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Automation and robotics in the cultivation of pome fruit: Where do we stand today?

Rafaël Verbiest[1] | Kris Ruysen[2] | Tanja Vanwalleghem[2] | Eric Demeester[1] | Karel Kellens[1]

[1]Department of Mechanical Engineering, ACRO Research Group, KU Leuven, Diepenbeek, Belgium

[2]Department of Environment and Technology, Research Center for Fruit (pcfruit) npo, Sint-Truiden, Belgium

Correspondence
Rafaël Verbiest, Department of Mechanical Engineering, ACRO Research Group, KU Leuven, Wetenschapspark 27, Diepenbeek 3590, Belgium.
Email: rafael.verbiest@kuleuven.be

Abstract

The cultivation of apples and pears in orchards consists of several tasks that still demand much human labor. The cost of this skilled labor increases while the number of competent seasonal workers becomes insufficient. These facts are a threat to the fruit industry. To find a solution, this paper addresses current as well as future automation possibilities for the main orchard tasks as a profitable alternative to human labor. Besides an activity research in pome fruit orchards, this paper contains an overall review of the research and developments that have been performed to automate each major activity (e.g., pruning, thinning, spraying, harvesting and mobile navigating) in the cultivation of pome fruit. These tasks are individually evaluated on feasibility and profitability of the developed automations. Finally, this paper concludes that, despite the large amount of research, almost no fully automated and cost-efficient solution has been developed. A possible option to increase the viability of the prototypes might be the simplification of the tree structures, and consequently the orchard architecture, to make it "robot-ready." Another option in this perspective is combining several techniques, for accomplishing individual tasks, in one multipurpose robot platform. As a result, the usability and efficiency of the robot increases.

KEYWORDS
agriculture, automated cultivation, mobile manipulation, orchard tasks, pome fruit

1 | INTRODUCTION

In 2017 the production of apples in the European Union (EU) was valued at €3.8 billion. This accounts for 16.5% of EU-28's fruit production. Pome fruit in total (apple and pear) is the only type of fruit with a higher export than import value (De Cicco, 2019). It is fair to say that pome fruit is an important part of EU's fruit industry. The main share of the activities in this sector is still performed manually, often by hired seasonal workers. The related high labor costs, the low market prices and the lack of qualified workers are putting an ever-increasing pressure on the fruit sector today. Therefore, automation and robotics in orchards may provide a solution that additionally considers the increasing environmental challenges.

In the past five decades, there has already been performed a considerable amount of research on the automation of several tasks in an orchard, like harvesting and spraying. Most of these research projects concentrate on one specific task. There are for example several prototypes of automated apple harvesting robots, as will be discussed further in Section 6. This review paper summarizes the current status of automation for each major orchard management

task that is needed to cultivate pome fruit. First, in Section 2 an activity research is discussed. The status for pruning, thinning, spraying, harvesting, and mobile navigating in orchard environments are described in Section 3, Section 4, Section 5, Section 6, and Section 7, respectively. Hereafter, Section 8 will discuss the progress on automated cultivation of other relevant fruits and vegetables. Finally, the paper offers a conclusion for each task, which discusses the major difficulties and potential next steps for the future in Section 9. A graphical overview of the paper structure is given in Figure 1.

Several review papers about innovations in agriculture already exist. However, these are either very specific and detailed for one task in a certain cultivation, such as He and Schupp (2018) reviewing sensing methods for automated pruning for apple trees, or very broad covering a whole sector to give a general overview, such as Vougioukas (2019) reviewing automation in the whole agricultural sector. This review paper specifically focuses on the recent developments and innovations within the last few decades for the automation of cultivating pome fruit. Hence, the paper presents an overall view covering all the parts of a certain cultivation, but in a detailed way for each part. Specifically for pome fruit, no such review exists, as far as the knowledge of the authors reaches. Furthermore, this review paper is substantiated by an activity study, which exposes the actual needs of the sector.

In the majority of the following sections, a first step towards full automation is described as mechanization. This replaces the expensive and slow manual labor with a mechanical substitute, which is faster and cheaper. However, there is no sensing or controlling, which results in systems that are nonselective in their handlings. In the industrial sector, mechanization is very useful because the circumstances are controlled and continually steady. Fruit trees, and nature in general, however, are never totally controllable or steady. There are no two trees that can be perfectly treated nonselectively in

the same way and still have the most ideal outcome for both. Therefore, mechanization implies some constraints, but it has advantages and useful effects as well. Hence, it is relevant to discuss mechanization before reviewing automation.

2 | ACTIVITY RESEARCH

Besides reviewing the state of the art regarding automation and robotization of pome fruit cultivation, the current state of activities and related amount of labor for cultivating pome fruit need to be explored as well. This will give a clear vision on the actual needs of the cultivators. The study has been performed in cooperation with the Flemish institution for fruit cultivation *Research Center for Fruit, (pcfruit) npo*, with the overall goal to uncover the major issues in labor and costs of the sector, as well as uncovering for which cultivation tasks the largest progress can be made by automating a specific part of it.

The research has been performed according to the Methods of Time Management—Universal Analysing System (MTM-UAS) from the International MTM Directorate (IMD) MTM-UAS-IMD (2015). Based on the distance, weight, accuracy, and type of a manual action, this method estimates the duration of the action, by combining data with predefined time tables. This technique is commonly used in time and quality management in the manufacturing sector. Based on observations in the field, the average number of actions for each specific task was calculated. Combining this with the results of the MTM time tables, the total amount of labor time that an orchard task requires was estimated. These time estimates take into account a 13% loss due to organizational issues, such as unplanned time-outs and worker fatigue. Finally, this outcome was presented to five experienced fruit cultivators to confirm the results by comparing these to their know-how of field work. Despite this general verification, all these results have to be nuanced because they are theoretical estimates and thorough validation tests in the field were not carried out yet, but they are planned (ACROFRUIT—KU Leuven HBC2019.2051, 2020).

2.1 | General distribution of labor

A first result of the activity research is a general overview of the distribution of labor for each orchard task. For apples, the calculations have been done specifically for the cultivar *Jonagold* with a *Tall Spindle* tree architecture, an estimated production of 50 tonnes/ha and counted for three harvesting rounds. The latter has a large influence on the labor time, due to extra checking of ripeness during the picking and extra logistical efforts. The results for the distribution of labor for cultivating apples is shown in Figure 2a. In the study concerning pears (cultivar: *Conference*), the same tree architecture as for apples has been used (*Tall Spindle*), as well as the same estimated production of 50 tonnes/ha, but the harvesting of this type of fruit is done in one harvesting round. Therefore, the share of harvesting will
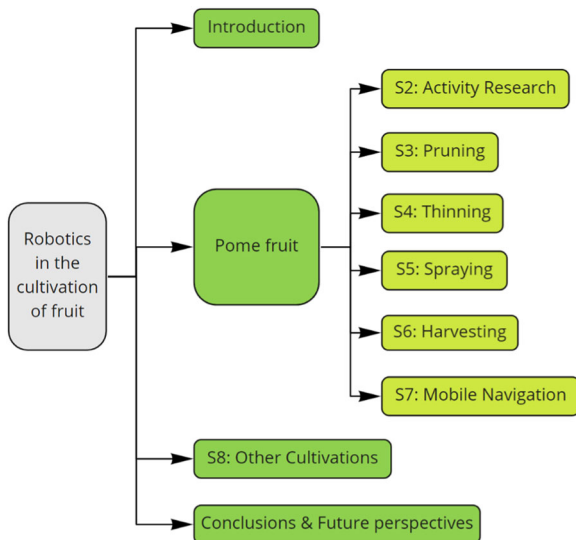

FIGURE 1 Graphical overview of the content of this review paper [Color figure can be viewed at wileyonlinelibrary.com]
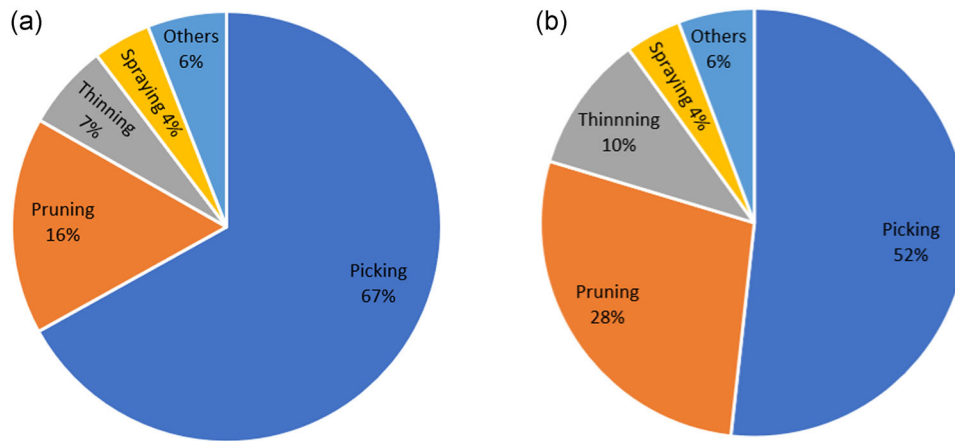
FIGURE 2 Results of the activity research for the distribution of the amount of yearly labor for cultivating (a) apples (Jonagold—Tall Spindle) with a total average amount of yearly labor of 466 h/ha and (b) pears (Conference—Tall Spindle) with a total average amount of 482 h/ha [Color figure can be viewed at wileyonlinelibrary.com]

be smaller. The results of this study for pears are displayed in Figure 2b.

Out of the diagrams of Figure 2 mainly two important conclusions can be drawn. (1) Focussing on the total amount of labor, for both cultivations these numbers are excessive. To cultivate apple, a total amount of 466 h/ha is needed and for pear it even goes up to 482 h/ha. Spread out over an entire year it seems no problem, but many of these hours have to be performed within small time windows, which puts much stress on the cultivators, who have to organize the amount of seasonal workers based on the quantity of work and available time windows. (2) For both cultivations, the tasks of harvesting and pruning clearly take the largest shares of labor. Those two handlings are the most labor-intensive. For this reason, the highest need for labor reduction lies with these two tasks. The next two paragraphs will discuss the time study for harvesting and pruning more deeply. The small time windows mentioned above are especially problematic for harvesting, whereby this high share of labor has to be performed in only a few weeks. This is in contrast with pruning, for

which a time window of multiple months is available. Besides harvesting and pruning, in future work the task of thinning will be investigated in the same way.

2.2 | Time study: Harvesting

In this activity research, two harvesting methods have been compared: a basic method using ladders and static bins (Method 1); and an advanced method using working platforms and moving bins (Method 2). Again, -this study has been done for cultivating apple and pear. As shown in Figure 3a, the second method applied to apple saves 30.6% of the needed time. For pear a reduction of 12.6% was obtained. This reduction is higher for apple because in every harvesting round there is some profit to be made. For apple three rounds were counted, unlike for pear with only one harvesting round. Despite the reduction, still over 216 h/ha are needed for the harvesting task of both cultivations.
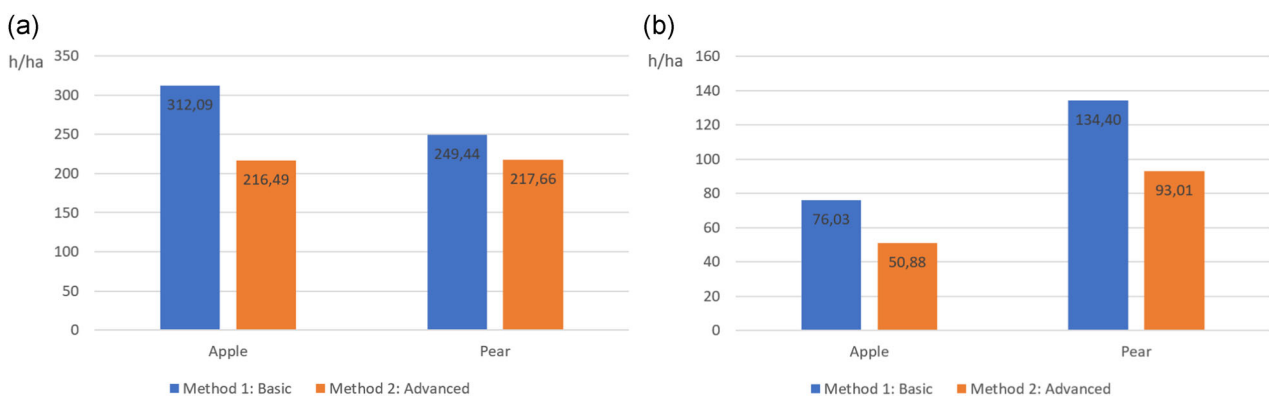

FIGURE 3 Comparison in consumed labor time between basic methods without the use of extra tooling (Method 1) and methods using aiding tools and platforms (Method 2), specifically for the orchard tasks of (a) harvesting and (b) pruning [Color figure can be viewed at wileyonlinelibrary.com]

2.3 | Time study: Pruning

For the activity of pruning two methods have been compared as well: the basic method involves a manual shear and the use of ladders (Method 1); the second method uses electrical shears and a working platform (Method 2). The results in Figure 3b display a reduction in labor time of 33.1% and 30.8%, respectively for pruning apple trees and pear trees. However, these results still need to be validated with thorough field tests, which are planned next pruning season. As the results indicate, the use of mechanized aiding tools could reduce the working pressure. The next section discusses the current state of the art dealing with mechanization and automation of this part of cultivation.

3 | PRUNING

Pruning fruit trees has several purposes. On the one hand, the main purpose is to control the size and structure of the tree. On the other hand, it is possible to control the crop load at an early stage (Costa et al., 2013). By pruning, the tree structure can be manipulated to provide a balance between the energy for growing fruits and the energy for growing branches. Parts that would consume too much energy without future profit, such as old, unproductive or diseased branches, can be cut away. Moreover, making cuts at specific places could trigger the growing process, which can be useful in the next years (e.g., new twigs that could guarantee production 2 years later). In the future, pruning will have another important purpose for the implementation of robotics in orchards. By pruning fruit trees into the right and simplified tree architectures, it is possible to make an orchard "robot-ready" (He & Schupp, 2018). Robinson and Hoying (2013) describe the different tree architectures and orchard systems, and which effect they have on yield and labor costs. They concluded that future orchards need a narrower canopy to decrease the complexity and to increase the visibility and graspability of the features of the tree. In literature, these "robot-ready" tree structures are also described as simpler, narrower, more accessible, and productive (SNAP) tree architectures (Karkee et al., 2014). Bloch et al. (2018) underlined the importance of adjusting the robot as well as the tree architecture in a way that both designs match together. Therefore, they demonstrated a methodology for simultaneously optimizing both the robot kinematics and the working environment. Besides the advantages of "robot-ready" orchards for robotics, these simplified structures will have the same advantages for manual labor, so the related costs will reduce as well.

3.1 | Mechanization

Mechanization of pruning is called hedging. As shown in Figure 4, a tractor is driven along the row of trees with a vertical trimming bar. This results in a nonselective pruning system whereby every branch is cut off at the same distance from the trunk without taking into

account the importance of the branch (floral buds, light coverage, age, diseased, etc.). Ferree and Rhodus (1993) concluded that replacing manual pruning in winter with this kind of mechanical pruning decreases the cumulative yield per tree with 35%. However, there are some advantages of hedging if it is applied in the right way. (1) Hedging can be used as an a priori tool to speed up the normal way of pruning. Hedging the outer branches and top of the trees can be useful to reduce an amount of manual pruning labor. (2) Using this principle in summer can be interesting as well. By hedging the outer layer of leaves during summer, the penetration of light through the canopy increases and the fruit matures better. In temperate climates, this can result in fruit of higher quality (Ferree & Rhodus, 1993). In warmer climates, this technique is less advisable or must be handled carefully, due to a greater risk of possible defects to the fruits like sunburn.

3.2 | Automation

For manual pruning a certain amount of knowledge and skills is needed to evaluate the tree structure and to decide where to prune, without damaging the fruit tree. The detection of those complex tree structures, pruning decisions, and collision-free robot planning make it even more challenging to automate this part of fruit cultivation. The activity research reported that manual pruning for cultivating apples corresponds to 16.3% of the total amount of labor. For pears this number rises even up to 27.9%, due to the more labor-intensive

FIGURE 4 Example of a nonselective hedging system with a vertical hedging bar that trims the branches at the same distance from the trunk (He & Schupp, 2018) [Color figure can be viewed at wileyonlinelibrary.com]

tree architectures of those orchards. Thereby, pruning can be ranked as the orchard task with the second largest share in the manual labor. He and Schupp (2018) confirm these numbers as they reported that pruning includes more than 20% of the costs for orchard management, although these numbers may vary depending on the practised orchard structure and tree architecture. Furthermore, the activity research reported specifically for pruning that the use of tooling, such as electrical shears and working platforms, reduces the labor time by more than 30%. Consequently, the need for and relevance of extra mechanical aiding tools and the next step of automating this manipulation in the orchard is clear.

A first important step towards automated pruning is the identification of the branch structure. Karkee et al. (2014) developed an algorithm that could identify the branches out of 3D images of a time-of-flight (ToF) camera. The algorithm is based on two simplified pruning rules considering both branch spacing and aimed length. They tested on a SNAP tree architecture and trained the model based on a data set of three different human pruners and 20 different trees. The obtained results were comparable with human pruning decisions, but the tests were done in simplified conditions and without actual robotic cutting. Amatya et al. (2017) used a combination of Red Green Blue (RGB) color images and ToF to identify trunks and cherries. Although their purpose was robotic harvesting, the used principle of detecting branches could be applied to robotic pruning as well. J. Zhang et al. (2018) trained a regions-convolutional neural network (R-CNN) with 3D images of a Kinect v2 camera to detect branches in planar tree architectures. The maximum obtained accuracy for detecting branches was 92%. Another conclusion was a 6% higher accuracy when adding the depth data compared to the system without including depth images. Chattopadhyay et al. (2016) and Elfiky et al. (2015) used the Kinect v2 camera as well to measure, reconstruct and model apple trees with the aim to automate pruning. Because existing reconstruction algorithms (e.g., Visual Hull Reconstruction) failed on thin textureless objects, such as fruit trees, Tabb (2013) developed a voxel-based formalism. Four years later, Tabb and Medeiros (2017) validated this system in field trails. Besides scanning and reconstructing the tree structure, they measured several characteristics of the tree as well (e.g., branch diameter, branch length and branch angle). They reported mean-square errors of 0.99 mm for diameter, 45.64 mm for length and 10.36 degrees for angle, and this in an average run time of 8.47 min per tree. Hence, it is a relatively accurate but slow method for reconstructing and measuring fruit trees. Finally for branch detection, Livny et al. (2010) used point cloud data to reconstruct trees and bushes as a Branch Structure Graph (BSG). Large advantages of this method are that it can be used on trees with leaves and on scenes with multiple trees of different varieties. The algorithm can deal with relatively large gaps of missing points in a branch as well. Only results for run time were reported, which vary from 1 s up to 30 min depending on the size and complexity of the scene. A scene with only one tree could be reconstructed in 1 to 30 s. For a complex scene of more than 20 trees, the reconstruction time went up to 30 min.

Although it is not developed for fruit orchards, a fully working prototype that can trim bushes and prune roses in regular gardens is the aim of the Trimbot 2020 project. The goal of the project is a commercial robot, which is similar to a lawn mower robot, that can be found in many gardens these days. In this project, much progress has been made in path planning for outdoor platforms, object detection in gardens and automated trimming (Kaljaca et al., 2019; Strisciuglio et al., 2018). More specifically for cherry orchards, You et al. (2020) recently developed a conceptual pruning robot. The detection of branches and the possible cutting points has been performed with a RealSense RGB-D camera in combination with an OctoMap model. They reported an average success rate of 92%, with an average throughput time of 5.71 s for each cut. These averages were based on the data of ten test runs done on a self-made indoor test setup. Finally, Botterill et al. (2017) developed a pruning system for grapevines that uses three cameras to model the tree lay-out and an Artificial Intelligence (AI) system that decides where to prune. This system obtained a low error of 1% on the trajectory estimation and reached an acceptable working speed of 2 min per vine in field trails, which is comparable to human labor. Despite the above mentioned developments of robotic pruning prototypes, no developments have yet been made specifically for pome fruit orchards, which have a more complex branch structure than the cases of cherries and grapevines. Hence, still much progress can be made in this field of research.

4 | THINNING

The thinning principle practices the rule of *quality over quantity*. Controlling the crop load is very important to indemnify the quality of the fruit. By removing a certain number of fruit, the remaining fruits will receive a higher share of necessary nutrients, producing more high-quality fruit instead of a high quantity of lower quality fruit. Furthermore, by selectively removing fruits with less potential (e.g., too small or with deformations), the fraction of high-quality fruit can be increased. As mentioned above, this can be done in an early stage by pruning in the correct way. However, this is not sufficient, so additional thinning is required. There are two types of thinning: blossom thinning and fruit thinning, which are compared in Table 1. Both thinning types could be done with several methods, like mechanical thinning, chemical thinning, and thinning by shading. In this paper, only mechanical thinning will be discussed, because of its lower environmental impact than the chemical alternative. For other methods the reader may consult (Byers et al., 1986; Greene et al., 2013; Wouters, 2014).

4.1 | Mechanization

String thinners are a first kind of mechanical thinning whereby the most common type is called the Darwin machine (Miller et al., 2011). This nonselective mechanization of the thinning process

TABLE 1 Advantages and disadvantages of both blossom and fruit thinning

	Blossom thinning	Fruit thinning
Advantages	• The required nutrients to grow into fruitlets will be saved for other fruit.	• Small fruits are easier to handle than flowers.
	• At the stage of blossom the leaf volume is not at its maximum, allowing an easier detection of the blossoms.	• There is more certainty about the expected yield.
Disadvantages	• A higher risk on lower yield because of late frost.	• The tree needs to deliver more energy to the starting fruitlets that eventually will be thinned.

uses flexible strings rotating around a vertical bar to hit a certain number of blossoms or fruitlets from the tree (Jacobus De Villiers et al., 2014). The thinning rate depends on the rotational speed of the strings and the driving speed of the tractor. The achieved thinning rates of this method are acceptable, but there are some disadvantages. First of all, the resulting amount of high quality fruit is difficult to control. Second, the aforementioned rotating strings do not only hit a certain percentage of flower buds or beginning fruitlets, but they cause significant damage to the leaves, annual shoots and bark of branches as well. Finally, the strings make physical contact with every tree, facilitating the spread of some diseases throughout the whole orchard. A comparable mechanized thinning process is the Baum machine, which uses rotating strings as well, but has more rotating bars in other directions, which has the advantage of more penetration into the canopy (Jacobus De Villiers et al., 2014). Both mechanizations are shown in Figure 5a and 5b, respectively. Besides string thinners, spiked drum shakers can be used to shake a number of fruitlets out of the tree as a manner of thinning. This method has the same disadvantages of nonselectivity, damage, and disease spreading. Moreover, it has the additional downside of shaking the largest fruitlets away, due to a higher inertia. However, these large fruitlets have the highest potential of reaching high quality and are preferably not removed (Wouters, 2014).
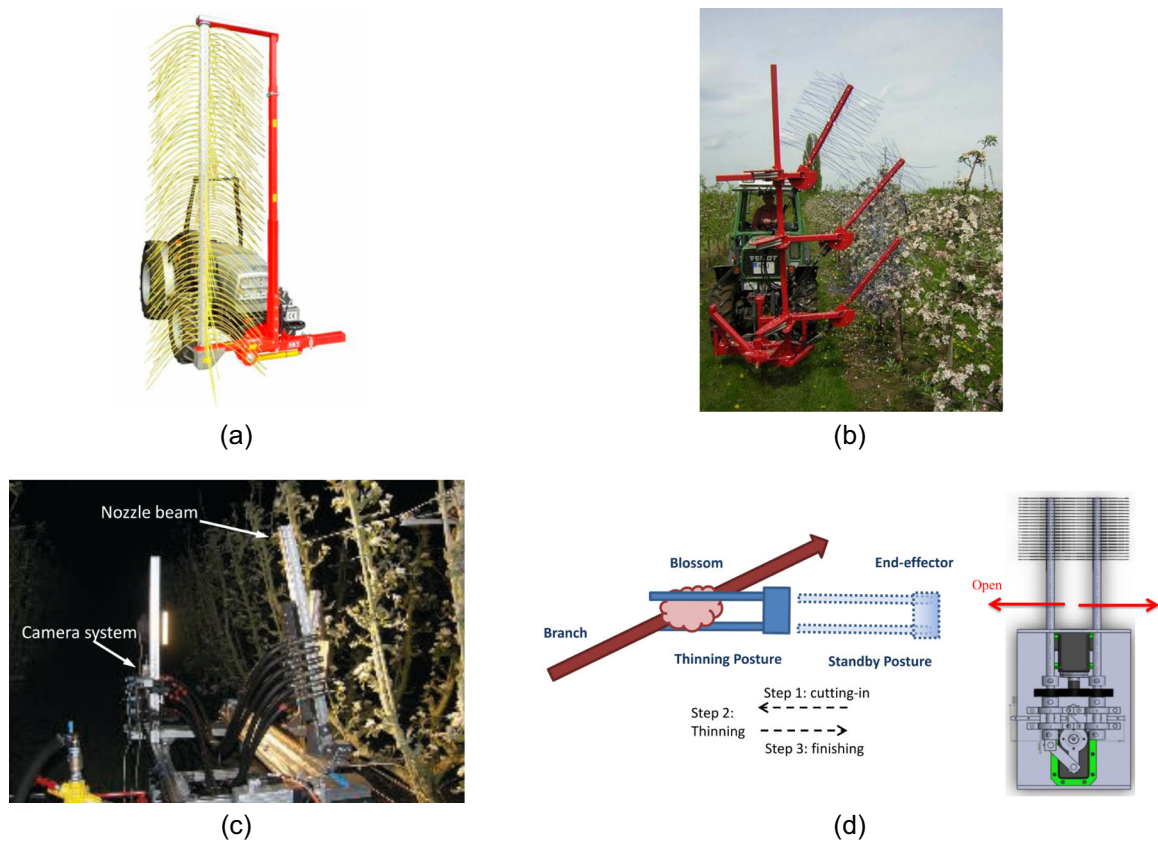

FIGURE 5 Thinning: (a) example of the Darwin machine (Mechanical blossom thinner, 2020); (b) example of the Baum machine (Damerow et al., 2007); (c) prototype of thinning machine with pressured air (Wouters, 2014); (d) the concept of the end effector for the thinning machine of Yang (2012) [Color figure can be viewed at wileyonlinelibrary.com]

4.2 | Automation

A fully operational and commercially available automated robot for this orchard activity has not yet been developed. However, Wouters (2014) engineered a working prototype, which solved some disadvantages of the mechanized solutions described above. By using pressurized air, multispectral computer vision, and precisely positionable nozzles, it is possible to selectively blow floral buds away. This method does not touch any part of the tree nor does it cause any extra damage to it. Therefore, the system will not spread diseases. However, the prototype (Figure 5c) is very slow and uses a large amount of pressurized air. Hence, the efficiency of this technique, in its current form, is too low to be used in an orchard in a profitable way.

Also Yang (2012) engineered a robot for automated thinning of fruit. However, this was a down-scaled prototype, tested in laboratory conditions. As a result out of these tests came a design of an end effector for selective thinning, which resembles a miniature version of a string thinner as shown in Figure 5d. Although the results were promising, many improvements need to be made towards a full-scale robotic fruit thinner. Future steps in this project could be the actual development of the end effector for outdoor field tests and validating the principle in orchard circumstances.

5 | SPRAYING

To protect an orchard against diseases, such as apple scab (*Venturia inaequalis*) and powdery mildew (*Podosphaera leucotricha*), it is necessary to spray pesticides. In recent years, the regulations about the use of these chemicals have become increasingly stern (ISO 22866:2005; ISO 22369-2-2010; ISO 16119:2013; ISO 16122:2015). The largest challenge is decreasing the amount of chemicals and the impact on the environment to a minimum. Therefore, drift reduction is very important. These days, drift reduction is mostly applied by using drift reducing spraying nozzles that produce bigger drops whose trajectory is less affected by wind. To validate spraying systems or to measure drift, water sensitive paper could be used, such as in De Moor et al. (2000), or more advanced leaf wetness sensors, such as in Foqué et al. (2018). To further decrease the used amount of plant protection products, research has been done on quantifying and modeling spraying flows and drift. Duga et al. (2017) developed a 3D computational fluid dynamics (CFD) model to calculate the drift of different types of nozzles, with the overall conclusion that under all circumstances drift reducing nozzles reduced the drifting distance by 50%. Holterman et al. (2017) captured 10 years of data to establish an empirical model for predicting the pesticide spray drift in pome fruit orchards. The model designed by Salcedo et al. (2017) focused on the effects of canopy density on the spraying flow and the drift of the product in citrus orchards. This study reported that 28% of the sprayed volume is not deposited on any fruit tree.

Because spraying in pome fruit orchards is always done with machines, the subdivision of mechanization and automation is not totally appropriate. For this task, another subdivision is preferable, namely the one used by Tona et al. (2018). The spraying equipment can be categorized into three technological levels. The first level L0 contains the conventional spraying techniques, level L1 contains the partly controlled spraying techniques and L2 is the level of precision spraying. Figure 6 shows the conceptual difference between the three levels.

5.1 | L0: Conventional spraying level

Conventional air-blast spraying is the most used type of spraying, but also the least automated one. An axial fan blows an air flow that carries the drops created by the nozzles towards the canopy. There is no measurement unit and the amount of spraying fluid is fixed throughout the whole orchard. However, the density of the canopy in an orchard is not constant, so a fixed setting of spraying is not efficient. Another issue is the height of the trees. To reach the top of the canopy with pesticide the fan has to blow hard, which means a certain part of the chemicals will be blown right through the canopy and the related drift will increase. Endalew et al. (2010) modeled the pesticide flow through the air and through the canopy in an orchard when using a conventional air-blast sprayer. With this model they calculated that only 55% of the pesticides is deposited on the leaves, around 10% falls on the ground beneath the tree and the remaining part will drift away. For this level, many commercial systems are available and nowadays the modern systems are equipped with a spraying computer that manages the outflow with the objective to reduce the use of chemicals.

5.2 | L1: Controlled spraying level

By measuring the canopy, it is possible to know where it is necessary to spray more and, more importantly, where it is sufficient to spray less. These sensor data can be captured in advance and summarized in a map or can be collected in real time. Balsari et al. (2008) used ultrasonic sensors to identify the canopy and studied the repeatability of such a crop identification system (CIS) at different driving speeds. These tests confirmed that such systems are suitable to detect the features of the canopy in real time at all tested speeds (2 → 8 km/h).

At this technological level (L1) controlling the amount of fluid per area is done by switching sections of the nozzles on and off. Walklate et al. (2003) recorded the orchard crop structure with LiDAR. Based on these sensor data the amount of pesticide per area was adjusted. Taking into account the growth stages of the trees, they were able to reduce the pesticide application rate by a factor five and give the same pesticide deposit as the reference structure. For spraying applications in citrus and olive orchards Moltó et al. (2001) and Tberger et al. (2016) used ultrasonic sensors to identify the canopy. Based on these data Moltó et al. (2001) controlled the spraying flow and reported a decrease of 37% of the use of product, while maintaining the
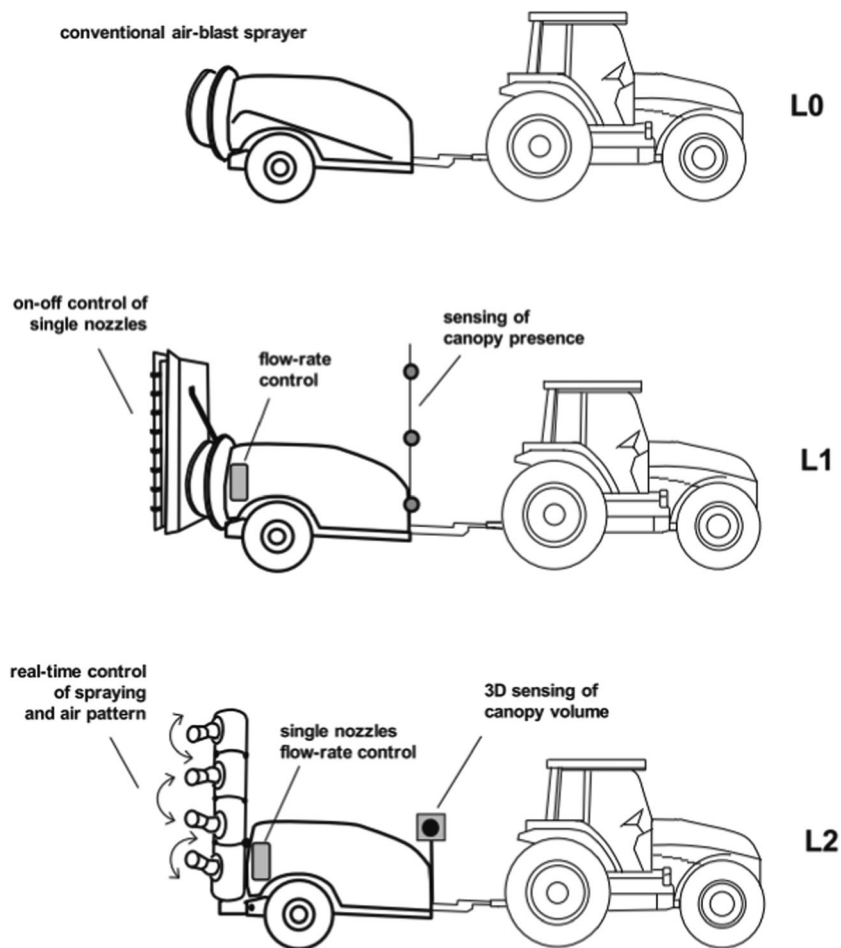
FIGURE 6 Conceptual overview of the technology levels for spraying systems. L0: conventional spraying level; L1: controlled spraying level; L2: precision spraying level (Tona et al., 2018)

quality of the treatment. Tberger et al. (2016) reported a drift reduction by 50% and 38.5% saving of fuel. Solanelles et al. (2006) used ultrasonic sensors as well and reported pesticide savings from 28% up to 72% compared to a conventional sprayer of level 0. Using an RGB camera Esau et al. (2014) developed a controlled spraying system for spraying blueberries. They reported a saving of pesticide ranging from 10% to 50% relative to a conventional sprayer accompanied by an increase in yield of 31%–35%.
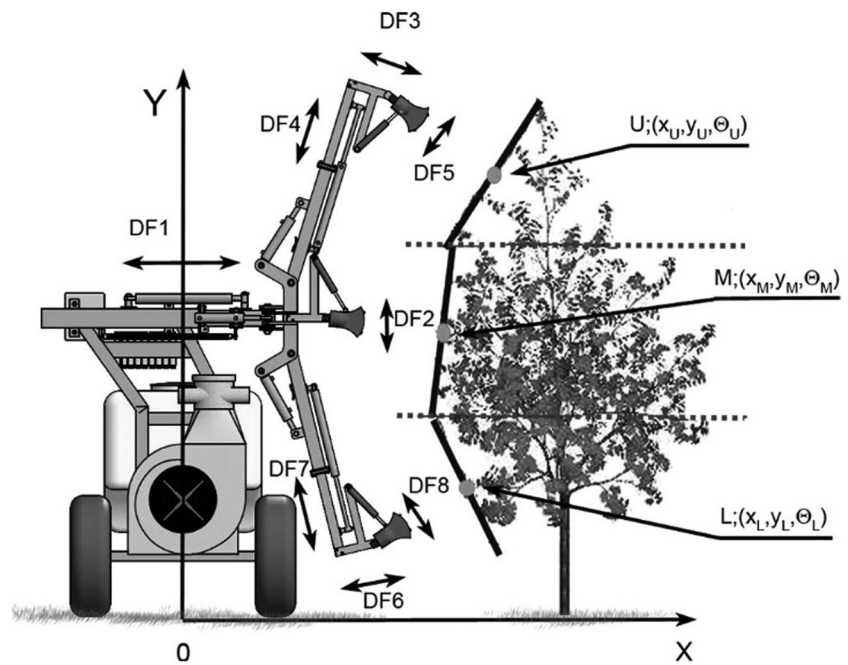
5.3 | L2: Precision spraying level

Precision spraying refers to canopy-optimized spraying systems that are based on 3D sensor data to record the full characteristics (volume, density, shape, etc.) of the trees in the orchard. Based on these 3D data the spraying can be controlled in amount and flow with controlled nozzles, in spraying distance and in spraying angle with certain actuators.

Hočevar et al. (2010) developed and tested an automated system for precision spraying in orchards. They used RGB images as input to calculate the contours of the canopy. Out of the field test results could be concluded that a saving of chemicals of 23% in relation to traditional spraying systems (L0) is possible. However, they also

noticed that these savings depend on the structure of the orchard. In high-density orchards the savings will be lower than in low-density orchards in relation to a conventional spraying system in such orchards. Osterman et al. (2013) modified this design using real-time laser scanner measurements as input data to record the canopy as a point cloud, whence they filter the contours. Based on the formation of this contour the optimal spraying flow, spraying distance, and spraying angle are calculated and executed with a controllable spraying arm consisting of three movable parts as shown in Figure 7. In the Netherlands, Nieuwenhuizen and Stallinga (2013) used laser scan data for their fully autonomous spraying system, which could also navigate autonomously through the orchard. This system was tested and they reported a saving of product up to 53%. Berk et al. (2019) used a 3 × 3 matrix of ultrasonic sensors and a fuzzy technology in their design of a precision spraying system. They tested if changes in certain parameters would affect the coverage with plant protection product (PPP) on the canopy. This resulted in an intelligent automated system which uses 4.8 times less spraying mixture than a conventional system. Gil et al. (2007, 2013) used ultrasonic sensors as well and reported a saving of pesticide ranging between 12.5% and 31.4% for their system, depending on the volume of the canopy. Vieri et al. (2013) used in the RHEA-project a set-up with eight ultrasonic sensors and eight movable nozzles and could

FIGURE 7 Precision spraying system with eight degrees of freedom. According to the canopy segments, the spraying distance, spraying angle and flow will be adapted (Osterman et al., 2013)

save up to 50% of product. Another precision spraying system that can autonomously navigate through an orchard as well is called Global Unmanned Spray System (GUSS; GUSS, 2019). This system is already commercially available, specifically for walnut orchards.

Within precision spraying, a next level could be defined as changing the treatment, based on the detection of diseases in real time. Methods to detect diseases, like powdery mildew or rottenness caused by Penicillium, have been proposed by Gómez-Sanchis et al. (2008), B.-H. Zhang et al. (2015), and Oberti et al. (2014). In the research project of Oberti et al. (2016) such a disease-sensing system was integrated on a robotic precision sprayer with the purpose of spraying grapevines autonomously. A red, green, near-infrared (R-G-NIR) multispectral camera system was used to detect powdery mildew. This was integrated on a robot platform which was part of the CROPS project. They reported that 85%–100% of the diseased canopy was treated with a reduction of 65%–85% in pesticide usage.

5.4 | Technical-economic analysis

Tona et al. (2018) analysed for the three technological levels whether it is profitable to implement them, depending on the size of the orchard (apple). They concluded that for orchards smaller than 17 ha level L0 is the most profitable, for orchards larger than 17 ha it is more profitable to use level L1. The level of precision spraying (L2) is currently not profitable, because the high investments could not be recovered by the additional saving of pesticides. The same analysis was done for vineyards (grapevines). In vineyards smaller than 10 ha the conventional level L0 is more economical, for vineyards of 10 ha up to 100 ha it is more profitable to use level L1 and for vineyards bigger than 100 ha it is more profitable to use a precision spraying

system of level L2. However, these conclusions are based on a generic model. Depending on the circumstances and the used technologies, these numbers could be very different.

6 | HARVESTING

The goal of all previous tasks and labor is to harvest fruit of good quality in a profitable way. However, this harvesting has a high labor cost as well. The activity research discussed in Section 2 shows that for the manual picking of pears, the amount of labor could go up to 51.8% of the total labor load and for apple this amount is even 66.9% of the total labor hours for cultivating apples. Back in 1993, Sarig (1993) already reviewed the then actual possibilities of automating the task of picking apples. Although no cost-effective product was yet available at that time, they concluded that much research presumed that it would only be a matter of time and money before further robotization of fruit cultivation would replace manual laborers in orchards. The current status of mechanized and robotic harvesting is discussed below.

6.1 | Mechanization

The first type of mechanized harvesting is the nonselective harvesting machine such as a limb shaker, a trunk shaker, or rotating beater bars. As the names already indicate, these machines apply a brusque mechanical force whereby the fruit will fall off the trees. However, these nonselective mechanical forces injure fragile high-quality fruits like apples, causing many bruises, and decrease the quality and price of the fruit. In addition, the branches of the fruit

trees will be damaged too. It can be concluded that this kind of mechanization is only applicable for industrial fruit (for jams, juice, etc.) and for less fragile classes of fruit (e.g., citrus and olives). More information about mechanized harvesting is reviewed in P. Li et al. (2011).

Another method for the mechanization of harvesting pome fruit is the use of a mechanical aiding platform. The picking will still be done by workers, but the actuation of the platform height, the outflow and the collection of fruit in bins will be done by a mechanical and partially automated platform. An example of a commercial harvest aiding platform is the *Pluk-O-Trak*, as shown in Figure 8 (Pluk-O-Trak; Munckhof, 2019). According to Baugher et al. (2009), mobile orchard platforms could increase the working efficiency with 19% and even up to 67%, depending on the platform type and the performed tasks. These numbers were confirmed by the performed activity study of Section 2.2, reporting a reduction in labor time of 13% up to 30%. Hence, these systems can reduce the labor cost, but they still include interaction with manual laborers.

6.2 | Automation

The automation of the orchard task of harvesting can be divided in two major automation challenges. On the one hand, the detection system for detecting the fruits. On the other hand, the robotic part of gripping and picking the apple. After describing these two parts, both detection and robotics, will be combined in the discussion of the currently developed robotic harvesting prototypes.

The first part of the automation process is the detection of the fruit. Several techniques have already been investigated to integrate machine vision in an apple harvesting robot. Baeten et al. (2008) placed an RGB camera in the center of the gripper and used the changes in the image, while moving the robot arm, to calculate the position of the detected apples. Bargoti and Underwood (2016, 2017a, 2017b); Hung et al. (2015) all used normal RGB images as well, but combined these with extra metadata of the circumstances

FIGURE 8 The Pluk-O-Trak from the company Munckhof as an example of an orchard aiding platform (Pluk-O-Trak; Munckhof, 2019) [Color figure can be viewed at wileyonlinelibrary.com]

(like the position of the camera, the position of the sun, time, weather data, etc.) to train convolutional neural networks (CNN) for identifying apples in the canopy. Sa et al. (2016) utilized CNN as well and combined RGB images with near-infrared (NIR) images to teach their system. However, this approach was tested to detect sweet peppers and rock melons instead of pome fruit. Besides 2D images, some research utilized 3D sensor data. Nguyen et al. (2014) developed an algorithm using an RGB-D camera. Based on the spectral information of red and green colors, they could separate apples from leaves and based on depth information the size, shape, and pose of the apple could be defined. This algorithm had a 100% detection rate for totally visible apples and an 85% detection rate for partially occluded apples. Davidson et al. (2016) and Silwal et al. (2017) both used ToF to recognize apples for their proof-of-concept robotic harvester. Other sensing techniques for detecting fruit are summarized in Gongal et al. (2015) and Zujevs et al. (2015). Besides knowing where to harvest, the information on the position of fruits in an orchard is interesting for yield estimation as well. This information can be used by the cultivators to optimize their activities throughout the orchard. For Hung et al. (2015), Bargoti and Underwood (2017a), Liu et al. (2018), and Häni et al. (2019) yield estimation was one of the main applications of their fruit detection system. An extra advantage of advanced fruit detection for robotic harvesting is that each picked fruit can be evaluated and classified (e.g., by size) simultaneously while harvesting, which could reduce the sorting costs drastically.

As already mentioned above, apples and pears are fragile products that must be handled with care. Therefore, several research projects were dedicated to develop proper grippers for picking pome fruit. Setiawan et al. (2004) designed a low-cost gripper and Kahya and Arin (2019) developed a pneumatic cutting tool to cut stems of apples. Davidson et al. (2016, 2017) and Onishi et al. (2019) used a three-fingered gripper that encases the apple. For such a three-fingered gripper J. Li et al. (2016) tested the influence of different picking patterns on the detachment process of an apple during robotic harvesting. The goal of this study was to analyse the minimal pressure required to detach an apple from the tree with a robotic gripper. Baeten et al. (2008) and the company Abundant Robotics (Abundant Robotics, USA-CA, 2019) developed a suction cup gripper to pick fruit without putting a local concentration of pressure on the apple. Cramer et al. (2018) studied hybrid grippers containing magnetorheological fluids that could be used as a solution between soft, forceless grippers and rigid, damaging grippers, with picking apples as potential application. Some examples of the previously mentioned grippers are shown in Figure 9. More grippers for this purpose were reviewed by Blanes et al. (2011). One step further, Eizicovits et al. (2016) developed the concept of graspability maps for gripping fruit and vegetables with their own developed gripper for sweet peppers. These maps contain a 3D point cloud of the positions where it is possible to grab the vegetable without damaging the pepper or its surroundings.

Some robotic apple harvesters were developed in research environments. Ceres et al. (1998), Davidson et al. (2016, 2017), and
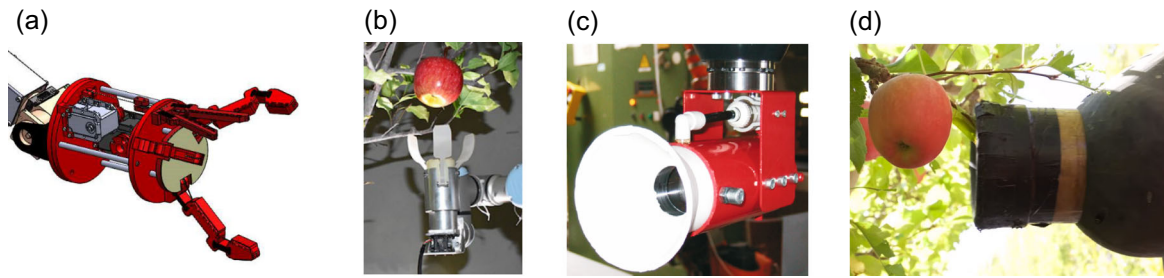
FIGURE 9 Examples of developed grippers for picking pome fruit: (a) the concept of a three-fingered gripper designed by Davidson et al. (2016); (b) the prototype of an enclosing three-fingered gripper developed by Onishi et al. (2019); (c) the suction cup gripper with camera in its center engineered by Baeten et al. (2008); (d) the suction cup gripper with integrated outflow pipe behind it, developed by Abundant Robotics, USA-CA (2019) [Color figure can be viewed at wileyonlinelibrary.com]

Onishi et al. (2019) engineered and tested their concepts under controlled lab circumstances. Baeten et al. (2008) and Silwal et al. (2017) developed a picking robot for apples as well and validated its functionalities in field experiments. Baeten et al. reached a successful picking rate of 80% but spent 8–10 s for the whole picking process of one apple. Silwal et al. reported that 84% of the apples could be detected and that the system has an average picking time of 6 s. Although more than 50 robots for picking fruit and vegetables were reviewed in Bac et al. (2014), only a few had the objective to harvest apples and none of them could be commercialized because of a lack of efficiency and a high development cost. Very recently, the Israeli company FFRobotics (FFRobotics, 2017) as well as Abundant Robotics from the United States (Abundant Robotics, USA-CA, 2019) both engineered a fully working automated apple harvester, which could be profitable in certain circumstances, whereby these systems could be commercialized. These two examples seem very promising for the future of automated fruit manipulation.

7 | MOBILE NAVIGATION IN ORCHARDS

All the above mentioned orchard management tasks have the common need for a mobile platform to navigate the actuators through the orchard. Out of personal consultations with different fruit cultivators can be concluded that farmers have to drive up to approximately 70 times a year through their orchard to do all the necessary tasks to guarantee yield (start meeting ACROFRUIT—KU Leuven HBC2019.2051, 2020—10.10.2019). Consequently, it is important to automate this part of fruit cultivation as well. However, there are many additional challenges for autonomous outdoor navigation compared to navigation in indoor environments.

Outdoor mobile navigation is an extensive field of research, which is not only applicable to the automated cultivation of pome fruit. Therefore, this paper does only contain a general overview of the challenges and developments of outdoor mobile navigation directly linked to orchards. It goes beyond the scope of this paper to give a detailed description of every technological realization in this broad field of research.

7.1 | Challenges

First of all, the changing weather and light conditions may considerably complicate outdoor navigation. On the one hand these conditions, like heavy rain, fog, sunny versus cloudy weather, angle of the sun, snow, and so on, could affect the measurements of sensors that are needed for localization and navigation. A way to take this into account is described in Bargoti and Underwood (2016) where these circumstances are added to the algorithms as metadata. On the other hand, the weather has consequences for the state of the terrain. Rain, freezing, or fallen leaves can cause a slippery underground. Morales et al. (2009) describe that piles of leaves or branches could be incorrectly recognized as obstacles, although it is possible to drive over these. Apart from the influence of weather, the state of the terrain is a big problem for outdoor navigation as well. Negative obstacles (holes and depressions) as well as sudden slopes can be unpredictable and due to this the vehicle could get stuck or tip over. Heidari (2014) shows an approach to detect and handle those negative obstacles. By pointing a 3D laser scanner at an angle to the ground, irregularities in the surface can be calculated as shown in Figure 10. Another challenge for outdoor navigation, especially in orchards, is the seasonal change of nature, which changes the orchard's visual aspect continuously. Again this could be countered by
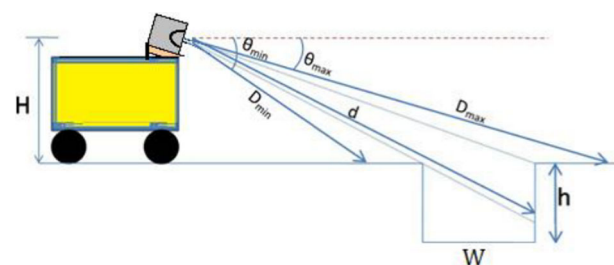

FIGURE 10 Conceptual presentation of the method of detecting negative obstacles, while navigating through outdoor environments, used by Heidari (2014). Based on LiDAR measurements, depressions can be detected if certain range values are larger than expected in relation to surrounding values. By means of triangulation, the depth of the depressions can be calculated as well [Color figure can be viewed at wileyonlinelibrary.com]

providing enough metadata to the localization system as described in Bargoti and Underwood (2016). Strisciuglio et al. (2018) suggested segmentation as another possible solution for this issue. A segmentation algorithm distinguishes drivable from nondrivable areas. Thus by doing this, an apple tree will always be treated as a tree, with or without leaves. Although an orchard is an outdoor environment, global navigation satellite systems (GNSS) are not always reliable because of signal occlusions by the trees surrounding the vehicle. Underwood et al. (2015) and several others describe this as a large issue for mobile navigation in orchards. Therefore, they developed GNSS-free localization and navigation systems that will be summarized below.

7.2 | Developments

The navigation of mobile platforms through an orchard needs to be accurate. Besides the accuracy for navigating from point A to B within the orchard, the system has to take into account the manipulations towards the tree or fruits that will be executed simultaneously, whereby its trajectory has to be adapted. Consequently, for the localization and navigation of mobile platforms in orchards multiple investigations and developments have been made. Hansen et al. (2009), as well as Andersen et al. (2010), tested a GNSS-free system based on laser scan data, odometry and an Extended Kalman Filter (EKF). The same principles were used in the developments of Subramanian et al. (2006), Barawid et al. (2007), Hamner et al. (2010), Libby and Kantor (2011), and Thanpattranon et al. (2015), reporting mean localization errors ranging between 2.8 and 135 cm, depending on the length of the trajectory. Brooker et al. (2006) tested a millimeter wave RaDAR instead of LiDAR in outdoor environments because radar has, next to its higher range, an improved penetration through canopies, but it has some disadvantages with relation to LiDAR as well. In most cases an EKF or particle filter algorithm is used for fusing information from different sensors. Hansen et al. (2011) and Blok et al. (2019) tested and compared those different filters and concluded that all the tested filters have similar results, although Blok et al. suggested that for in-row navigation, which is aimed at orchards, the particle filter with laser beam model is preferable.

All mentioned navigation and localization systems need an a priori map. Several mapping systems were tested in orchard environments. Dong et al. (2020) used RGB-D cameras to create a semantic map of an orchard. These maps contain more information than just coordinates. It could be used for phenotyping, yield estimation and to build a 3D reconstruction of the canopy. Combining trunk detection with LiDAR mapping, Bargoti et al. (2015) developed a mapping system which matches coordinates with tree numbers. This system reached a positioning accuracy of 87% and even up to 99% depending on the season. Underwood et al. (2015) used a Hidden Semi-Markov Model (HSMM) and a segmentation algorithm to map orchards and localize the mobile platform in that map. Except for the application of an orchard, many other Unmanned

Autonomous Vehicles (UAV) in unstructured outdoor environments have been developed. Examples of such developments are described in Crane et al. (2006), Ball et al. (2016), Paton et al. (2017), Gu et al. (2018), and Kragh and Underwood (2020).

All previous projects were developed for research purposes and none of them are commercially available. However, the company ASI Robots (Robots, 2019) offers fully automated hardware and software modules that could transform a normal tractor into an autonomous driving vehicle. Other commercially available vehicles are: (1) for autonomous spraying the GUSS (GUSS, 2019); (2) from the German company *Robot makers*® the Driverless Vineyard Crawler (Driverless Vineyard Crawler—robotmakers GmbH, 2020) and (3) the Dutch company *Precision Makers* presents the *Greenbot* for ±€100 000 (Greenbot—Precision Makers, 2020). Figure 11 shows examples of the discussed autonomous vehicles. As mentioned above, the field of research is too broad to discuss it in detail in this paper; more detailed information about other autonomous navigating agricultural vehicles is reviewed in M. Li et al. (2009), Shalal et al. (2012), and Gao et al. (2018).

8 | ROBOTICS IN OTHER RELEVANT CULTIVATIONS

Besides for pome fruit, research has been performed for other cultivations as well. Although these research projects had another crop as purpose, the used technologies could also be useful for apples and pears. In this paper, the discussed crops are subdivided in cultivations in greenhouses, and outdoor cultivations.

For greenhouse environments, the following projects were conducted: Van Henten et al. (2003) tested an autonomous cucumber picking robot. The CROPS project, followed by the SWEEPER project (SWEEPER, 2019) coordinated by Wageningen University, developed a fully operational harvesting robot for sweet peppers. Bac et al. (2017) and Arad et al. (2019) evaluated the performance of this sweet pepper harvesting robot. Over the years, this performance increased from only 2% of harvesting success in the initial tests up to a success rate of 61% (for the best fit crop conditions) in the reports of 2019. Another robotic sweet pepper harvester, called *Harvey*, was developed by Lehnert et al. (2017), which achieves similar results of a success rate of 46% on unmodified crops and up to 58% on modified crops. They also reported a detachment success rate of 90%. Zhao et al. (2016) designed and tested a dual-arm harvesting robot for tomatoes. Hayashi et al. (2010) and Xiong et al. (2019) both engineered a strawberry harvesting robot and the company Octinion (Octinion-Rubion, 2019) produces a commercially available strawberry harvester for certain greenhouse set-ups. For cherries Tanigaki et al. (2008) developed and tested a picking robot under controlled circumstances. Even for the most fragile fruits like raspberries, Fieldwork Robotics (Williams, 2019) developed an autonomous harvester.

In outdoor environments, a large amount of automation has already been implemented for the cultivation of grapevines, because
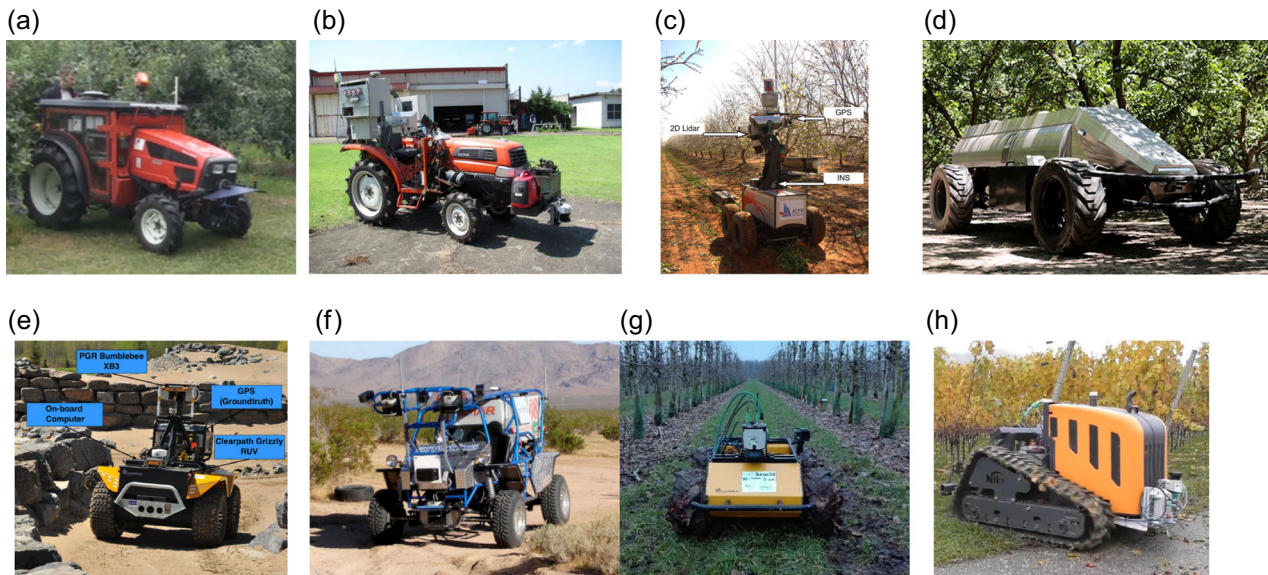
FIGURE 11 Examples of autonomous vehicles in outdoor environments: (a) experimental autonomous Hako Tractor (Hansen et al., 2009); (b) experimental Autonomous Kubota Kingwel tractor (Thanpattranon et al., 2015); (c) the perception research ground vehicle "Shrimp" (Underwood et al., 2015); (d) the Global Unmanned Spray System GUSS (GUSS, 2019); (e) clearpath Grizzly RUV and its sensor configuration (Paton et al., 2017); (f) team CIMAR's NaviGATOR: An Unmanned Ground Vehicle for the 2005 DARPA Grand Challenge (Crane et al., 2006); (g) Husky A200 robot with 2D LiDAR scanner used for orchard navigation (Blok et al., 2019); (h) the Driverless Vineyard Crawler from Robot makers® (Driverless Vineyard Crawler—robotmakers GmbH, 2020) [Color figure can be viewed at wileyonlinelibrary.com]

this crop is very suitable for automation. The vines can be pruned and tied up so that the grapes are visible and free to pick. Matese et al. (2015) reviewed the currently used technologies in precision viticulture. The cultivation of kiwifruits has the same advantages as grapevines. The branches of kiwi plants are trained in a horizontal plane. Because of gravity, the heavy fruits hang below the canopy and are visible. Williams et al. (2019) developed and tested a robotic harvesting platform that navigates underneath the horizontal canopy and harvests kiwis with a success rate of 86.0% of reachable fruit, and 55.8% of all fruit with a cycle-time of 2.78 s/fruit, which is comparable to human picking speed. With those results, they claim that this harvester is one of the most effective selective harvesters in the world. The same platform was used earlier in the project by Duke et al. (2017) for robotic pollination of kiwifruit flowers. Duke et al. (2017) reported that the system can detect 89.3%, localize 71.9% and hit 80.1% of the flowers with pollen at a driving speed of 0.36 m/s. Some other interesting research projects about robotic fruit cultivation were reviewed by Hua et al. (2019).

In every part of the agricultural sector, precision farming, innovative technologies, and robotics are being investigated. In a similar way as this paper reviews the recent innovations for the cultivation of pome fruit, Bechar and Vigneault (2016, 2017), as well as Fountas et al. (2020), both reviewed the developments in agricultural robots for field operations, and Vougioukas (2019) reviewed the recent innovations in the total agricultural sector. However, the latter only provides a general overview without detailed descriptions.

9 | CONCLUSIONS AND FUTURE PERSPECTIVES

An overview of all mentioned developments in this review paper is displayed in Tables 1, 2, and 3 of Annex 1. The tables show that for the orchard management tasks harvesting, spraying and mobile navigation quite some progress has already been made. The systems in these areas claim high accuracy, but their efficiency, and consequently their profitability, is still too low to be directly applicable for average fruit cultivators. Furthermore, these systems are typically developed for specific and simplified circumstances, which are not generally present in standard orchards. For the orchard tasks thinning and pruning less progress has yet been made. Completely automated and selective pruning or thinning robots (or prototypes) for pome fruit trees have still not been developed. Combining this lack with the need for reducing the high amount of manual labor, indicates that these fields of research could have a high potential.

As this review paper covers all major parts of the cultivation of pome fruit, no general conclusions can be made that are applicable to every part. Concluding the review of thinning and spraying in one sentence is like comparing apples with oranges. Therefore, a proper and detailed conclusion will be made for each discussed part of cultivating pome fruit.

Activity research. The outcome of this study proves that harvesting takes the largest part of labor for cultivating apples (67%), as well as for pears (52%). Also manual pruning and thinning require a high amount of labor, even relatively higher for pears than

for apples. Investigating more deeply on harvesting and pruning, the study shows an important reduction in labor by using aiding tools and platforms. Hence, extra automation will lead to more viable circumstances, economically, as well as ergonomically. This proves the importance of future mechanization and automation in the fruit sector. In future work, a detailed study of the thinning process and extra validation tests of all performed studies will be executed.

Pruning. For the orchard task of pruning, it can be concluded that hedging is not a good replacement as mechanized pruning system, although it could have some advantages as well. Furthermore, for selective and automated pruning, the major challenges in this area consist of scanning and measuring tree structures, and based on those measurements, deciding where to prune. These challenges are already partly addressed in multiple research projects, but, despite these research efforts, no complete development has yet been made towards a fully automated and working pruning system for pome fruit trees. Nevertheless, it exists in the cultivation of grapes. For robotic pruning in a profitable manner and with respect for nature, more research on generalized and objective pruning decisions is important, which could have some advantages for manual pruning as well.

Thinning. For this task not much progress has been made until now. There are a few mechanized solutions available with acceptable results, though with many disadvantages as well. Regarding the activity research, the sector still has a high need for profitable automated and selective thinning principles and related prototypes. The future of automated thinning lies in new thinning principles that are fast, accurate, safe and preferably contactless to prevent disease spreading.

Spraying. These days, the automation of spraying systems is an important topic, due to the related environmental concerns. Therefore, much R&D has already been done and will be done in the future, because the regulations continue to become stricter. Precision spraying is promising for the future, but it is still too expensive to be profitable. The profit of extra saved pesticides is not enough to counter the high development costs of a complex precision spraying system. Nevertheless, this level of sprayers probably will break through, not due to an economical motive, but due to the stern environmental regulations of the government.

Harvesting. Automated harvesting is probably the activity in an orchard with the highest amount of research. Many prototypes have been developed and tested. Still, there are some technological bottlenecks, whereby implementation on larger scales is not yet happening. An important issue is the need for simplified orchard structures to reduce the difficulties of automated solutions. In consequence, the systems could become more efficient. Still, such harvesting robots are expensive and can be used only in a short time window throughout the year, which makes it difficult to recover the costs and make it profitable.

Mobile navigation in orchards. To deal with the challenges of outdoor navigation in a continuously changing environment as an orchard, there is a need for robust mobile navigation systems.

Several prototypes have already been developed and some vehicles for this application are even commercially available. Most systems are based on GNSS, or LiDAR measurements for recognizing trunks because these are fixed, but future steps towards more advanced maps could become a new perspective. This means that the maps should not only include basic information, but the data of entire trees. On top of that, the map has to be season-independent, and a multidata storage where data, such as yield estimation, can be saved and managed.

Robotics in other relevant cultivations. The developments for other cultivations contain much interesting knowledge that could be transferable to pome fruit, certainly the techniques from vineyards. Cross-fertilization can be useful for future progressions. Multiple developments in cultivations, like kiwifruits and sweet peppers, prove that less complex crop structures are designated to implement robotics in a smart and viable way.

Out of these conclusions, multiple concerns are repeatedly highlighted. For future robotic manipulation in orchards it is important to focus on four prospects.

(1) It is necessary to make the orchards suitable for robotic automation, as previously called making them "robot-ready." This will simplify the complexity of the automation solution, whereby the automation cost could decrease. However, this will take time, because changing the orchard structure means growing trees in another way. To guarantee yield for the farmer, this changing of orchard system can be done gradually by replacing old trees with new trees, with the right structure, over the years. Even for manual cultivation, a simplified orchard will reduce labor. Hence, this is a critical point for the future of pome fruit cultivation. A point that should be taken, with or without future implementation of robotics.

(2) For each task, the existing automations need to be optimized. On the one hand, this means for well explored topics, such as harvesting, that less expensive techniques could be combined into a profitable and real-time system (e.g., RGB vision with CNNs and suction cup grippers). On the other hand, for the less explored topics, such as thinning, extra research is needed. However, several techniques used for other tasks could be transferred, as discussed above.

(3) All mentioned developments are dedicated to one specific task, making it not profitable at all. A dedicated harvesting robot, for instance, can only be used for four weeks each year and cannot be profitable in this short time of use. Therefore, future orchard robots need to be developed for more than one orchard task. If the platform could be used for several tasks, the profitability will increase. For example, the robotic manipulator used for picking apples could change its end effector into a selective thinning device. Consequently, by combining multiple modular units into one multipurpose robot platform, the profitability, the feasibility and the efficiency of the system will increase, so that regular cultivators can use it as a realistic solution for the challenges in their sector.

(4) The majority of the discussed research projects tried to find a solution for either the detection of features, or the performance of an actuation in an orchard. Nevertheless, besides sensing and acting, robotics relies on decision-making as well. Where should be pruned? Which fruits should be harvested? What thinning rate is preferable according to the detected blossoms of that tree? Only a few of the discussed research projects investigated this part of robotics, instead of generically choosing fixed parameters for these possible decisions of their system. The quality of robotic fruit cultivation will increase by making the right and selective decisions in pruning, thinning, harvesting, and so on. Besides this quality, it could influence the performance of the system as well. Taking the example of picking, the decision of which apple should be picked first could also affect the difficulty of the picking task itself. By choosing the less complex and more effective picks, performance rates of the harvesting robot will increase. Although this means a second manual harvesting round will be necessary, for the current developments this is still necessary as well. So, in relation to the current developments, this kind of decision-making will not affect the amount of complementary manual labor. In conclusion, including more evolved decision-making in the think-part of future developments in the field of robotic fruit cultivation could have a positive effect on both quality and quantity of the cultivation.

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ORCID

Rafaël Verbiest http://orcid.org/0000-0002-2254-7475
Tanja Vanwalleghem https://orcid.org/0000-0003-2073-4426
Eric Demeester https://orcid.org/0000-0001-6866-3802
Karel Kellens https://orcid.org/0000-0002-0340-6669

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.