Sect. 6.4).

Various types of 3D imaging techniques, such as laser scanners, stereo cameras, time-of-flight 3D cameras, and recently developed consumer RGB-D cameras (e.g., Zed 2, Stereolabs Inc.), can improve the detection and localization of flowers. A 3D imaging system consisting of a video camera and plane laser scanner was used by Emery et al. (2010) to detect and locate blossoms in peach trees for precision blossom thinning. Nielsen et al. (2011) used a stereo-vision camera system to map blossoms in peach trees for precision blossom thinning. Similarly, Underwood et al. (2016) used a color camera and 2D LiDAR sensor mounted on a ground robot to scan almond trees during different fruit-bearing stages (peak bloom, fruit set, and just before harvest) to estimate yield, which could assist in precision blossom thinning. Bhattarai et al. (2020) collected RGB-D information in apple orchards using a Kinect sensor to develop a machine vision system for robotic blossom thinning (Fig. 6.11). Segmentation of apple flower clusters was carried out using a Mask R-CNN-based model.

The earliest indication of potential crop load in a given tree would be the number of flowering buds. Good estimation and localization of buds would help make desired pruning and flower thinning decisions. Only highly trained human eyes can differentiate if a given bud will be a vegetative bud or a flowering bud in the crops like apples and cherries. The authors' experience in the field has shown that it is challenging to develop a machine vision model that can differentiate vegetative and floral buds using only color and shape features. However, there have been some efforts to develop spectral sensors that go beyond the color and shape information so that a reliable, automated floral bud counting system could be developed. For example, Wouters et al. (2015) mounted a multispectral sensor on the ground-based mobile platform to detect pear tree floral buds.

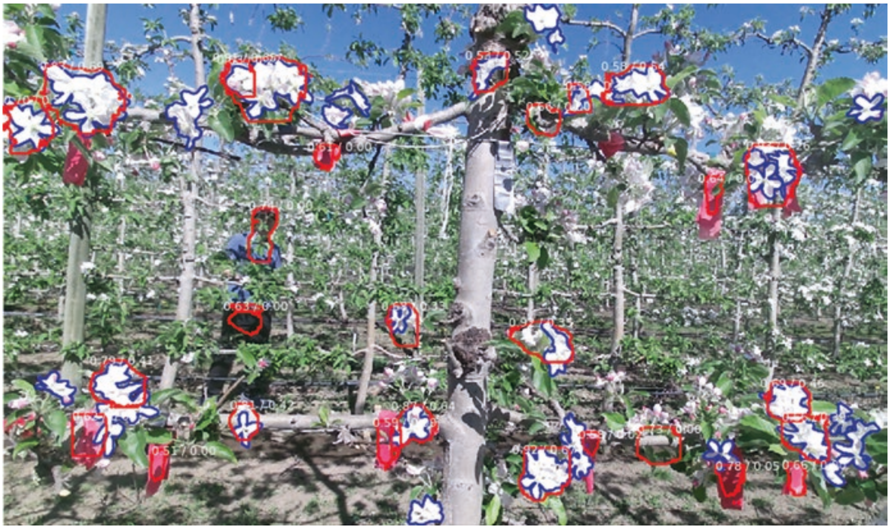

Fig. 6.11 Blossom detection with deep learning; blue and red polygons indicate ground-truth and detection results, respectively

6.3.3 Integrated Thinning Systems

In addition to machine vision systems, there have been efforts to develop integrated automated or robotic systems for flower thinning. For example, Aasted et al. (2011) mounted a LiDAR scanner on a tractor and string thinner, which sensed the flower density in apple tree canopies and automatically controlled the position and orientation of thinning heads for precision blossom thinning. Lyons et al. (2015) developed an automated precision blossom thinning system for peach trees. This system consisted of a six-DoF robotic arm and rotating brushes mounted at the robot's end. A stereo-vision-based system developed by Nielsen et al. (2011) was used to detect thinning targets. A heuristic algorithm was used to mimic the ways growers make thinning decisions. This precision blossom thinner achieved a ± 10.33% margin of error to place the thinning end-effector at the target position.

Similarly, Ou Yang (2012) developed an integrated robotic platform targeting the robotic blossom thinning of peach and tested it on the model tree. This system consists of a custom-build six-DoF manipulator and clamp-type end-effector. An inverse kinematic-based task planning algorithm was used to reach the targeted locations. This system takes around 7.7 s to find the path toward the target.

Currently, green fruit thinning is largely manual, and there have been only a limited number of efforts in developing machine vision and integrated systems for robotic thinning. Xiong et al. (2020) completed one tangentially relevant study using an unmanned aerial system (UAS) to collect RGB images of mango trees. Then, the YOLOv2-based deep learning model was used to detect green mangoes to estimate yield. Similarly, as discussed before, Underwood et al. (2016) used a ground robot to scan almond trees during the green fruit stage to estimate crop yield. These studies could provide some basis for developing robotic fruit thinning systems in the future.

As with robotic pruning, robotic thinning has not been commercially adopted yet. Robotic thinning faces the same challenges, such as lack of desired speed and high cost. In addition, a few specific factors make robotic thinning uniquely challenging to reach its full potential in in-field operation. First, there has been a wide range of studies on detecting flowers in fruit trees, as discussed before. However, these studies have only successfully segmented flower regions. Detecting individual flowers within a given cluster and estimating their orientation remain a great challenge for precision robotic thinning and robotic pollination (Zhang, 2017). Second, the robotic thinning of individual flowers of fruit crops such as apples and cherries is challenged by their small size, their growth in tight clusters, and high level of self-occlusion, making it almost impossible to approach and selectively remove individual flowers. Under these constraints, current efforts in robotic thinning have been to delineate individual clusters of flowers and use an end-effector that can remove a proportion of flowers within the cluster without regard to type, location, and developmental stage of flowers. In these efforts, multiple off-the-shelf end-effectors operated via different actuation mechanisms were investigated and evaluated for their performance in blossom thinning, including pneumatic hose, waterjet, and electrically actuated wire brush system. Additionally, the effectiveness of commercially available handheld blossom thinner, Bloom Buster/Bandit, from Automated Ag was tested. The miniature design of a similar concept to Bloom Bandit showed better efficiency for precision thinning (Fig. 6.12).

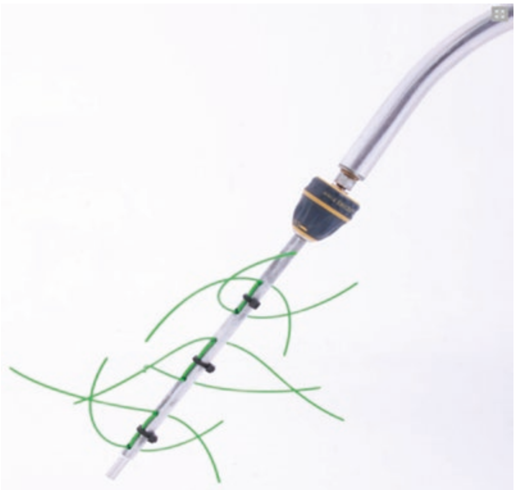

Fig. 6.12 Miniature design of a Bloom Bandit for precision thinning. (Picture from https://www.automatedag.com/bloom-buster-gallery)

In the future, it is important to put more effort into developing decision support tools for the integrated systems to achieve the desired level of flower and green fruit thinning. Moreover, continual improvement of the manipulation and end-effector technologies for precision thinning would be essential to improve the accuracy and speed while reducing the overall cost.

6.3.4 Green Shoot Thinning in Vineyards

Like flower and green fruit thinning in tree fruit orchards, green shoot thinning is performed in grapes every year. Green shoot thinning is a task to remove a proportion of shoots growing on horizontal cordons and all the shoots growing on trunks, which is one of the important field operations in the annual life cycle of a vineyard. This operation improves the spacing and direction of shoot growth, which is essential to creating and maintaining healthy and productive crop canopies by improving light penetration and air movement. An appropriate level of shoot thinning will adjust the leaf-area-to-crop ratio and crop load and therefore is one of the greatest determinants of potential yield and quality. When done properly, it also sets the stage for the next year's pruning and training decisions.

When green shoots of grapevines are growing, they heavily occlude each other and cordons, making it extremely difficult to accurately analyze the density of shoots on cordons for the precise removal of green shoots. For green shoot thinning, mechanical thinning machines are being used by the grapevine growers in different states of the USA. Mostly, these machines are mounted on the tractor, and their end-effector consists of a thinning roller on which flappers are attached. When the thinning roller rotates, flappers hit the cordons and remove the shoots from the cordons. The thinning level is controlled by adjusting the height of thinning end-effector to the varying shape of cordons and thinning roller speed by the operator while driving a tractor. However, shoot removal efficiency varies widely (between 10% and 85%) because varying shapes and locations of cordons cause difficulty in precisely controlling the thinning end-effectors against them (Dokoozlian, 2013).

Moreover, various string thinners have been developed and tested to remove the flower clusters for peach trees (Baugher et al., 2010). In these string thinners, plastic strings are attached to the rotating spindle. The thinning efficiency of flower thinning is controlled by adjusting the angular position of string thinner and rotational speed of the spindle.

At the green shoot thinning stage for grapevines, a shoot density of 15–25 shoots/m of cordons is desired to achieve the optimum yield and quality of grapes (Reynolds et al., 1994). If the density is above the desired level, the extra shoots are removed. Moreover, depending on the accuracy of the shoot thinning in vineyards, if needed, later fruit cluster thinning is also adopted for the fine-tuning of crop load. Additionally, not necessarily all three stages of thinning are adopted for each fruit species. For example, for grapevines, more emphasis is given to shoot thinning and fruit cluster thinning, and for apples, blossom/flower and fruit thinning are preferred.

Green shoot thinning, a highly labor-intensive operation, costs growers more than \$650 per hectare (\$265/acre on average), as reported by Dean (2016). If a mechanical shoot thinner is used successfully, the cost could be reduced to about \$25 per hectare (~\$10 per acre). In addition, 1 machine can replace up to 25 workers (productivity 25 h/ha vs. 1 h/ha; Dean, 2016). Therefore, mechanical shoot thinning is essential for the profitability and sustainability of wine grape production. However, currently available machines do not generally offer sufficient precision and speed. Some only focus on removing suckers from the trunk (e.g., Clemens Vineyard Equipment Inc., Rotary Brush).

In contrast, others remove green shoots with an unacceptable level of variability (10–85% shoot removal, Dokoozlian, 2013). The large variation of shoot removal is caused by (i) non-selective removal of shoots by the machine (many non-fruiting shoots arising from latent buds could be retained, while primary shoots bearing clusters are removed) and (ii) the need for manual adjustment of the height of the thinner (thinning heads) to keep it just below the cordon so that most of the shoots growing from the underside are removed. Because of the difficult viewing position, uneven ground surface, and irregular cordon position and orientation, it is highly challenging (sometimes even impossible) to maintain the desired height and orientation of the thinning heads.

Automated thinning using a machine vision system to locate and estimate the orientation of the cordon trajectory would offer a more efficient and effective alternative to mechanical thinning. Majeed et al. (2021) developed a machine vision system and integrated prototype (Fig. 6.13) for vineyards' automated green shoot thinning. First, a machine vision system was developed using deep learning algorithms to estimate cordon trajectories from different growth stages of green shoots (even when cordons are highly occluded with green shoots; Majeed et al., 2020a, b). A Kinect sensor was used to acquire the R-GBD information of grapevine canopies. Then, an integrated prototype was developed that can automatically position the thinning end-effector against the cordon trajectories. The field evaluation results showed that the integrated prototype could precisely position the thinning end-effector within ±1.5 cm of the cordon center. Further improvement in the vision, actuation, and control systems are currently going on to achieve the capability to replace the human operator.

6.4 Artificial Pollination

6.4.1 Introduction

As discussed in Sect. 6.1, profitability for fruit crop producers depends heavily on product quantity and quality – two components determined by the rate of pollination during the brief (but crucial) flowering stage. Currently, growers generally rely on a pollination system that includes renting hives of honeybees (i.e., *pollinators*) and planting extra trees to provide compatible pollen (i.e., *pollenizers*). Even after those

Fig. 6.13 An integrated prototype for automated green shoot thinning in vineyards consisted of a Kinect sensor, platform bed, and thinning manipulator

arrangements, environmental and weather conditions need to be favorable to achieve the desired level of pollination. This traditional approach to pollination is limited by variability and threatened by the changing climate and perennial challenges to the pollenizer-pollinator model. Tree fruit production could not exist as it does today without managed pollinators (i.e., *Apis mellifera*). Yet, in the past several decades, bee colonies have declined by over 40% nationwide.

Furthermore, variability in spring weather conditions affects pollinator activity and can result in smaller fruit set. These emerging issues are complicated by a host of perennial hurdles related to both pollinators (e.g., poor bee activity, uncertainty about how many hives are necessary and where to place them, increasing costs for hive rental, distribution of pollen-borne viruses by bees) and pollenizers (e.g., poor bloom overlap, uncertainty over pollenizer density and distribution, pollenizer trees as disease sources). The result is a multi-billion-dollar industry riddled with uncertainty about the quantity and overall quality of its annual product.

There have been recent efforts to investigate the use of alternative pollenizers and/or insect pollinators. However, this effort is unlikely to yield sustainable improvements in the long term, as more crops are needed to feed a growing world population. Alternatively, mechanical and robotic approaches (e.g., ground sprayers, UAS-based pollen spraying, robot bees, robotic precision pollinators) are currently being developed and evaluated in orchards that are expected to yield solutions that minimize the biological variability of the current pollinator + pollenizer model.

6.4.2 Mechanical and Robotic Pollination Techniques

Researchers worldwide are developing different types of artificial (or mechanical) pollination techniques for various types of crops. Both aerial platforms and ground platforms have been used in developing these techniques. UAS-based systems generally use small platforms and apply a bombing technology to spray pollens on canopy surfaces from the top. Alternative to these UAS platforms is bee-line flying robots developed and tested by Berman et al. (2011) and Abutalipov et al. (2016). These tiny platforms mimic bee behavior and have shown potential for pollinating fruit crops in orchards using a swarm robotics concept.

Artificial pollination using ground vehicles generally uses similar systems to agrochemical application systems. The machines are often designed to spray pollen suspended in a liquid or dust medium to target canopy areas. Electrostatic spraying and other spraying technologies have been tested to optimize the type and size of nozzles, operating pressure, flow rate, carrier medium, and distance to bloom so that the level of pollination and fruit set could be achieved. One such study was carried out recently at Washington State University by Whiting (2017) (Fig. 6.14). An

Fig. 6.14 An electrostatic sprayer retrofitted by Dr. Mathew Whiting and his team at Washington State University to apply pollens, being evaluated in a cherry orchard in Prosser, WA. (Picture by TJ Mullinax/Good Fruit Grower)

electrostatic sprayer was tested to broadcast pollens onto cherry canopy surfaces, which showed increased effectiveness in depositing pollens on flower stigma than natural pollination with bees.

Similarly, Gan-Mor et al. (2003) and Gan-Mor et al. (2009) developed and tested electrostatic pollen sprayers to artificially pollinate almond, date, kiwifruit, and pistachio. Such mechanical pollination technologies have been demonstrated to be effective and useful in various production needs and show potential to be an alternative to the natural pollination process. In addition to an evaluation in research programs, there have been some commercialization efforts to bring this technology to commercial orchards (e.g., a mechanical blower system commercialized by PollenPlusTM, New Zealand).

The mass artificial pollination techniques discussed above are simpler and easy to operate. Still, they are inefficient as they broadcast pollens to wide canopy regions without regard to where the target flowers are. To address this challenge, researchers are developing machine vision and robotic systems (with manipulators and end-effectors) for targeted pollination of desired flowers (e.g., Fig. 6.15). Various studies on detecting/segmenting flowers and flower clusters in fruit trees have been discussed earlier in the "Precision Thinning" section (see Sect. 6.3.2 for more details). In addition, there have been a few specific efforts to develop robotic pollination systems for fruit crops. One such study was conducted by Duke et al. (2017) and Barnett et al. (2017). Their robot was evaluated in kiwifruit using an autonomous platform and a spray manipulator. The vision system included an RGB camera and a CNN-based image processing technique for flower detection. Field evaluation results showed that

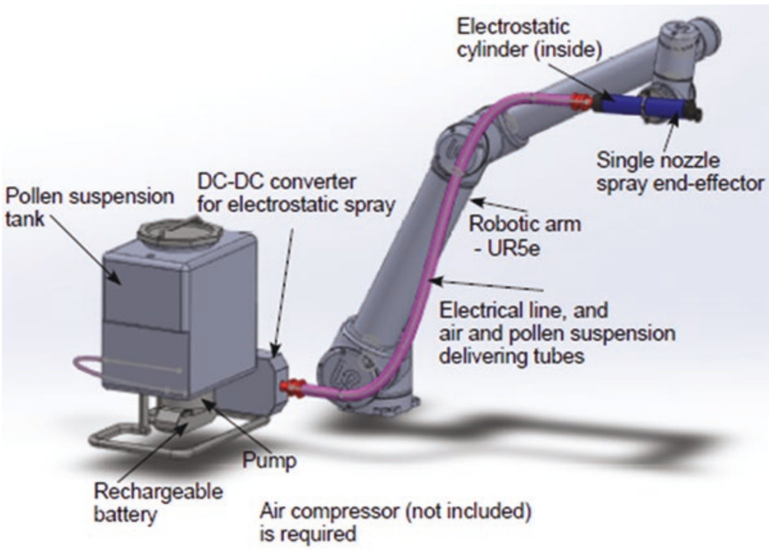

Fig. 6.15 A schematic of the robotic precision pollinator system currently under development at Washington State University. (The project also includes researchers from Pennsylvania State University)

the flower detection accuracy was >70%, and more than 80% of the detected flowers were pollinated with the robotic system. Similarly, Yuan et al. (2016) presented a robotic solution for pollinating tomato flowers in a greenhouse. This robotic system was mounted on a mobile platform and consisted of four-DoF manipulators and a spray nozzle as its end-effector. The system used a binocular camera to capture flower clusters' images, and color and size features were used to segment the clusters out. The robotic system can recognize 80% of the flower clusters with at least two flowers and pollinate (spray the pollen) with a 69.6% success rate.

When successfully adopted in commercial operations, the targeted application of pollens with robotic machines – rather than spraying trees en masse – will play a critical role in the efficient use of pollen and may increase deposition, improve crop-load control, and minimize off-target drift (Patel et al., 2016; Sparks, 2014; Dung et al., 2013; Bechar et al., 2008). These innovative technologies also can alleviate growers of considerable risk associated with insufficient pollination as it relies currently on natural processes that are in decline, sensitive to environmental conditions, and amenable to distributing viral diseases. The success of the robotic pollination will also avoid complexity in the cropping system (for planting pollenizer trees and hiring beehives) and increases the planting area for target crops (e.g., apples).

The development of practical robotic systems for thinning faces various challenges, like the robotic thinning systems discussed in Sect. 6.3.2. One of those challenges is the capability of the vision system to identify the king flower to perform pollination at the right window when only the king flower is open in most of the floral buds. The challenge originates from the fact that the blossom in fruit trees opens over a few days to a couple of weeks. In comparison to the continual presence of natural pollinators like bees over the flowering window, artificial pollination is generally a one-time operation, thus limiting the opportunity to pollinate sufficient flowers. However, suppose there is a possibility of choosing the window smartly. In that case, it could provide an excellent opportunity to implement an effective crop-load management via artificial pollination using mechanical or robotic means. More studies on this aspect would be essential in the future.

6.5 Challenges and Future Directions

As discussed in the earlier sections, there has been a wide range of research and development activities worldwide to develop automated and robotic solutions for precision and selective crop-load management operations. Some private companies such as Vision Robotics (San Diego, CA) and ATRIA Innovation (Nave, Spain) have also been developing robotic pruning, thinning, and/or pollination solutions. However, no commercial success has yet been achieved in crop-load management operations. In general, robotic operations in the agricultural fields are challenged by three factors: (i) uncertain, variable, and complex canopy, lighting, and environmental conditions; (ii) plant and produce damage; and (iii) slower speed, high cost, and lack of adoption (Karkee & Zhang, 2021). For example, flowers grow in uncertain canopy locations in tight clusters, whereas tree branches vary widely in shape, size, and location over space and time.

Many studies have been conducted in the area of perception of fruit tree canopies for various crop-load management operations (e.g., pruning and thinning) using different kinds of sensors/cameras and image processing techniques. However, many of these past studies utilized some environment control mechanisms to improve uniformity and minimize the uncertainty in the canopy lighting conditions. For example, some of these studies used canopy covers (Botterill et al., 2017). Other studies were carried out in laboratory conditions to avoid direct sunlight, provide uniform illumination using artificial lighting, and remove complex backgrounds from the desired tree canopies. Though such amendments helped improve the performance of the vision system in the orchard environment, they added complexity to the overall system. They reduced the practical feasibility of commercial adoption of robotic crop-load management techniques in field conditions. Advancement in AI tools such as deep learning has, to some extent, addressed this problem and has improved the accuracy and robustness of machine vision systems both in indoor and outdoor conditions. Further development and adoption of deep learning-based and other robust, efficient, and reliable machine vision systems remain critical for developing practically applicable and commercially viable robotic/automated systems for crop-load management.

It is also noted that commercial viability can further be improved by developing multipurpose robotic machines. There has been a great advancement in robotic picking machines by researchers like the authors of this chapter (Silwal, 2016; Silwal et al., 2017) and private companies, such as FFRobotics (Haifa, Israel). However, those complex and expensive machines would be operating in the field only about 3 months over the year. If such a machine could be designed to perform multiple field operations ranging from canopy management (e.g., tree training), crop-load management (e.g., flower thinning), and pest control (e.g., targeted application of pesticide) to crop harvesting by only replacing the end-effectors of the machine in a modular fashion, the high cost of such machines could be more justifiable, and commercial adoption could be accelerated.

The structure of the fruit tree is complex due to its biological nature. Fruit tree growers in recent decades moved toward the trellis trained structure because of the possibility of achieving a high density of fruit trees, high yield, and quality of fruit, which also opened up the opportunities for the mechanical and robotic operation for various field operations (Majeed et al., 2020c). Simplified training systems make pruning, thinning, and other crop-load management operations viable. For example, UFO cherries offer a system where pruning can be, theoretically, a mass removal of all the secondary branches growing laterally from the vertical offshoots. In such a case, a pruning system could now be simplified to include a round cutter that can follow the trajectory of the offshoot from bottom to top so that everything growing laterally would be removed without regard to their location and size.

Similarly, all the secondary branches growing vertically above the horizontally trained branches could be removed using a chainsaw end-effector in the formal apple orchards. These opportunities indicate that further simplification of canopies, particularly to keep them narrow and have a simpler canopy skeleton, would allow for simpler, objective crop-load management strategies (e.g., objective pruning rules) and relatively simpler robotic manipulation (e.g., linear access to thin flowers). These opportunities can lead to more effective and commercially viable robotic solutions for various crop-load management operations.

Studies found that various tasks, including perception, decision-making, and field implementation of the robotic operation, have unique challenges in the orchard environment. For example, Karkee et al. (2014) found that implementing various pruning strategies, such as removing diseased branches, was not easy for a robotic system due to the lack of a desired sensing system. This finding indicates that precision crop-load operations such as pruning, thinning, and pollination of fruit trees may best be achieved through human-robot collaboration, where human performs tasks requiring strong sensing capabilities, human judgments, and complex manipulation. In contrast, robotic systems perform tasks that can be performed with efficient machine vision systems, objective rule-based decisions, and simpler (e.g., linear) manipulation. Bechar and Edan (2003) found that a proper level of human-robot collaboration could substantially increase fruit detectability in orchards, applying to flower and branch detection and localization. One essential requirement for such technology is to have a proper training method for robots to acquire human knowledge in in-scenario data.

For real-time field operation with desired precision, robotic solutions for orchard operations require high-resolution imaging and image analysis, fast sensing systems, effective end-effector techniques, and fast and low-cost manipulation. Newer, low-cost sensors, AI tools such as deep learning, modular robotic technologies, and increased capability and decreasing cost of computation (e.g., graphics processing units) are providing new opportunities to develop faster, reliable, and robust robotic solutions that could soon lead to commercially viable systems for selective pruning for fruit trees.

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