Harvesting Robots for High-value Crops: State-of-the-art Review and Challenges Ahead

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This review article analyzes state-of-the-art and future perspectives for harvesting robots in high-value crops. The objectives were to characterize the crop environment relevant for robotic harvesting, to perform a literature review on the state-of-the-art of harvesting robots using quantitative measures, and to reflect on the crop environment and literature review to formulate challenges and directions for future research and development. Harvesting robots were reviewed regarding the crop harvested in a production environment, performance indicators, design process techniques used, hardware design decisions, and algorithm characteristics. On average, localization success was 85%, detachment success was 75%, harvest success was 66%, fruit damage was 5%, peduncle damage was 45%, and cycle time was 33 s. A kiwi harvesting robot achieved the shortest cycle time of 1 s. Moreover, the performance of harvesting robots did not improve in the past three decades, and none of these 50 robots was commercialized. Four future challenges with R&D directions were identified to realize a positive trend in performance and to successfully implement harvesting robots in practice: (1) simplifying the task, (2) enhancing the robot, (3) defining requirements and measuring performance, and (4) considering additional requirements for successful implementation. This review article may provide new directions for future automation projects in high-value crops.

1. INTRODUCTION

Harvesting is performed several times during production of a high-value crop and is a candidate operation for automation. High-value crops are generally nonstaple crops such as fruit, vegetables, ornamentals, condiments, and spices (Temu & Temu, 2005). A major reason for a crop to be classified as a high-value crop is the high labor input required. Labor costs in Dutch greenhouse horticulture, for instance, constitute 29% of the production costs (Jukema & Van de Meer, 2009). These high costs motivate automation of harvesting, and other motivations involve social, environmental, and food quality aspects (Lewis, Watts, & Nagpal, 1983; Van Henten, 2006).

To automate the harvesting process, robots have been actively developed over the past 30 years (Grift, Zhang, Kondo, & Ting, 2008; Li, Lee, & Hsu, 2011; Li, Vigneault, & Wang, 2010; Sarig, 1993). Reviews specifically targeting harvesting robots included reviews of complete systems (Li et al., 2010, 2011; Sarig, 1993) or a subtask of the robot such as guidance and navigation (Bechar, 2010; González, Rodríguez, Sánchez-Hermosilla, & Donaire, 2009; Li, Imou, Wakabayashi, & Yokoyama, 2009) and fruit localization (Jiménez, Ceres, & Pons, 2000a; Kapach, Barnea, Mairon, Edan, & Ben-Shahar, 2012). These reviews indicate that the robots were capable of harvesting fruit autonomously, under a certain range of environmental conditions. Yet harvesting robots are still far from mature, and harvesting is still manual due to the limited performance of current robots. A gap in the literature exists regarding a better understanding of this limited performance, and future challenges that can generate a positive trend in performance.

We attempted to close this gap by pursuing the following three objectives. First of all, we characterized the crop environment, which is defined as the working environment

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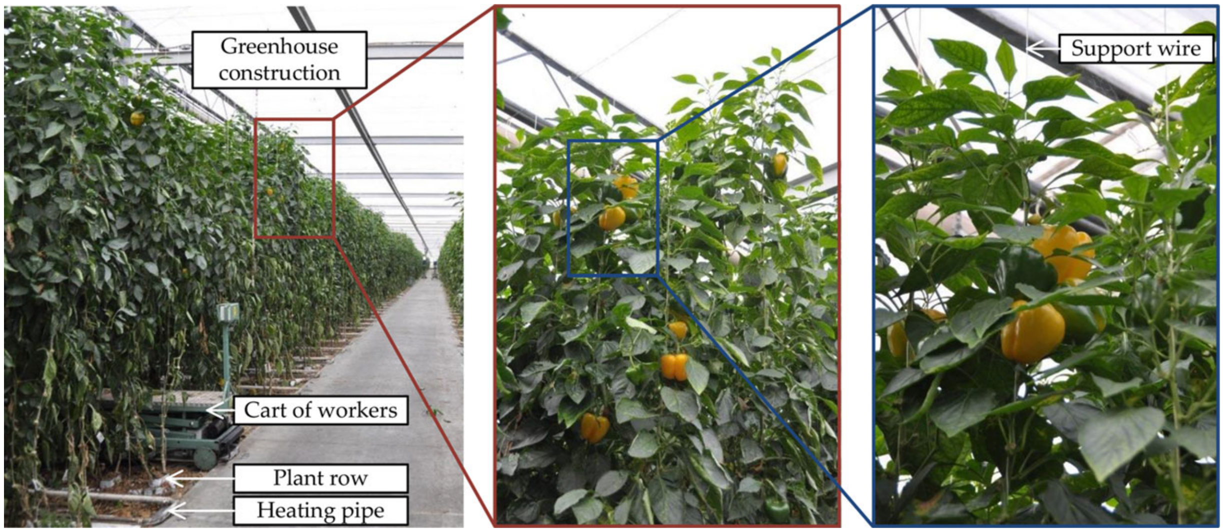

Figure 1. Sweet-pepper crop in a commercial greenhouse. The center photo is an enlargement of the left photo. The right photo is an enlargement of the center photo.

of the robot. We describe three sources of variation to elucidate how the complexity of the crop environment forms the main bottleneck to better performance. This description also supports terms and findings posed throughout the paper. Second, quantitative performance indicators were reviewed in only one article (Jiménez et al., 2000a), whereas they can be useful to compare robots, to determine the state-of-the-art in performance, and to identify future challenges for development. Therefore, this review tries to identify and review quantitative performance indicators for harvesting robots developed in the past 30 years. Third, we obtained new insights by completing the first and second objectives, and we complemented these insights with our experience to establish future challenges and R&D directions for development of harvesting robots.

These three objectives inspired the outline of this paper. Section 2 characterizes the crop environment in which harvesting robots have to operate. Section 3 presents the method, Section 4 presents the results, and Section 5 contains a discussion of the literature review. Finally, Section 6 presents future challenges and R&D directions written from the authors' perspective. In fact, this section can be viewed by the international robotics community as a plea to tackle the remaining challenges to develop reliable, economically viable, and useful harvesting robots, as asserted in a similar way for a review dealing with transmission line maintenance robots (Toussaint, Pouliot, & Montambault, 2009).

2. CHARACTERIZING THE CROP ENVIRONMENT FOR ROBOTIC HARVESTING

A crop environment includes three sources of variation relevant for robotic harvesting. First, there is a lot of variation of objects within a crop. Harvesting is performed on objects with ill-defined positions, shapes, sizes, and colors. Objects are also hard to see and reach due to occluding branches and leaves (Section 2.1). Second, the environment in which the robot must operate provides a lot of variation. Crops are grown in different production environments, where lighting conditions can vary. Growers employ different cultivation systems to support, train, and maintain their crops, and these systems influence the visibility and accessibility of fruit (Section 2.2). Third, many different kinds of crops are grown, and technical challenges and market potential for robotic harvesting can vary among crops (Section 2.3). Consequently, these three sources of variation render fruit harvesting a complex task and, furthermore, define harvesting robots as a unique and challenging field of agricultural robots.

2.1. Variation of Objects in a Crop

Objects, i.e., fruit and other plant parts, in a crop vary in position, size, shape, and reflectance due to the natural variation that exists in nature. High-value crops all contain this object variation. For example, a sweet-pepper crop is shown in Figure 1. The positions of the fruit are widely distributed in a height range of about 1 m. Currently, crop growth models cannot predict where fruit will occur, and each fruit must therefore be localized. Furthermore, the shapes of the fruit vary (e.g., sweet peppers are cylindrical, but the width/height ratio is not constant and widths vary from 6 to 11 cm; tomatoes can be round or elongated, and they vary in size). As a result, sensory techniques must cope with this variation. Reflectance (mostly color and near-infrared) of fruit is a visual cue often used to distinguish fruit from other plant parts, and it varies strongly. Further challenges for fruit detection regarding position, shape, size, reflectance, and texture are discussed by Kapach et al. (2012).

Color is used as a ripeness indicator for many crops, and the required ripeness level can vary. For example, in the beginning of the season (March–April), sweet-peppers are considered ripe if >80% of the fruit surface is colored. Later (May–October), temperature rises and coloring of 50% is acceptable for a fruit to be ready for harvesting. Furthermore, these percentages can vary depending on market demand. Consequently, a robot must handle this color variation.

When a robot grasps sweet-peppers, it requires a mechanism that can handle a range in sizes (the width of sweet-peppers varies between 6 and 11 cm) and shapes. A fruit's susceptibility to damage is another important factor for grasping. For instance, apples and avocado must be handled with great care, whereas kiwis can be handled with little risk of bruising.

Another aspect for harvesting is the accessibility and visibility of fruit. The right photo in Figure 1 displays a fruit cluster consisting of two ripe fruits and two unripe fruits. Accessing these ripe fruits with a gripper is a challenge because the other three fruits must be avoided to prevent damaging them. Also, other obstacles such as plant parts (leaves, stems, fruit), support wires, and construction elements need to be avoided once a gripper follows a path toward a targeted fruit. Therefore, localization of these objects is required to avoid damage to the crop, fruit, or construction elements. Obstacles not only block access to the fruit, but they also reduce visibility. Fruit visibility can be occluded by other fruit and leaves (Figure 1), causing difficulties for fruit localization (Kapach et al., 2012).

The age of the plant, pests and diseases, and cultivation practices of the growers can influence object variation as well. An old rose crop, for instance, produces fewer straight stems than a young rose crop, and such a change can decrease the performance of a robot. Also, pest and diseases can influence leaf angle and the color of objects. Furthermore, growers sometimes apply different fertilization regimes or climate management, which can cause variation in objects and their locations.

The object variation described so far already holds for one specific cultivar of a crop. However, this variation becomes even larger when considering that different cultivars exist for each crop. A cultivar exhibits slight genetic differences resulting in fruit and plant parts with differences in position, shape, size, and color. For peppers, for instance, about 25 different cultivars are grown in The Netherlands. Worldwide this number is even larger (Figure 2).

In view of this variation, an additional complicating factor is the short market lifetime of cultivars nowadays (about eight years). Breeding companies are continuously developing new cultivars for better production or to respond to new market demands. Ultimately, a robot should be able to handle each of these cultivars.

Figure 2. Pepper cultivars commercially offered by Westland Seeds. Source: www.westlandseeds.nl.

2.2. Variation in the Environment

A crop grows in a production environment, and a cultivation system is used to guide and maintain the plant. In this section, we describe production environments and cultivation systems and their impact on robotic harvesting.

High-value crops grow in four production environments: orchard, greenhouse, indoor, and open field (Figure 3). Large plants, such as trees, typically appear in orchards, whereas smaller plants typically appear in the other three production environments. Although few crops are grown indoors, this production environment is increasingly being investigated, such as a plant factory to grow lettuce (Shimizu, Saito, Nakashima, Miyasaka, & Ohdoi, 2011).

We identified several factors that may influence the design and performance of harvesting robots and that differ among production environments (Table I).

A robot must handle wind and rain as additional disturbance factors for crops grown in orchards and the open field. Lighting conditions can only be controlled for indoor crops, and they are a strong disturbance for image processing, which can limit harvest success. For instance, Plebe and

Figure 3. High-value crops appearing in four production environments: orchard hosting apples (left; source: http://fruit.cfans.umn.edu/apples/beforeyoustart/), greenhouse hosting tomatoes (center-left), indoor hosting mushrooms (center-right; source: http://www.tuinadvies.be/champignons_telen.htm), and open field hosting melons (right; source: http://angelvalleyfarm.files.wordpress.com/2012/06/melons.jpg).

Table I. Differences among four production environments for factors that can have an effect on harvesting robots. Factors scored from poor (–) to excellent (++).

	Production environment			
Factors	Orchard	Green house	Indoor	Open field
Wind and rain protection	–	+	++	–
Controllable lighting	–	–	++	–
Consistent plant development	+/−	+	++	–
Visibility of objects	–	–	+	+/−
Accessibility of objects	–	–	+	+/−
Ease of navigation	–	+	++	–
Suitable for stationary robots	–	+/−	++	–

Grasso (2001) showed that harvest success in a cloudy sky was 85%, but it was only 52% under a low sun angle. Plant development is more consistent for crops grown in greenhouses and indoors because climate conditions (CO_2, temperature, humidity) can be controlled. As a result, objects in these crops will be more consistent in terms of position, shape, size, and color, rendering them easier for a robot to handle. Nevertheless, the visibility and accessibility of objects are generally worse for orchard and greenhouse crops due to a denser canopy with a stronger presence of obstacles (such as construction elements and other plant parts) that need to be avoided by the robot. Navigation in orchards and the open field is more challenging because robots have to rely on guidance systems, whereas in greenhouses and indoors robots can drive on rail systems. Crops grown indoors can be suitable for stationary robots if the crops grow on movable benches that can be transported to the robot. Such benches are sometimes applied in greenhouses as well (Hayashi et al., 2011). Movable benches cannot be used in the open field because there is little economic incentive, and they cannot be used in orchards because trees are too heavy to transport. In conclusion, an indoor production environment seems most suitable for harvesting robots (Table I).

Growers use different cultivation systems (also referred to as "training system") to grow crops, such as the

Figure 4. Fruit are more visible and accessible in the "fruit wall" cultivation system (left) than in the conventional cultivation system (right). Photos courtesy of PCFruit, Belgium (http://www.pcfruit.be/Homepage/22724/pcfruit).

V-system and the "Spanish" system for sweet-peppers (Jovicich, Cnatliffe, Sargent, & Osborne, 2004). The cultivation system influences the accessibility and visibility of fruit. For instance, in the conventional cultivation system for cucumbers, the fruit is more occluded than in the high-wire cultivation system (Van Henten et al., 2002). In apple orchards, a "fruit wall" cultivation system is under investigation (Saeys & Nguyen, 2012) to simplify both manual harvesting and robotic harvesting (Figure 4). This system involves small tree spacing with tightly pruned trees.

Pruning is performed to influence plant growth, and it can have a large effect on the geometry of the tree. Orange trees, for instance, are short and wide or narrow and tall. These different geometries influence the traveling distance along the different ripe fruit to be picked. It turned out, obviously, that horizontal traveling is shorter for short and wide trees, whereas vertical traveling is shorter for narrow and tall trees. Furthermore, it was shown that vertical traveling was 5% shorter than horizontal traveling for typically shaped orange trees (Edan, Flash, Shmulevich, Sarig, & Peiper, 1990). In conclusion, the cultivation system influences the suitability of the crop environment for robotic harvesting.

2.3. Variation among Crops

As indicated in the previous sections, there exists a lot of variation within one crop and also the environment adds variation, but variation becomes even more pronounced when considering all high-value crops. To demonstrate how the geometry of plants differs among crops and how geometry determines the challenges for harvesting, we compare a rose crop and a tomato crop (Figure 5). Such a comparison can be made between other crops as well.

Figure 5. Rose crop (left) and a tomato crop (right). The cutting position of a rose stem is located deep into the crop, at the bottom, whereas the cutting position for the tomato truss is reasonably accessible, at the intersection between the main stem and the vine of the truss.

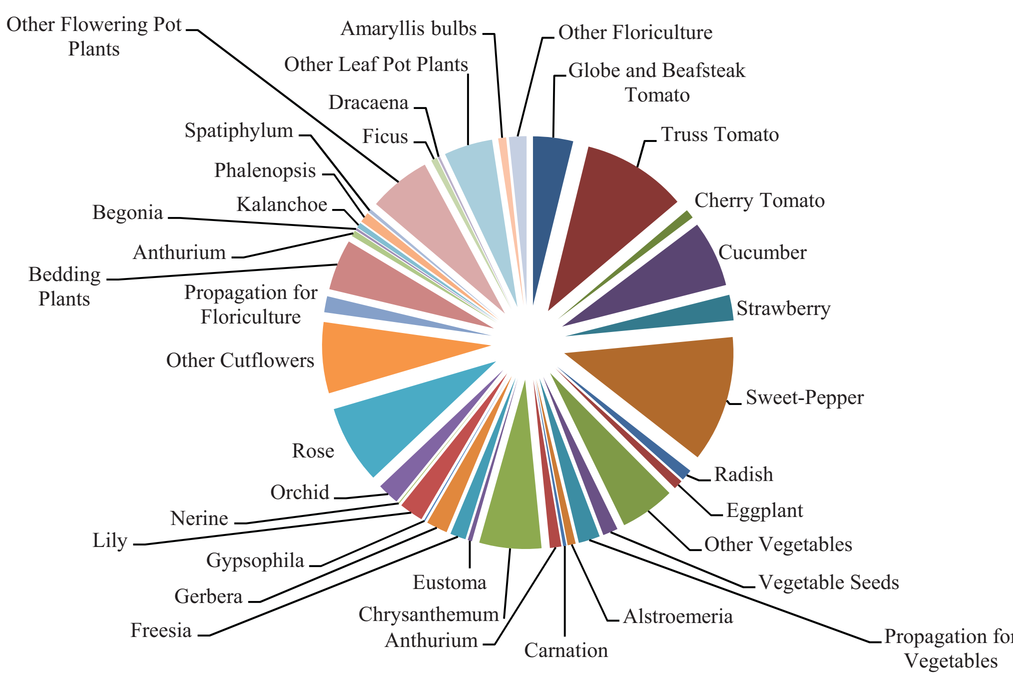

Figure 6. Area distribution of crops grown in greenhouses in the Netherlands in 2006. A large number of crops are grown and most cover a small area. Sweet-pepper and truss tomato are the only crops covering an area > 1,000 ha. The total area of greenhouses is 10,603 ha. Source: adapted from LEI & CBS (2009).

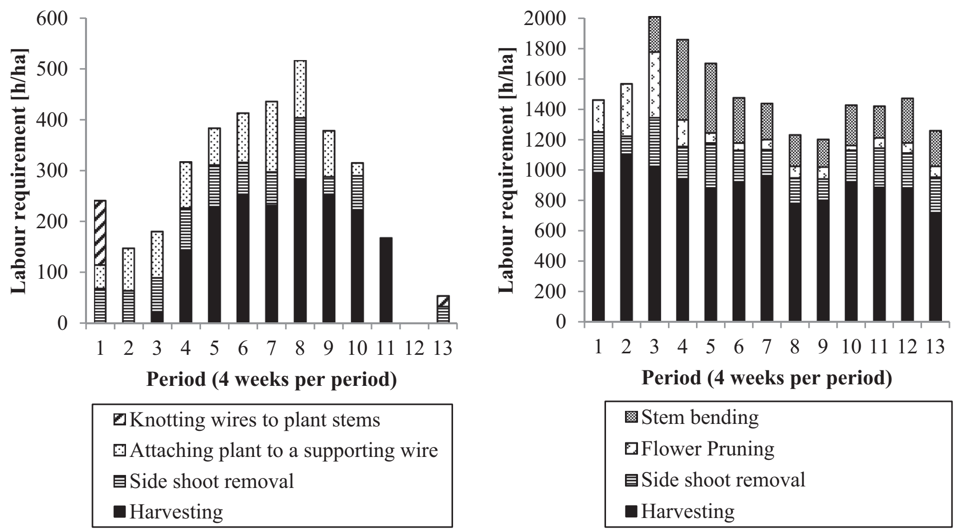

Figure 7. Annual human labor requirement of plant-maintenance operations performed in sweet-pepper (left) and rose (right). Labor requirement for harvesting in sweet-pepper is more irregularly distributed over the year than for rose.

The challenge for rose harvesting is to travel over a long distance through a dense canopy to finally reach the cutting position, whereas for tomato harvesting the cutting position is easier to reach and not surrounded by many obstacles. The challenge for tomato harvesting is to accurately determine ripeness while large parts of the fruit are not visible, whereas ripeness determination is a relatively simple task for rose harvesting because, when viewed from the top, the flower bud is completely visible.

The total variation aggregates when considering all high-value crops grown. To illustrate the large number of crops, we show crops grown in greenhouses in The Netherlands (Figure 6); such distributions probably hold for other countries as well. These crops impose specific technical challenges, and crops with similar challenges for robotic harvesting may exist. Researchers should therefore thoroughly analyze the crop of interest to design a robot that can handle the crop.

Another aspect that can strongly vary among crops is the market potential a crop offers for robotic harvesting. We discuss two factors. First, the area covered by a high-value crop is generally small (Figure 6). Even if a robot would be able to handle all cultivars included in this area, few robots can be marketed for a crop. This small market potential provides little incentive for industry to develop harvesting robots, as also indicated in a review on robotic harvesters in the United States (Glancey & Kee, 2005). Second, depending on the crop, the demand for harvesting can be irregularly distributed over the year. As an example, Figure 7 displays labor requirements for two crops: sweet-peppers and roses.

In sweet-pepper cultivation, harvesting is performed in periods 3 through 11, which is 36 weeks of the year, and a robot would be out of use in the other periods of the year. A rose harvester clearly has a better market potential because roses are harvested year-round and the robot is therefore better utilized. The stable demand for rose harvesting is because of continuous supplementary lighting and because rose plants grow for at least five years, whereas sweet-pepper production is restarted annually and they are mainly grown without supplementary lighting.

3. LITERATURE REVIEW METHOD

Harvesting robots were reviewed in line with the threefold complexity of the crop environment (Section 2) with a focus on performance, design, and algorithms. State-of-the-art performance was quantitatively assessed to determine how well robots handled object and environment variation (Section 3.1), and performance was compared among projects (Section 3.2). Since the robot design influences the robot's ability to deal with object and environment variation, we assessed how researchers carried out the design process (Section 3.3) and what design decisions they made (Section 3.4). For algorithms, we reviewed if they were reported and on the presence of adaptive algorithms so as to enable adaptation to object and environment variation (Section 3.5). We defined adaptive algorithms as algorithms that change their parameters or actions based on online feedback data. Examples of adaptive algorithms are adaptive thresholding techniques used in image processing and adaptive motion-planning algorithms using, for instance, visual servoing or learning controllers. If the robot contained an algorithm to perform another harvest attempt after failure, we considered such an algorithm nonadaptive because actions were not adapted online, i.e., during the operation.

Results of the review were ordered by the production environment (orchard, open field, greenhouse, or indoor) and by the particular crop on which the research had been focused. In summary, the review addressed the following questions:

- Which crops have been investigated for robotic harvesting?
- Which performance measures were reported and which are relevant to assess a harvesting robot?
- What percentage of harvesting robots was autonomous?
- Which tested conditions were reported?
- What is the overall performance of robots developed so far?
- How does performance compare between production environments, crops, and over time?
- How did researchers carry out the design process in terms of systematic design and economic analysis?
- What hardware components did researchers select?
- Which algorithms were reported for the main tasks of fruit harvesting?
- Which robots contained adaptive algorithms, and did those perform better?

A project was included in the review if and only if a complete functional system was built and reported in an English-written conference paper or peer-reviewed journal article.

3.1. Performance Indicators

The performance indicators were selected based on measures reported in the literature. For each indicator, an explanation is given for its relevance. Performance indicators considered included categorical and continuous indicators.

Two performance indicators were measured categorically: whether robots were autonomous (true/false), and whether robots were tested in the lab or the field. We defined a robot as autonomous if the robot performed tasks without human intervention once a human operator placed the robot in the field and set the hardware and algorithm parameters at the start of each field test. The difference between lab and field tests was considered important because a lab environment is usually much more structured than a field environment. As a result, higher performance can be achieved in a lab environment than in the field. Performance reported under field conditions is relevant because a harvesting robot must eventually be implemented under field conditions.

Eight performance indicators were analyzed as continuous indicators.

- Fruit localization success [%]: The number of localized ripe fruit per total number of ripe fruit in the canopy. This indicator was included because a fruit must be localized to determine fruit ripeness and it must be approached for detachment.
- False-positive fruit detection [%]: The number of objects falsely detected as fruit per total number of ripe fruit in the canopy. This indicator was included because false-positive detections can cause failed pick attempts, damage to fruit or plants, and increased cycle times.
- Detachment success [%]: The number of successfully harvested ripe fruit per total number of localized ripe fruit. This indicator was included because it measures the performance of collision-free motion planning toward a fruit, and of interaction between the end-effector and the fruit.
- Harvest success [%]: The number of successfully harvested ripe fruit per total number of ripe fruit in the canopy. This indicator measures the overall performance of a harvest cycle.
- Cycle time [s]: time of an average full harvest operation, including ripeness determination, localization, fruit detachment, transport of a detached fruit, and robot transport to the next fruit. This time includes time loss caused by failed attempts. This indicator is relevant to determine the economic feasibility of the robot.
- Damage rate [%]: the number of damaged fruit or peduncles per total number of localized ripe fruit, caused by the robot. A peduncle is the connecting stem between the fruit and the main stem or branch. Peduncle pull of apples was considered peduncle damage. Damage to fruit or peduncle reduces the market value of fruit and is therefore relevant for the economic feasibility of the robot.
- Number of fruit evaluated in a test [#]: The number of fruits that were evaluated to calculate localization success, false-positive fruit detection, detachment success, harvest success, damage rate, and cycle time. Such numbers are useful to evaluate the statistical significance of the reported performance indicators. Field test results, if reported, with statistical significance allow for performance comparison with other research projects.
- Detachment attempt ratio [-]: The number of detachment attempts [#] divided by the number of successfully detached ripe fruit [#]. This performance measure was included to show the relevance of the detachment success reported. The relevance of reported detachment success is partly influenced by the number of attempts made by the robot. That is, more attempts, especially from different platform positions, increase detachment success.

Ripe fruits were chosen for the performance indicators because high-value crops require ripeness determination. Though incorrect from an agronomic point of view, we will use the term “fruit” throughout the article to indicate harvestable fruit, vegetables, and flowers.

The accuracy of ripeness determination was not reviewed because we did not find a common ground truth measure that holds for several crops. Also, the positioning accuracy of the manipulators and end-effectors was not reviewed because accuracy requirements are not expected to be critical for harvesting robots. An end-effector positioning accuracy of ± 0.5 cm is satisfactory to grasp a fruit because of the required wide tool aperture to accommodate for varying fruit size. Such accuracy can be achieved by most mechanisms.

In this article, units were chosen such that multiplication of fruit localization success and detachment success yields harvest success. If one of these three values was missing, the missing value was calculated based on the other two, provided all units were clearly defined in the article, and a "(C)" was added after the performance indicator. Also, a "(C)" was added if performance values had to be converted to match the units of this review article (Table II). Some authors, however, did not report units of the performance indicators, which complicates conversion into similar units. For instance, some authors report cycle times of a "full harvest cycle," while it is unclear whether the harvest operation also includes platform transport to the next fruit. For cases in which conversion of cycle times was impossible, the unit unclear "(U?)" was added after the performance indicator.

3.2. Comparison of Performance

To assess the effect of the crop environment, performance indicators were compared among production environments and among crops in a production environment. In addition, performance indicators were compared between decades to determine how performance advanced over time. Decades were taken as the time step because the number of projects reported was too small for smaller time intervals. For comparison of performance indicators, the number of projects, the average, and the range were extracted for success rates, damage rate, and cycle time. If data for comparison of performance were too sparse for statistical significance, we only indicated if the data showed a trend.

3.3. Design Process Techniques

To determine if the use of design process techniques contributes to better performance, projects were reviewed on the use of systematic design methods and economic analyses. The literature indicates that these two design process techniques can greatly contribute to the technical and economic feasibility of a robot (Angeles, Park, Siciliano, & Khatib, 2008) and are common practice in industrial robotics implementation (Nof, 2009). Systematic design assists researchers in design choices, structures the design process, and stimulates creativity, whereas an economic analysis considers allowable costs of a system.

Systematic design methods reviewed include either process-based design methods or systems engineering methods. Examples of process-based methods are methodological design (Siers, 2007) or engineering design (Cross, 2008). An example of systems engineering is the determination of the number of robot arms, multiple arm configuration, degrees of freedom, and horticulture workspace design (Edan & Miles, 1994).

3.4. Hardware Design Decisions

Decisions for hardware design influence the robot performance and, eventually, the economic feasibility. Hardware design decisions were reviewed in terms of the number of degrees of freedom (DOF) used in manipulators and the use of off-the-shelf or custom-made components for the robot platform (traveling device), sensors, manipulator, and end-effector. If the DOF used were not reported, they were extracted from figures or pictures in the article. If we were uncertain regarding the DOF used, a question mark was added. Furthermore, we reviewed whether authors reported an analysis explaining the choice of the number of DOF.

Hardware components were considered off-the-shelf if it was clear that the component was purchased and used without any further modification to the component, such as an industrial manipulator. A multispectral camera that was assembled using off-the-shelf components was considered off-the-shelf. In other cases, hardware components were considered custom-made. Information was extracted from figures and pictures in the article if the details were not reported in the text.

3.5. Algorithm Characteristics

A description of algorithms is important for reuse in future projects. If algorithms were described, we determined whether these algorithms were described *partially* in text or *fully* in parametrized flow charts, equations, or code (or pseudocode). We considered a citation to or description of an algorithm to be *fully* described if parameter values were given. Details of the parameter values allow us to repeat the experiment.

The presence of algorithms was evaluated for five major tasks involved in fruit harvesting: fruit localization, ripeness determination, obstacle localization, task planning (i.e., which ripe fruit to pick first), and motion planning.

Furthermore we evaluated if any of the algorithms for these five tasks was adaptive (true/false) to determine if robots with an adaptive algorithm dealt better with object and environment variation.

4. LITERATURE REVIEW RESULTS

Projects included in the review are projects performed in the past 30 years (Table II). Information on older projects was hard to retrieve. To the best of our knowledge, 50 distinct research projects have been reported.

Table II. Performance evaluation of harvesting robots reported in the period 1982–2012, ordered by production environment, crop, and time (present to past).

Crop: Production environment	Crop: Name	Crop: Photo of fruit	Research Location (*Prototype name*) & References	Performance indicators: Autonomous	Fruit loc. success [%]	False-pos. fruit det. [%]	Detachment suc. [%]	Harvest success [%]	Damage rate [Fruit % / Peduncle %]	Cycle time [s]	Number of fruit [Loc. suc. # / False-pos # / Det. suc. # / Harv. suc. # / Cycle time # / Damages #.]	Detach. attempt ratio [-]	Test: Lab (Lab)/Field (Field)	Design process: Economic analysis	Syst. design methods	Hardware design choices: Manipulator DOF	Custom-made (C) / Off-the-shelf (O): Platform	Sensors	Manipulator	End-effector	Algorithm characteristics — Algorithms: Full (✓) / Partial (½) / Not reported (✗): Fruit loc.	Ripeness det.	Obst. loc.	Task planning	Mot. planning	Adaptive alg. used
Orchard	Apple		China (De-An, Jidong, Wei, Ying, & Yu, 2011)	✓	-	-	77	-	-/-	14.3	-/39/-/-/39/-	-	Field	✗	✗	5	C	O	C	C	✓	✗	½	✗	✓	✓
	Apple		Belgium (Baeten, Donné, Boedrij, Beckers, & Claesen, 2008)	✓	-	-	-	80 (U?)	0/30	9 (U?)	-/-/-/-/-/-	-	Field	✗	✗	6	O	O	O	C	½	✗	✗	½	½	✗
	Apple		Hungary (*AUFO*) (Kassay & Slaughter, 1993)	✗	70 (U?)	-	42 (U?)	-	1/-	2.4 (C)	∞/∞/-/∞/∞	-	Field	✓	✗	5?	O	O	C	C	✗	✗	✗	✗	✗	✗
	Apple/ Peach		USA (Sites & Delwiche, 1988)	✗	90 (U?)	20	-	-	-/-	-	145/145/-/-/-/-	-	Field	✗	✗	-	C	O	-	-	✓	✗	✗	✗	✗	✗
	Apple		France (*MAGALI*) (Grand d'Esnon, Pellenc, Rabatel, Journeau, & Aldon, 1987; Sarig, 1993);	✗	-	-	-	50 (U?)	0/25	3 (U?)	-/-/-/-/-/-	-	Field	✗	✗	4	C	O	C	C	✓	✗	✗	✗	✗	✗
	Date palm		Saudi Arabia (Aljanobi, Al-hamed, & Al-Suhaibani, 2010)	✗	-	-	-	-	-/-	-	-/-/-/-/-	-	Field	✗	✗	4	C	O	O	O	✗	✗	✗	✗	✗	✗
	Grape		Japan (Monta, 1995)	✓	-	-	-	-	-/-	-	-/-/-/-/-	-	Field	✗	✗	5	C	O	C	C	½	✗	✗	✗	½	✓
	Kiwi		New Zealand (Flemmer, Flemmer, & Scarfe, 2009)	✓	-	-	-	-	-/-	1 (U?)	-/-/-/-/-	-	Field	✗	✓	3	O	O	C	C	✗	✗	✗	✗	✗	✗
	Lychee		China (Liu, Zeng, & Ke, 2011)	✓	-	-	-	-	-/-	-	-/-/-/-/-	-	Field	✗	✗	-	O	-	C	C	✗	✗	✗	✗	✗	✗
	Oil Palm		Thailand (Sittichareonchai, Khaorapapong, & Limsiloratana, 1995)	✗	-	-	-	-	-/-	-	-/-/-/-/-	-	-	✗	✗	3	-	O	-	-	½	½	✗	✗	✗	✗
	Orange		USA (Lee & Rosa, 2006)	✗	-	-	84 (U?)	-	-/-	-	-/917/-/-/-	-	Field	✗	✗	3?	O	O	C	C	✗	✗	✗	✗	✗	✗
	Orange		Italy (Muscato, Prestifilippo, Abbate, & Rizzuto, 2005)	✗	-	-	-	-	-/-	8.7	-/-/-/11/-	-	Field	✗	✗	3	C	O	C	C	✓	✗	✗	✗	½	✓
	Orange		Italy (*OPR*) (Plebe & Grasso, 2001)	✓	87	15	-	52-85 (U?)	-/-	5.5-9.7 (U?)	673/673/721/721/721/-	-	Field	✗	✗	5	-	O	C	C	✓	✗	✗	✗	½	✗
	Orange		Spain (*AGRIBOT*) (Ceres, Pons, Jiménez, Martín, & Calderón, 1998; Jiménez, Ceres, & Pons, 2000b)	✗	80	0	-	-	-/-	2	-/-/-/-/-/-	-	Lab	✗	✗	4	C	O	C	C	✓	✗	✗	✗	½	✗
	Orange		France and Spain (*CITRUS*) (Plá, Juste, & Ferri, 1993; Sarig, 1993)	✓	75	8	75 (U?)	-	-/-	-	165/165/-/-/-/-	-	-	✗	✗	4	-	O	-	-	✓	½	✗	✗	✗	✗
	Orange		USA (*CPR*) (Harrell, Adsit, Munilla, & Slaughter, 1990; Pool & Harrell, 1991)	✓	-	-	69	-	7/-	3-7	-/-/154 -/154/-	-	Field	✓	✗	3	C	O	C	C	✓	✗	✗	✗	✓	✓
Greenhouse	Cherry		Japan (Tanigaki, Fujiura, Akase, & Imagawa, 2008)	✓	59	-	67	40	-/-	14 (U?)	80/-/12/12/-/-	-	Field	✗	✗	4	C	C	C	C	½	½	½	✗	½	✗
	Cucumber		China (Tang, Zhang, Liu, Xiao, & Chen, 2009)	✓	-	-	93 (U?)	-	-/-	-	-/-/60/-/-/-	-	Lab	✗	✗	6	-	O	C	C	✗	✗	✗	✗	✗	✗
	Cucumber		The Netherlands (*CUPID*) (Van Henten et al., 2002; Van Henten et al., 2003)	✓	95	18	78 (C)	74	-/-	124	106/106/179/195/195/-	2.1	Field	✗	✓	7	O	O	O	C	½	✓	✗	✗	✓	✗
	Cucumber		Japan (Arima & Kondo, 1999)	✓	-	-	-	-	-/-	-	-/-/-/-/-/-	-	Field	✗	✗	7	C	O	C	C	½	✗	✗	✗	✗	✗
	Eggplant		Malaysia (Wan Ishak, Kit, & Awal, 2010)	✗	-	-	-	-	-/-	42 (U?)	-/-/-/-/-/-	-	Lab	✗	✗	-	-	O	C	C	✗	✗	✗	✗	✗	✗
	Eggplant		Japan (Hayashi, Ganno, Ishii, & Tanaka, 2002)	✓	-	-	63	-	13 (C)/-	64.1	-/-/40/-/40/40	-	Lab	✗	✗	5	C	O	O	C	✓	✗	✗	✗	½	✓
	Gerbera		Germany (Rath & Kawollek, 2009)	✓	97	-	82 (C)	80	5/-	197 (C) (U?)	111/-/-/232/-/57	-	Field	✗	✗	6	-	O	O	C	✓	✗	✗	✗	✓	✗
	Rose		The Netherlands (Noordam et al., 2005)	✓	-	-	-	-	-/-	-	-/-/-/-/-/-	-	-	✗	✗	-	-	O	-	-	½	✗	✗	✗	✗	✓

(*Continued*)

Table II. Continued.

Crop: Production environment	Crop: Name	Crop: Photo of fruit	Research Location (*Prototype name*) & References	Performance indicators: Autonomous	Fruit loc. success [%]	False-pos. fruit det. [%]	Detachment suc. [%]	Harvest success [%]	Damage rate [Fruit % / Peduncle %]	Cycle time [s]	Number of fruit [Loc. suc. # / False-pos # / Det. suc. # / Harv. suc. # / Cycle time # / Damages #.]	Detach. attempt ratio [-]	Test: Lab (Lab)/Field (Field)	Design process: Economic analysis	Syst. design methods	Manipulator DOF	Hardware design choices: Custom-made (Custom) / Off-the-shelf (Shelf): Platform	Sensors	Manipulator	End-effector	Algorithm characteristics: Algorithms: Full (✓) / Partial (½) / Not reported (✗): Fruit loc.	Ripeness det.	Obst. loc.	Task planning	Mot. planning	Adaptive alg. used
Greenhouse	Strawberry		Korea (Han et al., 2012)	✓	-	-	-	-	-/-	7	-/-/-/-/-/-	-	Field	✗	✗	4	Shelf	Shelf	Custom	Custom	✓	✓	✗	✗	✗	✗
	Strawberry		China (Feng, Zheng, Qiu, Jiang, & Guo, 2012)	✓	-	-	86	-	-/-	31.3	-/-/100/-/-/-	-	Field	✗	✗	6	Shelf	Shelf	Shelf	-	✓	✓	✗	✗	✗	✗
	Strawberry		Japan (Hayashi et al., 2010)	✓	60	12	69 (C)	41	-/-	12.5	-/1130/1130/1130/ 1130/-	1.3	Field	✗	✗	3	Custom	Shelf	Custom	Custom	½	✓	✗	✗	½	✗
	Strawberry		Japan (Guo, Cao, & Masateru, 2008)	✓	93	-	-	-	5/-	30	100/-/-/-/100/100	-	Lab	✗	✗	3	NI	Shelf	Custom	Custom	✓	✓	✗	✗	✗	✗
	Sweet Pepper		Japan (Kitamura & Oka, 2005)	✓	-	-	-	-	-/-	-	-/-/-/-/-/-	-	Field	✗	✗	-	Custom	Shelf	Custom	Custom	✓	✗	✗	✗	½	✓
	Tomato (truss)		Japan (Kondo, Yamamoto, Yata, & Kurita, 2008)	✓	65	-	-	-	-/-	-	17/-/-/-/-/-	-	Lab	✗	✗	6?	Custom	Shelf	Shelf	Custom	✓	✗	✗	✗	✗	✗
	Tomato		USA (Ling et al., 2004)	✓	95 (U?)	-	85 (U?)	-	-/-	227	-/-/-/-/-/-	-	Field	✗	✗	6	-	Shelf	Shelf	Custom	✗	✗	✗	✗	✓	✓
	Tomato		Italy (*AGROBOT*), (Buemi, Massa, Sandini, & Costi, 1996; Jiménez et al., 2000a)	✓	90	-	-	-	-/-	-	-/-/-/-/-/-	-	-	✗	✗	6	-	Shelf	Custom	Custom	½	✗	✗	✗	✗	✗
	Tomato (cherry)		Japan (Kondo, Nishitsuji, Ling, & Ting, 1996)	✗	100	-	-	70	-/-	3-5 (U?)	-/-/-/62/-/-	3.3 (C)	-	✗	✗	7	Custom	Shelf	Shelf	Custom	✓	✗	✗	✗	✓	✓
	Tomato		Japan (Hayashi & Sakaue, 1996)	✗	-	-	-	-	-/-	41	-/-/-/-/-/-	-	Lab	✗	✗	5	-	Shelf	Custom	Custom	✗	✗	✗	✗	✗	✗
	Tomato		France (Balerin, Bourly, & Sévila, 1991)	✓	-	-	60	-	-/80	-	-/-/-/-/-/-	-	Lab	✗	✗	6	Custom	Shelf	Shelf	Custom	½	½	✗	✗	½	✗
	Tomato		Japan (Namikawa & Ogawa, 1989)	✓	-	-	-	-	-/-	22 (U?)	-/-/-/-/-/-	-	-	✗	✗	3	-	Shelf	-	Custom	✗	✗	✗	✗	✗	✗
	Tomato		Japan (Kawamura, Namikawa, & Fujiura, 1984)	✓	-	-	-	-	-/-	-	-/-/-/-/-/-	-	-	✗	✗	5	Custom	Shelf	Custom	Custom	✗	✗	✗	✗	✗	✗
Indoor	Mushroom		UK (Reed, Miles, Butler, Baldwin, & Noble, 2001)	✓	90	-	84 (C)	76	-/-	6.7	-/-/2290/2506/-/-	1.3	Field	✗	✗	3	Custom	Shelf	Custom	Custom	✓	½	✗	✗	✗	✗
	Mushroom		UK (Reed, 1994)	✓	84	-	68 (C)	57	-/-	-	815/-/689/815/-/-	-	Field	✗	✗	3	Custom	Shelf	Custom	Custom	✓	✗	✗	✗	✗	✗
Open Field	Asparagus (white)		Greece (Chatzimichali, Georgilas, & Tourassis, 2009)	✓	-	-	-	-	-/-	-	-/-/-/-/-/-	-	Field	✗	✗	3?	Custom	Shelf	Custom	Custom	½	✗	✗	✗	½	✗
	Asparagus		Japan (Irie, Taguchi, Horie, & Ishimatsu, 2009)	✓	-	-	-	-	-/-	13.7	-/-/-/-/-/-	1.0	Field	✗	✗	6	Custom	Shelf	Custom	Custom	✗	✗	✗	✗	½	✗
	Asparagus		USA (Clary et al., 2007)	✗	-	-	69	-	10/-	-	-/-/-/-/-/-	-	Field	✓	✗	-	Custom	Shelf	Custom	Custom	✗	✗	✗	✗	✗	✗
	Asparagus		Australia (Arndt, 1997)	✓	-	-	-	-	-/-	-	-/-/-/-/-/-	-	-	✗	✗	-	Custom	Shelf	Custom	Custom	✗	✗	✗	✗	✗	✗
	Asparagus		USA (Humburg & Reid, 1991)	✓	86-97	-	-	-	-/-	-	-/-/-/-/-/-	-	Field	✗	✗	-	Custom	Shelf	Custom	Custom	✗	✗	✗	✗	✗	✗
	Melon		USA, Israel (Edan, 1995; Edan, Rogozin, Flash, & Miles, 2000)	✓	94	20	92 (C)	86	7/-	15	400/400/374/400/ 400/400	1.3 (C)	Field	✓	✓	3	Custom	Shelf	Custom	Custom	✓	✓	✗	✓	✓	✗
	Radicchio		Italy (Foglia & Reina, 2006)	✗	100	-	-	-	-/-	7	6/-/-/-/-/-	-	Field	✗	✓	2	Shelf	Shelf	Custom	Custom	✓	✗	NI	✗	½	✓
	Saffron		Italy (*Zaffy*) (Antonelli, Auriti, Beomonte Zobel, & Raparelli, 2011)	✓	-	-	60	-	-/-	-	-/-/-/-/-/-	-	Field	✗	✗	3	Custom	Shelf	Custom	Custom	✗	✗	✗	✗	✗	✗
	Watermelon		Japan (Sakai, Iida, Osuka, & Umeda, 2008)	✓	-	-	87	-	0 (U?)/-	14	-/-/-/-/-/-	-	Field	✗	✓	4	Custom	Shelf	Custom	Custom	✗	✗	NI	✓	✓	✗
	Watermelon		Korea (Hwang & Kim, 2003)	✓	-	-	-	-	-/-	15	-/-/-/-/-/-	-	Field	✗	✓	4	Custom	Shelf	Custom	Custom	✗	✗	NI	✗	½	✗
	Watermelon		Japan (Tokuda, K., Suguri, Umeda, & Iida, 1995)	✓	-	-	-	-	-/-	-	-/-/-/-/-/-	-	Field	✗	✗	-	Shelf	Shelf	Custom	Custom	✓	✗	NI	✗	✓	✗

Legend: "-" = Not reported or unable to extract from figures or tables; "(U?)" = Unit unclear; "(C)" = Calculated value; "?" = Uncertain about value; "NI" = Task not of interest for the application

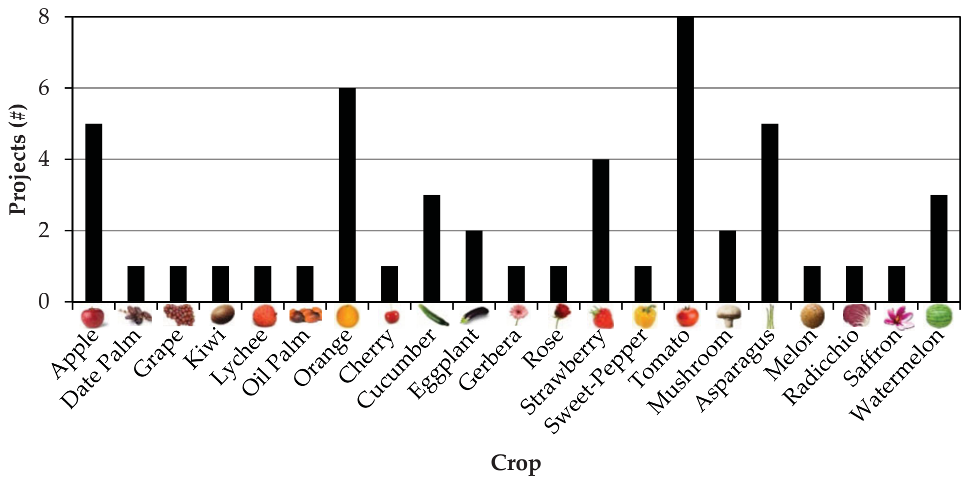

Figure 8. Number of distinct projects per crop. Most projects were aimed at tomato, orange, apple, or asparagus harvesting.

Results in Figure 8 show how many projects were performed per crop. Projects were aimed at many different crops (Figure 8). Only three projects were aimed at ornamental harvesting (rose, saffron, and gerbera), and all others focused on fruit or vegetable harvesting. Half of the projects—48% (24/50)—were aimed at tomato, orange, apple, or asparagus harvesting.

Results concerning performance indicators (Sections 4.1 and 4.2), design process techniques (Section 4.3), hardware design decisions (Section 4.4), and algorithm characteristics (Section 4.5) are reported in the following sections.

4.1. Performance Indicators

One or several quantitative performance indicators were reported for 76% (38/50) of the projects. However, few instances were reported for several of the individual indicators: 19 for localization success, 7 for false-positive fruit detection, 20 for detachment success, 11 for harvest success, 10 for fruit damage, 3 for peduncle damage, and 28 for cycle time.

Most of the projects concerned autonomous robots—74% (37/50). Only a few authors—12% (6/50)—reported the number of attempts the robot made to harvest a fruit. The average (σ) number of attempts was 1.7 (0.8) per successfully detached ripe fruit. Most performance tests were done in the field—68% (34/50), a few in the lab—16% (8/50), or the location of tests was not reported—16% (8/50).

The average values and range (minimum-maximum) of localization success, detachment success, harvest success, fruit damage, and peduncle damage are shown in Figure 9.

Localization success (85%; 59–100%) was, on average, slightly higher than detachment success (75%; 42–93%). Overall harvest success was 66% (40–86%). Fruit damage was 5% (25–80%) of the localized ripe fruit. Peduncle damage was 45% (25–80%) of the localized ripe fruit. Cycle time showed a large range of 1–227 s with an average of 33 s ($N = 28$).

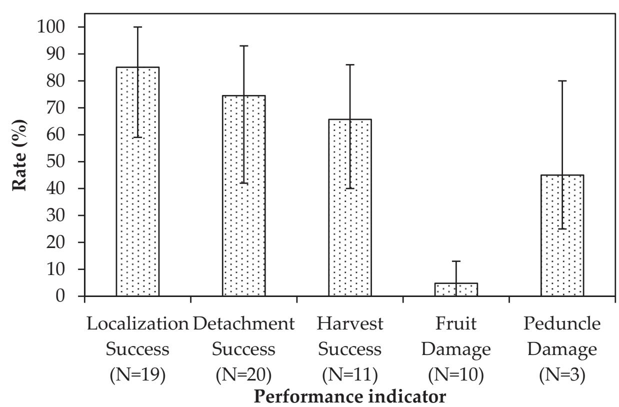

Figure 9. Averages and range of reported quantitative performance indicators: localization success, detachment success, harvest success, fruit damage, and peduncle damage. *N* represents the number of distinct projects.

4.2. Comparison of Performance

Data were too sparse to reveal statistically significant differences among performance indicators for the four production environments (Figure 10). Also, comparison of crops within a production environment revealed no statistically significant differences, and data were too sparse for visualization or analysis.

Analyses of averages and range of performance indicators for three decades (Figure 11) reveal that localization success, harvest success, fruit damage, peduncle damage, and cycle time did not improve over time. Only detachment success shows an improving trend.

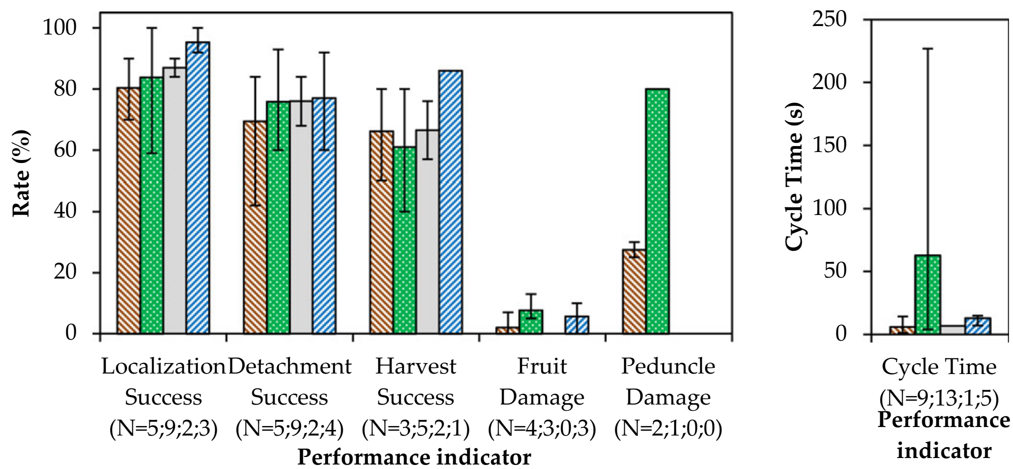

Figure 10. Performance indicators for four production environments: orchard (; 16 projects), greenhouse (; 21 projects), indoor (; 2 projects), and open field (; 11 projects). Averages and range of localization success, detachment success, harvest success, fruit damage, and peduncle damage (left). Average and range of cycle time (right). *N* represents instances per performance indicator per production environment.

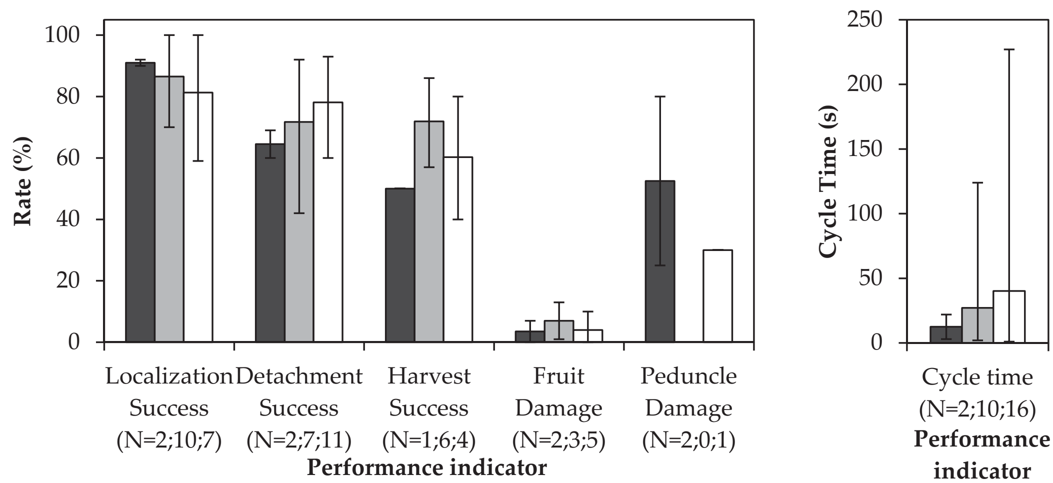

Figure 11. Performance indicators for three decades: 1984–1992 (; 7 projects), 1993–2002 (; 17 projects), and 2003–2012 (; 26 projects). Averages and range of localization success, detachment success, harvest success, fruit damage, and peduncle damage (left). Average and range of cycle time (right). *N* represents instances per performance indicator per decade.

4.3. Design Process Techniques

Only 12% (6/50) of the authors reported systematic design methods. Also, only 8% (4/50) of the authors performed an economic analysis. Unfortunately, performance indicators were missing for projects in which systematic design was used and the same crop (e.g., tomato) was harvested. Similarly, performance indicators were missing for projects in which an economic analysis was performed. We were therefore unable to determine if use of systematic design or an economic analysis contributes to better performance.

4.4. Hardware Design Decisions

It turned out that 82% (41/50) of the authors reported the degrees of freedom of the manipulator (Figure 12). In most of the projects, 3-DOF manipulators were used. These manipulators were mostly Cartesian manipulators and some were 3-DOF anthropomorphic arms. None of the authors reported an analysis explaining the choice of the number of DOF for their application.

The use of custom-made or off-the-shelf hardware components is shown in Figure 13. Most platforms were

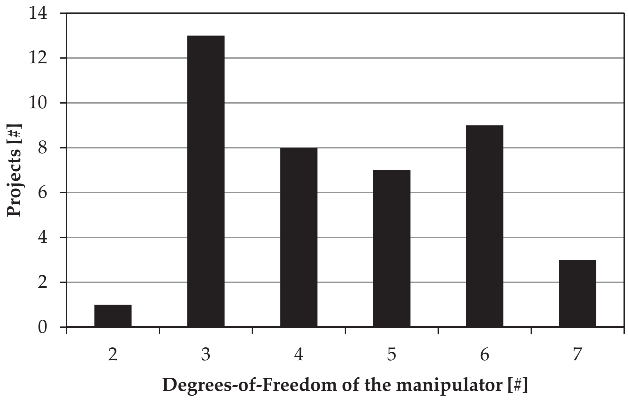

Figure 12. Degrees of freedom of the manipulators that were used in the projects. Most manipulators were 3-DOF Cartesian manipulators

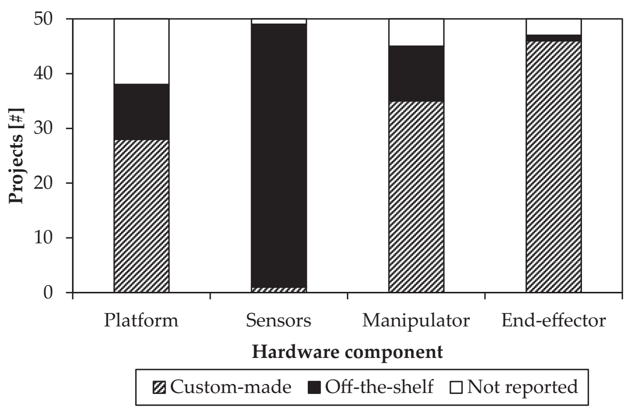

Figure 13. Use of custom-made or off-the-shelf hardware components in the projects. Sensors were off-the-shelf; the platform, manipulator, and end-effector were mostly custom-made.

custom-made—74% (28/38). Sensors were almost always off-the-shelf—98% (48/49)—and, for fruit localization, included mostly color and multispectral cameras. More details on the type of sensors used in agricultural robots can be found in other reviews (Jiménez et al., 2000a; Kapach et al., 2012; Li et al., 2011). Manipulators were mostly custom-made—78% (35/45). Almost all end-effectors were custom-made—98% (46/47).

4.5. Algorithm Characteristics

An analysis of whether algorithms were reported for the five major tasks performed during fruit harvesting, i.e., fruit localization, ripeness detection, obstacle localization, task planning, and motion planning, is shown in Figure 14.

Figure 14 clearly shows that algorithms for fruit localization were reasonably reported—64% (32/50). However, few authors reported which algorithms they used for ripeness detection—22% (11/50), obstacle localization—4%

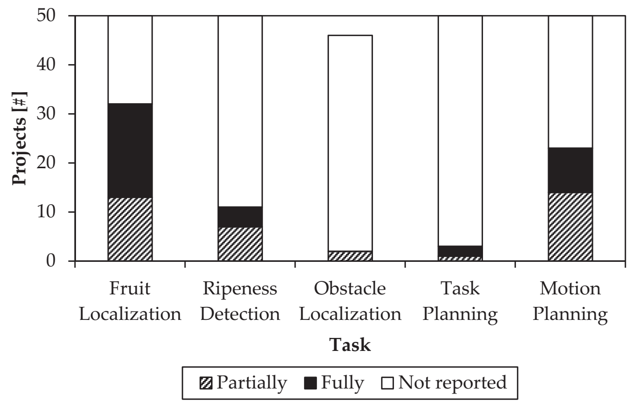

Figure 14. Reported algorithms for five major tasks, performed during fruit harvesting. If algorithms were reported, they were mostly partially reported and few authors fully reported algorithms.

(2/46), task planning—6% (3/50), and motion planning—46% (23/50). Although some authors even distributed the description of algorithms over several articles, none of the authors reported algorithms for all five tasks.

Adaptive algorithms were used in 20% (10/50) of the projects. Whether the use of adaptive algorithms resulted in better performance is hard to conclude because the number of projects performed on a crop was too small or because performance indicators were missing. The only minor observation that can be made is that fruit localization success was highest for the two tomato harvesting projects in which adaptive algorithms were used.

5. DISCUSSION

Results reveal that the performance of harvesting robots did not improve over the past three decades. We expected at least to observe a positive trend in performance because of two reasons. First, R&D advances in the field of sensors, mechatronics, computing power, computer vision, artificial intelligence, and other robot domains might have contributed better hardware and software. Second, the number of projects increased from 7 to 17 and 26 projects during the three decades investigated (Figure 10), and we expected a learning effect from previous projects. The absence of increasing performance may partly elucidate why, to the best of our knowledge, none of the 50 harvesting robots reached a commercial stage.

When discussing how far harvesting robots are away from the required performance for implementation in practice, the limited data regarding the average performance per crop (Table II) make it difficult to draw any conclusions. Exceptions include cucumber and orange harvesting. For cucumber harvesting, a cycle time of 10 s was proven to be economically feasible (Van Henten et al. (2002). The cycle time achieved was a factor of 12 too long (124 s) and clearly shows that a gap must be bridged. For orange harvesting, comparing cycle time was possible for only one project: 3 s required (Harrell, 1987) vs 3–7 s achieved (Harrell et al., 1990), i.e., a factor of about 2 too long. Although this gap is smaller, all performance indicators are required for a more conclusive analysis.

Despite the absence of increasing performance, we observed best practices (Brannan, Durose, John, & Wolman, 2008) that researchers may employ in future projects. In the following, we discuss hardware design, the design process, economic analysis, and testing the robot in the field. Sensing has already been discussed by others (Jiménez et al., 2000a; Kapach et al., 2012). Regarding hardware, the design of the 3-DOF manipulator and end-effector combination of the kiwi harvesting robot seems outstanding, which is also clear from the low cycle time of 1 s. The manipulator was custom-made and low-cost (5% of an off-the-shelf anthropomorphic arm), thereby improving economic feasibility. The manipulator did not contain motors at each joint—enabled by applying four-bar mechanisms—and therefore leaves and branches were prevented from getting stuck behind the motors. Furthermore, a pipe was mounted on the gripper for quick disposal of fruit in a storage bin (Flemmer et al., 2009). The melon harvesting robot (Edan et al., 2000) included the most complete description of the design process and performance indicators. The most thorough economic analysis was reported for orange harvesting (Harrell, 1987) and considered 19 variables affecting economic feasibility. The best practice for field tests was conducted for the strawberry harvesting robot (Hayashi et al., 2010). Performance was evaluated for five different classes of fruit positions, providing a better understanding of the influence of the crop environment on harvest success, and many fruits (>1,000) were evaluated. In addition, the effect of the gripping modes (suction on/off) and causes of unsuccessful harvesting attempts were quantitatively assessed.

To understand why performance is still limited (a harvest success of 66% and a cycle time of 33 s), we attempt to extract bottlenecks limiting performance (ordered in descending priority):

1. The threefold variation in the crop environment renders fruit harvesting a hard task.
2. It seems few attempts were made to simplify the task, and therefore the requirements to be met remained very challenging.
3. Robot designs were probably not optimized with respect to the requirements because requirements were hardly defined and because design process techniques were hardly used.
4. Since requirements, testing conditions, and performance indicators were hardly reported, it was hard to determine which techniques, devices, or algorithms are successful as is, and which need improvement.
5. The limited description of hardware and software complicated determining best practices and therefore enforced researchers to "reinvent the wheel" (Brannan et al., 2008). As a result, researchers may not always have implemented state-of-the-art techniques, devices, and algorithms.

To address these bottlenecks, we propose future challenges in Section 6.

6. FUTURE CHALLENGES AND R&D DIRECTIONS

To address bottlenecks and realize a positive trend in performance, we propose three challenges with R&D directions (Sections 6.1–6.3). The first two challenges, namely "simplifying the task" and "enhancing the robot," provide solutions to improve performance. The third challenge, "defining requirements and measuring performance," is a prerequisite to successfully implement the first and second challenges. The first challenge addresses bottlenecks 1 and 2, the second challenge addresses bottlenecks 1 and 3, and the third challenge addresses bottlenecks 4 and 5. Apart from a better performance, we believe more requirements must be met to successfully implement harvesting robots in practice, as discussed in the fourth challenge (Section 6.4).

The relevance of the challenge is explained at the start of a section and, subsequently, R&D directions are given. The identified challenges and R&D directions follow from the analysis of the variation in a crop environment (Section 2) and the literature review (Sections 4 and 5). Yet they are additionally based on the authors' 25 years of experience with the development of harvesting robots.

6.1. Simplifying the Task

Simplifying the task, by modifying the crop environment, helps to improve performance and should be investigated. This challenge relates to workspace design, a common practice when introducing robots into manufacturing systems (Nof, 2007), which was also applied when introducing the milking robot (Halachmi, Metz, Maltz, Dijkhuizen, & Speelman, 2000). We propose several modifications based on the crop environment described in Section 2. (More modifications will likely be identified in the future.)

6.1.1. Modified Cultivation Systems

To simplify the crop environment, the cultivation system can be modified. An example is the implementation of the high-wire cultivation system for cucumber. The high-wire system reduced occlusion drastically (Van Henten et al., 2002). For rose harvesting, plants were transported to a stationary robot by a movable cultivation system. This stationary robot allowed the implementation of parallel actuation mechanisms, which are known to be fast and accurate (Noordam et al., 2005).

Plant locations can be adapted in the row. For melon harvesting, it has been proven that by alternating the plants along the row, robot speed can be increased (Edan & Miles, 1993).

Trees or plants can be pruned to obtain suitable plant geometry for robotic harvesting. The literature indicated that differences in tree geometry can influence the cycle times and traveling distance along ripe oranges in a tree (Edan et al., 1990). A tree can be pruned such that traveling distances between fruit are short and, hence, the cycle time is reduced.

Growers might be reluctant to accept modifications because of the technical and financial risks of unproven cultivation systems. The researcher should therefore involve growers in the development of a modified cultivation system (Section 6.4.4).

6.1.2. Cultivar Selection and Breeding

Selection of cultivars can be aimed at increasing the free workspace of the robot. An example is the cucumber harvester that performed much better on cultivars with a long peduncle. Investigation of convenient cultivar characteristics was suggested for cherry tomato harvesting as well (Kondo et al., 1996).

An even more interesting option would be to include requirements for robotic harvesting in the process of breeding a new cultivar. For instance, Dutch breeding companies indicated to us that they are able to breed sweet-pepper cultivars that generate fruit at distributed positions, whereas currently fruit appears in clusters that are difficult to access and view. Plant breeders and roboticists seem to have worked separately so far, and collaboration may be beneficial for both disciplines, as also indicated in another review (Houle, Govindaraju, & Omholt, 2010).

6.1.3. Supportive Mechanisms

Mechanisms that temporarily mitigate occlusion or increase the free workspace can be used. Examples are canopy volume reduction for oranges by a mechanism (Lee & Rosa, 2006), leaf occlusion reduction for melon harvesting by an air blower (Edan et al., 2000), or mechanisms that pull or push neighboring plants aside.

6.1.3. Alternative Cultivation Practices

Additional operations, such as fruit or flower thinning in sweet-pepper or apple cultivation, can be applied to avoid fruit clusters. Fruit clusters typically cause occlusion of ripe fruit and therefore complicate fruit localization and detachment. Performing additional operations, however, increases costs, and a tradeoff should be made with revenues.

One option to reduce the peak demand for harvesting capacity is by using model-based climate control. Different climate management can smooth yield peaks, and as a result the required number of robots, i.e., the required investment, on a site might reduce. Such climate management techniques have been proposed for sweet-pepper cultivation (Buwalda, Van Henten, De Gelder, Bontsema, & Hemming, 2006; Van Henten et al., 2006). Shifting plant dates over the season can also spread yield peaks, as is done in melon cultivation (Edan, Benady, & Miles, 1992), and it is also applied in cauliflower and broccoli cultivation.

6.2. Enhancing the Robot

In addition to the advantages of a simplified task, the robot itself can be enhanced to achieve a positive trend in performance. Several options are discussed to improve the robot's design and ability to deal with the complex crop environment (Section 2). These options adhere to challenges discussed in the EU Strategic Research Agenda (euRobotics, 2013) and the Roadmap for U.S. Robotics (CCC, 2009).

6.2.1. Sensing, World Modeling, and Reasoning

Sensing is required to detect and localize the objects of interest. World modeling and reasoning manipulate, combine, and enhance sensor output to improve actuation. In addition to sensors already used (RGB, infrared, and multispectral cameras, and laser range finders), an R&D challenge is to advance algorithms for novel sensors (e.g., hyperspectral, time-of-flight, light-field, laser triangulation, structured light, and chlorophyll fluorescence cameras). Additionally, multiple sensors can be fused to enhance the performance of object detection and localization (Armada et al., 2014). Specific additional challenges for computer vision are described by Kapach et al. (2012). Given the large number of articles dealing with fruit detection (Jiménez et al., 2000a), it seems that researchers so far have focused mainly on developing improved sensing.

However, better performance may be achieved by combining sensing, world modeling, reasoning, and actuation. Such combinations may improve the actions and awareness of the robot, i.e., better cognition (euRobotics, 2013). Some examples of promising R&D directions employing such combinations are detailed in the following. Active perception (Bajcsy, 1988) can be used to move the camera until the visibility of the fruit improves. Visual servoing is already used for orange harvesting (Mehta & Burks, 2014) and involves updating object locations while an end-effector—with a camera mounted—moves toward a fruit. To plan appropriate actions, sensor data from multiple sensor types can be fused into a world model containing 3D crop models (Weiss & Biber, 2011) and other objects and behavior in the environment. These crop models and other objects can be based on *a priori* maps of a crop environment, similar to Google Street View, which is used as an *a priori* map for the Google driverless car. Such maps can be obtained with the help of image parsing (Yao, Yang, Liang, Mun Wai, & Song-Chun, 2010) or probabilistic approaches (Hiremath, van der Heijden, van Evert, Stein, & Ter Braak, 2014; Thrun, Burgard, & Fox, 2006). Other recent work regarding world modeling and reasoning include symbolic planning and control methods (Belta et al., 2007), fuzzy temporal logic (Lu, Augusto, Liu, Wang, & Aztiria, 2012), multiagent systems, dynamic Bayesian networks, and Markov logic networks (Lavee, Rivlin, & Rudzsky, 2009).

6.2.2. Adaptation and Learning

To better deal with the complex crop environment, a robot can be equipped with adaptation and learning capabilities. A learning system not only adapts to changing conditions, but also learns and improves to better handle changes over time, and preferably it learns online within a short time (Hagras, Colley, Callaghan, & Carr-West, 2002). We therefore consider a learning system to be an advanced way to tackle the complex sensing and manipulation problems involved in fruit harvesting.

The literature indicates the potential of adaptive algorithms both for sensing (Edan et al., 2000; Nieuwenhuizen et al., 2010) and manipulation (Grift et al., 2008). As an example of the effect of an adaptive classifier, Nieuwenhuizen et al. (2010) detected potato plants that occur as weeds in a sugar beet crop. Under changing natural light conditions, the classification accuracy improved from 34.9% (nonadaptive) to 67.7% (adaptive). Learning has been scarcely applied for agricultural robots, and we found examples regarding outdoor navigation (Hagras et al., 2002) and ground detection (Reina & Milella, 2012; Reina, Milella, & Underwood, 2012). One R&D direction explores learning capabilities, and another review (Ye, Dobson, & McKeever, 2012) discusses possible learning techniques.

6.2.3. Human-robot Collaboration

Given the moderate harvest success (66%) and complex crop environment (Section 2), human skills may still be needed to enhance robot performance. By taking advantage of human perception skills and the robot's accuracy and consistency, a combined human-robot system may result in improved performance and lower costs compared with an autonomous robot. Limited work has been done regarding human-robot collaboration for agricultural robots (Berenstein, Ben Halevi, & Edan, 2012; Murakami et al., 2008), but results indicate the potential of this direction due to the increase in performance, i.e., faster and higher detection rates (Bechar & Edan, 2003). Furthermore, it can simplify the robot providing reduced costs and increased robustness.

6.2.4. Specialized Hardware

Developing specialized hardware can enhance robot performance and might even reduce cost. For instance, an increasing number of DOF of a manipulator complicates motion planning, decreases manipulator speed and reliability, and increases costs. Despite these disadvantages, authors used manipulators with two to seven DOF, without further explanation of this particular design choice. Researchers prioritized the use and design of custom-made platforms (74%), manipulators (78%), and end-effectors (98%), but more analysis tools can be used to optimize a custom-made design or to assess available off-the-shelf components.

The literature provides several tools for optimization of a manipulator (Jian, Xueyan, Tiezhong, Bin, & Liming, 2007; Li, Liu, Li, & Li, 2008; Sakai et al., 2008; Sivaraman & Burks, 2006; Van Henten, Van't Slot, Hol, & Van Willigenburg, 2009). Systems engineering and modeling tools can help to address design issues regarding manipulation: type of arm (e.g., articulated, Cartesian), number of arms, required speed, and minimum required degrees of freedom (Edan & Miles, 1994). To enhance and compare end-effectors, developers can use systems engineering or employ modeling techniques such as finite-element modeling (FEM) (Cardenas-Weber, Stroshine, Haghighi, & Edan, 1991; Edan, Haghighi, Stroshine, & Cardenas-Weber, 1992).

6.2.5. Exploring Alternative Robot Designs

To best fit the requirements, alternatives to the standard robot design, consisting of a traveling device with a single manipulator and an end-effector, should be explored. Robot

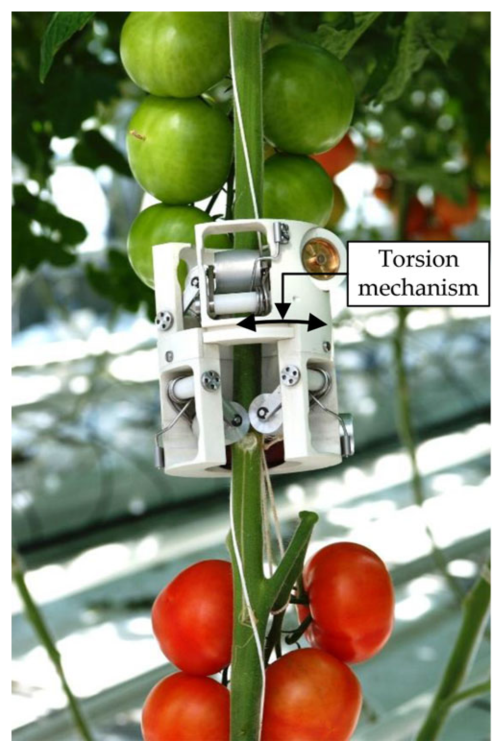

Figure 15. Functional model of a climbing robot for tomato. The torsion ability of the frame allows for peduncle or leaf avoidance during movement along the stem. Photograph courtesy of Bart van Tuijl, Wageningen UR.

designs such as snake robots, flying robots, spider robots, and climbing robots were never applied in high-value crops. Such designs can be investigated to determine whether they fit the requirements better than the standard robot design. The suggestion for such robot designs is not based on pure speculation; an attempt has been undertaken to develop a climbing robot for tomatoes (Figure 15). The example indicates that the development of climbing robots is a possible direction to pursue.

The choice for a certain robot design can be a rather difficult process, and multiple disciplines should be involved to develop a successful design (Section 6.4).

6.3. Defining Requirements and Measuring Performance

Requirements must be defined to identify the goals for performance indicators and, eventually, to measure if these goals are met. Performance indicators used (Section 3.1) can serve as benchmarks for the development of harvesting robots in future projects. Benchmarking and performance comparison are important to foster research and to enable implementation in practice (Bonsignorio, Hallam, & del Pobil, 2009; Madhavan, Lakaemper, & Kalmár-Nagy, 2009).

6.3.1. Defining Requirements

Requirements must be defined at the start of a project to define robot capabilities, to identify goals for performance indicators, and to determine research focus. Examples of requirements are as follows: the robot must be able to operate within a temperature range of 5–40 °C, the robot must detect 90–95% of the targets with less than 10% false detections, cycle time must be less than 6 s per fruit, and system cost must not exceed 100 k€. Only a few authors reported requirements (Belforte, Deboli, Gay, Piccarolo, & Ricauda Aimonino, 2006; Foglia & Reina, 2006; Hwang & Kim, 2003; Tillett, 1993; Van Henten et al., 2002). Reporting requirements, therefore, deserves attention in future projects.

Requirements must be defined for nontechnical aspects as well, such as economic, aesthetic, social, safety, ethical, and legal aspects (Section 6.4). These aspects are inspired by the 15 “aspects of experience” established by the Dutch philosopher Dooyeweerd (Clouser, 2010).

Setting technical and economic requirements is a complicated interplay between variables such as cycle time, success rates, and system costs, because these interact significantly. To illustrate, we demonstrate two economically feasible scenarios for sweet-pepper harvesting using an economics simulation model (Pekkeriet, 2011). In the first scenario, the maximum cost of the robot is 196 k€ if a cycle time of 6 s per fruit with 95% harvest success can be achieved for 20 h per day. In the second scenario, the maximum cost of the robot is 59 k€ if a cycle time of 20 s per fruit with 95% harvest success can be achieved for 20 h per day. As a result, design choices depend strongly on the scenario selected.

6.3.2. Reporting Performance Indicators

Performance indicators must be reported to verify if requirements are met and to enable performance comparison. There was only one project in which all quantitative performance indicators were reported (Edan et al., 2000), whereas all performance indicators should be reported to enable statistically significant comparison of, for instance, the effect of production environment and crop. Especially false-positive detections and damage rate were hardly reported and therefore deserve special attention.

Additionally, authors should explicitly state what results were obtained, under which conditions (field/lab, weather conditions, autonomous operation, and crop environment), and which hardware and software components were used. The results of the review clearly showed that these data were hardly reported, or only partially reported for 46% (33/71) of the reported algorithms. Once these data are reported, performance can be compared with respect to requirements defined. If requirements are not met, developers might either adapt the requirements or try to improve robot performance.

6.3.3. Reporting Test Samples

Test samples should be reported to determine the reliability of the performance indicator. In total, 57% (56/98) of the reported performance indicators were supported by the number of test samples evaluated. It is unclear what number of test samples the other authors evaluated to calculate the reported performance indicators.

Units were lacking in 21% (21/98) of the reported performance indicators. The unit should be reported to compare performance with other projects. Standardization of units can be useful for comparison, and units used in this review (Section 3.1) can serve as a starting point.

6.3.4. Testing the Robot under a Broad Range of Conditions

The robot must be tested under a broad range of climate conditions and crop environments to demonstrate if the required robot capabilities are met. The number of test samples evaluated varied from 11 to 2,506. Hence, given the complexity of harvesting, it is questionable whether the reliability of a performance indicator based on 11 fruit samples can represent the robot performance for a common harvest day, in which a human picks up to several thousand fruits, in a complex crop environment. Moreover, these test samples were probably evaluated on a specific hour on a day and did not include the weather variations throughout the day. Due to the large variation throughout and between seasons, it is important to conduct long-term tests. Evaluation methods should be developed to define the experimental setup and statistical analysis to ensure the performance indicators are not specific for the evaluated test cases (Cohen, Edan, & Schechtman, 2006).

6.3.5. Defining Additional Performance Indicators

Additional performance indicators are required to validate requirements that are not covered by performance indicators in Section 3.1. For instance, performance indicators are yet to be defined to validate to what extent a robot damages the plant. Plant damage reduces the vitality of the crop, and consequently yield can drop or wounds might act as access points for diseases. Also, it is a fact from practice that irrespective of quantifiable losses, farmers do not appreciate nor accept significant damage to the crop. In the literature, only Pool and Harrell (1991) reported that in 57 of the 154 pick attempts (37%), damage was caused to leaves or branches of the orange tree. Damages to the plant might be hard to quantify since a plant is capable of self-healing and a plant does not suffer from all damages.

Additional indicators can be reported for obstacle localization (Bac, Hemming, & Van Henten, 2013). Although obstacle localization received little attention (only 4% of the projects reported algorithms), it is required to avoid collisions that can damage the plant or construction elements.

6.4. Considering Additional Requirements for Successful Implementation

Simplifying the task and enhancing the robot can improve performance, but they are not sufficient for successful implementation of a harvesting robot in practice. Disciplines other than robotics must be involved in the development of the robot (Burks et al., 2005) to address the following requirements: the robot must be technically capable of performing the task, economically feasible, safe, match the logistics processes, and it must be accepted by growers and society. We believe all requirements must be met for successful implementation. Although most research focused on technical capability, as discussed previously (Sections 6.2 and 6.3), R&D directions for the other four requirements are discussed in the following sections.

To successfully involve all disciplines, reflexive design methods can be used. Such methods require all stakeholders (growers, engineers, scientists, and economists) to be involved and assure the needs of stakeholders are reflected in project objectives, requirements, functions, and working principles. Examples of reflexive design methods are reflexive interactive design (Bos, Groot Koerkamp, Gosselink, & Bokma, 2009), methodological design (Siers, 2007), and engineering design (Cross, 2008). The use of such design methods turned out to be effective in previous research (Bakker, 2009; Nieuwenhuizen, 2009; Van Henten, Van Tuijl, et al., 2006).

6.4.1. Economics

Incorporating economics is not only important to set performance requirements (Section 6.3.1), but it can also provide economic incentives that enable implementation in practice. To analyze economics, existing tools can be used as a starting point (Clary et al., 2007; Edan, Benady, et al., 1992; Harrell, 1987; Nof, 2009; Pedersen, Fountas, Have, & Blackmore, 2006; Sarig, 1993; Tillett, 1993). Economic analyses performed so far (four projects in Table II) dealt with only performance requirements, but examples of additional economic incentives are human-robot co-working or adding features apart from the harvesting task.

An emerging R&D direction to investigate is human-robot co-working because 100% replacement of human labor does not seem technically feasible with current harvest success (66%) achieved. Japanese researchers are currently investigating co-working for strawberry cultivation. Growers indicated they would accept a harvest success rate of 60% if such a rate improves economic feasibility by skipping complex harvest cases. Humans can harvest the remaining complex harvest cases (Hayashi, personal communication).

Examples of added features are tracking-and-tracing of food or better ripeness determination. Robots can log where each fruit grew, and, in the case of a disease outbreak, growers can quickly localize its origin and apply targeted crop protection treatments. A more equalized ripeness of harvested fruit will result in a longer shelf life of the fruit and probably a higher market value. As a result, higher prices can be generated if robots can determine ripeness better than humans, which may lower the performance requirements of the robot. Chlorophyll fluorescence imaging is a possible candidate to measure ripeness accurately (Bron, Ribeiro, Azzolini, Jacomino, & Machado, 2004; Polder, Van der Heijden, Van der Voet, & Young, 2004).

6.4.2. Logistics

Logistics must be analyzed to successfully integrate a robot in the logistics of operations and harvested fruit. Current logistics are already complex (Van 't Ooster, Bontsema, Van Henten, & Hemming, 2014) and become even more complex if future robots can perform more tasks in addition to harvesting. So far, most robots have been developed only for harvesting, with a few exceptions (Monta, Kondo, & Shibano, 1995; Van Henten et al., 2002, 2006). Examples of tasks that can be added apart from harvesting are chlorophyll fluorescence sensors for disease detection (Gorbe & Calatayud, 2012) or sorting and quality assessment of fruit directly after harvesting (Qiao, Sasao, Shibusawa, Kondo, & Morimoto, 2005). Developing such a multi-operational robot might even save development efforts because a platform and manipulator has to be developed only once.

6.4.3. Safety

Safe operation of robots is necessary in order to avoid harming humans, and it is critical for actual implementation (Pedersen, Fountas, & Blackmore, 2008). If humans (Section 6.2.3) or other robots appear in the robot workspace, safety becomes even more important. Safety seems to be an unexplored field for harvesting robots. The only work known dealing with safe manipulators is an article by Vermeulen & Wisse (2008). R&D directions for safety are provided in the Multi-Annual Roadmap for Robotics in Europe (euRobotics, 2014)

6.4.4. Acceptance by Growers and Society

Involving growers in the development is not only important for reflections on the design, but also to investigate acceptance to alternative cultivation systems or logistics, and to identify social aspects. A clear example, for which nontechnical aspects were relevant for implementation, is the milking robot. An incentive to purchase a robot was the flexible work schedule enabled by the release from fixed milking hours (Mathijs, 2004).

Acceptance by society is relevant for successful implementation as well, and it seems to be an unexplored field for harvesting robots. Society may have reservations about such innovations, and, in addition, employees may reject co-working with a robot (Section 6.4.1).

7. CONCLUSION

The first contribution of this review involves identifying and elucidating three sources of variation in a crop environment that must be considered in the development of a harvesting robot: variation in objects, environment, and crops. Consequently, this variation renders fruit harvesting a threefold complex task, and it is the main bottleneck to better performance. Approaches to overcome these unique variations are proposed.

The second contribution is a quantitative review of the literature on developed harvesting robots, which revealed that 50 distinct projects were performed in the past 30 years. The quantitative method resulted in the following findings. On average, localization success was 85%, detachment success was 75%, harvest success was 66%, fruit damage was 5%, peduncle damage was 45%, and cycle time was 33 s. Unfortunately, data were too sparse to provide averages per crop, which would have been more meaningful. Nevertheless, these results indicate the need for continued R&D to improve performance. Systematic design methods (12%) and economic analyses (8%) were scarcely used. Most manipulators were designed with two to seven degrees of freedom (DOF), where three DOF were common. Platforms (74%), manipulators (78%), and end-effectors (98%) were mostly custom-made, whereas sensors were taken off-the-shelf (98%). Algorithms were poorly reported for the five main robot harvesting tasks: fruit localization (64%), ripeness detection (22%), obstacle localization (4%), task planning (6%), and motion planning (46%). Moreover, if algorithms were reported, they were mostly only partially reported. Adaptive algorithms were used in 20% of the projects. The kiwi harvesting robot developed in New Zealand achieved the shortest cycle time (1 s), probably because a low-cost and specialized manipulator and end-effector were developed and because the fruit was easily accessible and hard to bruise. Cycle time was a factor of 12 too long for cucumbers and a factor of about 2 for oranges, compared with the required cycle time. Furthermore, the comparisons conducted on data from the review indicate that performance has not improved over the past three decades. Data should be reanalyzed as soon as more projects are available to supply statistically significant trends. We identified best practices that researchers can employ in future projects and five bottlenecks that limit the performance of current harvesting robots.

Our final contribution involves four future challenges combined with R&D directions to improve performance and implement harvesting robots in practice. The first two challenges—simplifying the task and enhancing the robot—provide solutions to improve performance. As a prerequisite, the third challenge must be implemented: defining requirements and measuring performance. The list of performance indicators provided in this paper could be used as benchmarks in the future development of harvesting robots, and it should be obtained from extensive field tests that include a wide range of conditions. The fourth challenge lists additional requirements that must be considered to successfully implement harvesting robots in practice. Robots will be needed more and more to optimize plant maintenance and, as a result, to contribute to the production of high-quality food for an increasing world population.

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