Intelligent Robots for Fruit Harvesting: Recent Developments and Future Challenges

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Abstract

Intelligent robots for fruit harvesting have been actively developed over the past decades to bridge the increasing gap between feeding a rapidly growing population and limited labour resources. Despite significant advancements in this field, widespread use of harvesting robots in orchards is yet to be seen. To identify the challenges and formulate future research and development directions, this work reviews the state-of-the-art of intelligent fruit harvesting robots by comparing their system architectures, visual perception approaches, fruit detachment methods and system performances. The potential reasons behind the inadequate performance of existing harvesting robots are analysed and a novel map of challenges and potential research directions is created, considering both environmental factors and user requirements.

Introduction

Fruit growers are facing an increasingly severe labour shortage due to the labour workforce's diminishing interest in agriculture (Luo and Escalante 2017). The problem is exacerbated by recent international travel restrictions in pandemic conditions, which have dramatically limited agricultural productivity due to unavailability of migrant workers. As a result, tons of fresh produce were left unharvested and rotting on fields where farms had long relied on seasonal overseas workers (Zahniser et al. 2018; Associated Press 2020; leg 2020; Chandler 2020).

The use of harvesting robots was sought to counter labour shortages and to provide an economically viable solution to rising labour costs, which have been actively developed over the past three decades (Bac et al. 2014b). The robotic harvesting systems analysed can be categorized into two groups: fully integrated systems, and subsystems used in harvesting such as vision (Tang et al. 2020a), gripper (Zhang et al. 2020a), and control (Zhao et al. 2016a). Since each of these subsystems is quite a broad research area by itself, this paper will be focused on reviewing integrated systems.

Existing review papers on integrated systems have collected and compared the harvesting robots in one or several specific perspectives. Li et al. (2011) examined mechanical harvesting systems as well as robotic harvesting applications before 2011 and discussed the machine vision approaches used in harvesting robots. Bac et al. (2014b) characterized the crop environment, summarized quantitative performance indicators for crop harvesting and conducted a thorough comparison on existing robots before 2014. In the last six years, Bachche (2015) emphasized analysing the design strategies behind various applications, Zhao (2016a) focused on vision control techniques and their potential applications in fruit or vegetable harvesting robots, Shamshiri (2018) and Fountas (2020) both collected and presented around twenty recent robotic harvesting applications as one section of their review paper on agricultural robots, and Jia (2020) and Zhang (2020) reviewed apple harvesting robots and harvest assist platforms.

There are two major gaps in which this work attempts to fill, regarding a state-of-the-art review of harvesting robots. Firstly, none of existing reviews in the past six years have compared the robot performance in recent applications to three key performance indicators that are critical for potential commercial viability: harvest success rate, cycle time, and damage rate. Only one review paper (Bac et al. 2014b) has covered performance indicators among 50 applications, but there was a lack of performance data to provide a conclusive comparison between harvesting robots at the time.

Secondly, there is a lack of systematic investigation on the underlying reasons for the inadequate performance of existing harvesting robots, relative to progress towards commercialisation. This paper will summarise all the challenges reported in recent literature and analyse the origin of these challenges from the point of view of both environment and requirements of fruit growers. With this investigation, a connected map of the challenges and corresponding research topics that link the environmental challenges of harvesting with customer requirements is identified for the first time.

To address the above gaps, this paper proposes a standardised framework to quantitatively compare state of the art robots in harvesting, and to gauge its commercial viability. This framework involves the following steps: (i) development of the review protocol regarding the inclusion and exclusion criteria; (ii) exploration and selection of related data; (iii) classification of selected data; (iv) analysis and interpretation of the selected data; and (v) reporting findings and results.

This review work will only include data and references related to fruit farming, applications that are closely related to integrated fruit harvesting robotic systems that underwent field tests and operations within the last 20 years (including the year of 2020). Studies focusing on only subsystems (vision, control, manipulator, path planning, and end-effector) of harvesting robot are not included in this work. In addition, integrated prototypes haven not been tested in the field (including open field and greenhouse) and fruit harvesting applications published before the year of 2000 are also excluded.

This paper is organised as follows: The Background section provides the definition of harvesting categories and production environments. The Recent developments section analyses 47 existing robotic harvesting applications and compares the applications based on system architecture, visual perception approaches, and fruit detachment methods. The System Analysis section presents systematic analysis on performance, system performance, and encountered challenges, The Potential Research Directions section clarifies and categorises future research directions based on the analysis conducted in previous section and, lastly, the Conclusion section summarises our analysis.

Background

Harvesting methods

Two types of harvesting approaches have been implemented by agricultural practitioners to reduce orchard overheads on labour expenses: selective harvesting and bulk harvesting.

Selective harvesting is a harvesting method for robotic systems utilising robotic manipulators with end-effectors for grasping. These are typically mounted on a mobile platform with end-effector and machine vision to selectively pick individual ripe fruit (Bac et al. 2014b). Since robotic systems may potentially

combine the efficiency of machines with the selectivity of humans on a long-term basis (Shewfelt et al. 2014), it is believed that the robotic harvesting approach has the potential to completely replace human pickers (Sanders 2005). Therefore, it has attracted extensive attention from both academia and industry and has emerged as the preferred method of robotic harvesting amongst fruit growers. The ongoing rapid development of artificial intelligence (AI) and robotics technologies is paving the last mile of commercial robotic harvesting, hence the focus of this review will be on robotic systems utilising selective harvesting.

The other method of harvesting is called the bulk harvesting method and is based on the principle of applying vibration to the fruit tree to force separate the fruit (Mehta et al. 2016). It has been adopted by growers of various fruits such as apples, oranges, cherries (De Kleine and Karkee 2015; Torregrosa et al. 2009; Zhou et al. 2016). Although mass harvesting systems come with high efficiency (Sola-Guirado et al. 2020), there are significant disadvantages. Growers have raised concerns over the excessive damage caused by the machines to both canopies and the fruit (Moseley et al. 2012). Since fruit damage affects its market acceptance, the research of reducing the bulk harvesting damage remains an active field (Wang et al. 2019; Pu et al. 2018). Another disadvantage of bulk harvesting is that the quality of picked fruits can vary considerately, where less mature fruits are inevitably harvested together with over mature fruits (Sanders 2005). Co-ordinating rates of maturity of fruit across an entire orchard is not a trivial task, and under a bulk harvesting scheme, the timing of harvest can depend on minimising losses due to harvesting immature and over-mature fruits.

Production environment & cultivar systems

Fruit plants can be grouped to trees, vines, and bushes or shrubs based on their growing habit. Trees and bushes can stand up on their own, while vines require physical support to attach themselves. Fruits that grow on vines and bushes tend to have pliable herbaceous stems which can be bent without breaking, like berries, kiwi, tomatoes, grapes, while fruits that grow on trees normally have hard woody stems that will break when bending, such as apples, pears, citrus, peaches, plums, and figs (FAO 1976). In production environments, two major groups are widely practiced: open field(orchards), and greenhouses. Typically, fruit trees are grown in orchards, fruit vines are planted in greenhouses, while fruit bushes and shrubs can be found in both open fields and greenhouses. Fruits grown in greenhouses are more consistent in colour, shape, position, and size, as the climate conditions can be controlled precisely (Bac et al. 2014b).

Cultivation systems also play a significant role in affecting the environmental complexity. Elements such as scaffolds and trellis introduce additional obstacles into harvesting tasks, but the elevation or support from these structures provide fruit with better lighting and ventilation (Van Dam et al. 2005) as well as consistent distribution. The accessibility and visibility of fruit can also be improved by practicing proper cultivation systems (Bac et al. 2014b). In this work, production environments with elevated or supported cultivation systems are labelled modified environments.

Recent Developments

Schertz and Brown (1968) proposed the idea of applying machines to perform citrus harvesting as early as the 1960s, with research and development on robotic harvesting gradually conducted (D'Esnon 1985; Kondo and Ting 1998). However, it was only until the recent two decades that fruit harvesting robotic applications have fully utilised the advances in machine vision, artificial intelligence, and robotics technology. This review covers 47 of the most recent or relevant applications on various fruit varieties that meet the criteria for analysis and comparison through the proposed standardised framework. The number of robotic harvesting systems by fruit variety is presented in Fig.1. Note that sweet peppers were included in this comparison, as they can be regarded as a fruit from a botanical perspective (Pennington and Fisher 2009) as well as their harvesting process being closer to a fruit than a vegetable. Images of different applications are shown in Fig.2, where different robot systems targeting the same fruits are arranged together and labelled, respectively.

Finally, Table 1 (see Appendix) presents detailed information about each application. To form a clear view of the major issues and challenges encountered in each project, the potential limitation of each system is summarised in the Issues to be improved column, as extracted from the Discussion or Conclusion sections in the publications reviewed, or the accessible comments on commercial websites.

System architecture

A harvesting robot is usually an integrated multi-disciplinary system which incorporates advanced features and functionalities from multiple fields, including sensing, perception, environment mapping and navigation, motion planning, and robotic manipulation. Thus, existing fruit harvesting robot generally consist of multiple sub-systems:

- a mobile base to carry the robot around the target,
- a machine vision system to detect and percept the environment,
- a control system to achieve overall control of the robot,
- a collector for storing the harvested fruits,
- one or several manipulators to approach the fruit while avoiding the obstacles, and
- one or several end-effectors to detach the target fruit from the plant.

Robots in (Bac et al. 2017; Bac et al. 2014a; Lehnert et al. 2016; Lehnert et al. 2017; Lehnert et al. 2020; Arad et al. 2020) have vertical lifting devices to extend the robot's workspace, while (Traptic 2020; FFRobotics 2019) have conveyors to prevent fruit damage in the process of collecting.

Vision systems

A functional robotic vision camera serves as the hardware interface for communication between the robotic harvesting system and the environment. The primary function of the vision system is to perform the fruit detection and localisation to achieve autonomous harvesting.

Sensors

To detect and localise the fruit, the images of the environment which record the information of targets and backgrounds are recorded and analysed, utilising either two-dimensional (2D) or three-dimensional (3D) imaging sensors.

2D imaging sensors record the two-dimensional information of the scene, typically in red, green, and blue colours (RGB), infrared (IR), spectral sensors, or a combination between any of them (Li et al. 2014). RGB cameras detect the target fruits from the background by extracting and analysing the fruit properties like colour, geometric shape, and texture by traditional machine learning methods or by using deep learning, which is known to be robust, accurate and efficient. However, RGB cameras are highly sensitive to illumination (Gongal et al. 2015) and detecting the target fruits that have similar colour with background is also challenging. Spectral sensors that provide spectral and spatial information, can be utilised to perform fruit detection based on the various reflectance at different wavelengths. Spectral imaging processing can potentially address the issue caused by the less distinct colour signature of target fruits and background, but the time-consuming data collection and image processing limits its practical application (Li et al. 2014). Thermal sensors record the temperature information of the objects and canopies, which can benefit the detection and segmentation of fruits from the less distinct background. This is because the fruits can absorb more heat and emit more heat compared to the canopies. However, its limitations are apparent when detecting fruits in shadowed areas located in the deep tree canopies. While 2D imaging sensors are low cost and easy to access, normally it alone cannot provide the accurate 3D spatial location of the target fruits in the work environment for robots utilising the selective harvesting method.

Several types of the 3D visual sensors exist on the market, such as stereo cameras, Light Detection and Ranging sensors (LiDAR) and RGB-D (RGB-depth) cameras (Jayakumari et al. 2021; Chen et al. 2021). The practical applications of these cameras are shown in Fig 3, with the maximum number of applications focused on the stereo cameras.

Stereo cameras take images using two or multiple RGB cameras separated by a fixed distance. The images are then fused, with depth calculated through triangulation (Gennery 1979). While effective, this sensor is slow due to the imaging fusing process and requires frequent calibration, which limits its real-time practicality. LiDAR is a remote range sensor that captures spatial information using pulsed laser reflections to generate a two or three-dimensional point cloud. These sensors are robust and generally perform well under strong natural light, but they cannot provide colour information that is critical for vision-based fruit detection. Although LiDARs can be combined with RGB cameras, data fusion can be slow and the high price of millimetre accurate LiDARs limits its wider application (Wolcott and Eustice 2017). RGB-D cameras are functionally identical to 2D RGB cameras, but can also process depth images simultaneously, offering a real-time stream of RGB images fused with depth information. These cameras use either time-of-flight (ToF) or structured light methods to calculate the depth distance. ToF sensors utilise an infrared light emitter, which emits pulses of light to measure distance to the target (Gongal et al. 2015). In the structure light technique, infrared light is emitted in a pattern, and depth information can be calculated based on the level of distortion of this light pattern when returning to the receiver (Gongal et al. 2015). Compared with stereo cameras, RGB-D cameras are far superior in the localisation accuracy, robustness, and computational efficiency, and are much cheaper than LiDAR sensors for the same accuracy, albeit with a smaller viewing range. These advantages of RGB-D camera over the others make it more suitable for the practical applications and it has been an essential component of vision systems in the agriculture applications (Fu et al. 2020).

All the visual sensors that were used in the reviewed projects have been listed in Fig 4 with its publication year. As observed, different 3D detection sensors can be combined for better accuracy such as Stereo and ToF. Also, RGB-D cameras (ToF and Strutured light) have become increasingly popular for practical applications.

Traditional machine learning methods

By working with the sensors mentioned in the previous section, traditional vision algorithms can extract and encode the features such as colour, geometric shape, texture. from the targets, then the machine-learning based classifier is applied to classify and recognise objects.

In a single feature-based fruit recognition system, colour remains one of the most explored features due to its proven accuracy and robustness in controlled environments (Tang et al. 2020). Arefi et al. (2011) processed colour information from RGB, HSI, and YIQ spaces to detect ripe tomatoes under greenhouse environments, and an accuracy of 96.36% on detection of the tomato was mentioned. However, most colour-based methods are suitable for specific fruit, with the colour space carefully selected to distinguish them from background. Its performance is limited when processing fruits with similar colour to the leaves under varying light conditions. Hence, this method is only feasible under regulated lighting conditions when the illuminations have less influence on their colours, due to its reliance on RGB cameras. To circumvent this issue, other features in the image can be utilised such as texture, light intensity, and edge detection to complement the RGB image. Kang et al. (2020) proposed an algorithm that applies the hierarchy multi-scale feature extraction of colour and shape features, then a K-mean was applied to achieve classification on extracted regions of interest. This is called a multiple feature-based detection system, in which multiple features are fused into a single data structure for object detection. The multiple feature-based method can enhance the detection performance in accuracy and robustness when handling uneven illumination conditions, partially occluded targets, and fruits with less distinct colour with background (Tang et al. 2020). Although multiple feature-based fruit recognition methods improve the performance, there is still a gap on the real-time detection performance such as computational efficiency, accuracy, and robustness to natural illumination that needs to be bridged to satisfy the requirements for autonomous fruit harvesting. Deep learning-based methods were developed as a proposed solution.

Deep learning methods

Deep learning methods based on the artificial neural network are widely explored. With multiple layer perceptron, deep learning methods can form more high-level attribute features (Tang et al. 2020). Both low level and high-level features can be analysed and utilised for final target detection. Among different types of deep learning, convolution neural network (CNN) is a supervised deep learning method that involves convolution and back-propagation to extract the features of the targets, which greatly improves the accuracy and generalisation of the recognition algorithm (Koirala et al. 2019).

Depth images that are acquired by an RGB-D camera can be used for fruit detection. Gene-Mola et al. (2019) utilised the depth images taken from Kinect v2 to detect apples using Faster R-CNN with VGG16, which has an average precision of 0.613. This is because the depth images are more sensitive to the ambient conditions compared with the RGB images. Kang et al. (2020) applied a redesigned one-stage detection network for RGB images based on YOLO-V3, to perform object detection in apple orchards, and an F1-score of 0.83 was achieved. Liu et al. (2020) processed the row RGB images taken from Kinect v2 as the input to the two-stage detection network, faster R-CNN with VGG16 to detect kiwifruits, and an F1-score of 0.884 was achieved. The fruit detection with RGB images can be affected by variation in the ambient lighting, level of maturity, and uncertain background features. Instead, researchers utilised infrared images taken from Kinect v2 to detect kiwifruit with the faster R-CNN with VGG16, and it achieved an average precision of 0.892. Researchers have been working to use multi-modality sensors and multi-images to detect fruit under complex orchard environments. RGB and infrared images were combined to detect sweet pepper through Kinect v2 and achieved an improvement of 4.1% on F1-score compared with single image detection algorithm (Sa et al. 2016). RGB and depth images were combined to detect kiwifruit, and a 3% higher detection rate was recorded. Although the deep learning method can be applied on various types of raw data such as depth images, RGB images, infrared images, or different combinations of these can achieve high detection accuracy, the training of the algorithm requires long time as well as large number of raw images labelling.

Fruit detachment methods

Fruit detaching methods have a direct effect on fruit damage rate, harvest success rate, and cycle time. Various detaching approaches have been demonstrated in all applications analysed in this paper, but to get a clear view of the status of robotic fruit handling techniques in the harvesting process, each method of fruit detaching and pericarp handling should be analysed in detail.

Many fruit detaching methods rely on stem detachment from the branch by exerting external force directly or indirectly on the stems, which can be categorised into five groups based on force application: stem cut, stem pull, fruit twist, fruit pull, and vacuum. Stem cut and stem pull methods apply their respective actions to the fruit while holding the stem, fruit twist and fruit pull applies their respective actions to the fruit, and vacuum methods create a suction force to extract the fruit without direct contact with either the stem or fruit. Fig. 5-a shows the stem cut and fruit twist tend to be two major detaching methods, with corresponding average harvest success rates presented in Fig. 5-b, where applications applied fruit twisting and stem cut recorded 75% and 65% average harvest rate respectively. Among the four systems adopted where stem pull is the detachment method, only two systems reported a 90% average harvest success rate. However, because the data sample is small, it is premature to claim that any detachment method is superior to another, especially due to the sparsity of the fruit damage data that is currently provided in literature (only 13 of the 47 systems had their damage rate specified in their works).

Fruit handling methods were also analysed, with 27 of the 47 applications applying various forms of external force on the fruit. These are shown in Fig. 5-c, where external forces include clamping, grasping, suctioning or a combination of suction and grasping. As observed, grasping is the preferred method for pericarp contact in fruit handling. There are 20 systems that were published with no pericarp contact during the entire harvesting process. Contactless handling is advantageous as it minimises fruit damage rate and is mostly used in harvesting fruits with high fragility such as strawberries and tomatoes. Fig. 6 shows a detailed breakdown of detachment methods per fruit, and vice versa. From observation, we can see that fruits with relatively fragile skin or pericarp are more likely to be detached via stem cutting, while fruit twisting can be applied on both fragile fruits like strawberries and relatively tough fruits like apples.

Fruit occlusions and obstacles

The occlusion of fruit from leaves, stems, and other obstacles presents a challenge to harvesting robots in grasping and path planning (Yamamoto et al. 2014). To simplify the problem, many published works require modification or simplification of the environment, such as applying proper supports to the plant for better lighting (Van Dam et al. 2005) as well as better accessibility and visibility for robotic systems. Only 8 of the applications claimed that their robot is applied in unmodified environments. For soft-obstacle occlusions such as leaves and stems, several approaches to temporarily move them aside have been demonstrated, such as using mechanical means to gather up leaves so that the target fruit can be fully exposed to the camera (Harvest CROO Robotics 2020), or utilising dual-arm cooperation to imitate human movements of pushing leaves to the side (Gesellschaft 2018).

For non-compliant obstacles such as branches and trellis, or complex structures in general, a multiple DOF manipulator with a properly designed path planning algorithm is usually implemented to avoid obstacles. The number of DoF implemented amongst researchers varies, including six (Kang et al. 2020b; Lehnert et al. 2017; Arad et al. 2020; Almendral et al.), seven (Baeten et al. 2008; Mehta and Burks 2014) and nine (Bac et al. 2017; Nguyen et al. 2013). However, it is observed that a high DoF manipulator tends to increase the system complexity and thus may lead to lower picking efficiency. For example, Kang's 6 DOF manipulator reported a 6.5 s cycle time (Kang et al. 2020b), while both Abundant Robotics' and FFRobotics' low DoF straight line approach manipulator achieved less than 2s cycle time (Courtney and Mullinax 2019). This approach resorts to using vision algorithms to filter out difficult-to-reach fruits, and those not filtered are assumed to be graspable using the straight-line path. Such methods have been applied to harvesting tomatoes (ROOT AI 2020), apples (Wheat 2019), and oranges (Harrell et al. 1990; Energid 2012).

The final mode of occlusion via fruit clustering is a significant challenge for harvesting robots in which no reliable solution to the problem has been found to date. Many researchers have tried various methods to separate the clustering of ripe and unripe fruits, which is commonly seen in strawberry harvesting. Methods such as applying compressed air to blow adjacent fruits away (Yamamoto et al. 2014), or the use of active obstacle-separation algorithms to isolate fruits (Xiong et al. 2019a) presented only a 50-75% harvest success rate. This rate worsens to just 5% if the target fruit is completely occluded by unripe fruit.

Systems Analysis

To evaluate the performance of the selected fruit harvesting robots in Table 1, three general performance indicators (Bac et al. 2014b) are adopted to make the below comparison.

- *Harvest success rate* quantifies the number of successfully harvested ripe fruits per total number of ripe fruits in the canopy. It should be noted that successfully harvested fruits may also include damaged fruits.
- *Cycle time* measures the average time of a full harvest operation cycle, including recognition, localisation, path planning, grasping, collection, and movement between fruit. Time lost due to failed attempts, where reported is included in the cycle time.
- *Fruit damage rate* indicates the number of damaged fruits. This includes peduncle damages per total number of localised ripe fruit.

Note that these performance indicators are not crop-independent, due to the large variation of geometrical fruit distribution and leaves and branch density among different crops or among different cultivars of one crop. For example, the crop distribution of different cultivars of sweet peppers can vary significantly (Bac et al. 2014b), which alters the cycle time for different cultivars for the same robot, making comparisons difficult to quantify. Similar concerns may also apply to some other performance indicators like harvest success rate and damage rate. A normalising factor can be introduced for each indicator to make the performance data comparable among different robots or crop cultivars, but this requires significant data collection and analysis to achieve a fair normalisation factor. Data of this magnitude is not available at this time, hence the performance indicators used in this comparison are not normalised. However, by focusing the comparison of each robotic system through its fruit application, it can provide an overall picture of the current state of harvesting robots.

Harvest success rate

28 out of the 47 applications have their harvest success rate documented. As shown in Fig. 7, although none of the existing robots have achieved a 100% harvest rate in apple, tomato and cucumber harvesting, significant progress has been made in harvesting rates with multiple prototypes and products recording higher than an 80% harvest success rate. Reported success rates for strawberry and sweet pepper harvesting are relatively low, citing environment complexity as a possible reason with a harvest success rate significantly increasing after environment simplification.

Cycle time and overall speed

Cycle time refers to the speed of harvesting for a single robotic arm, with a comparison of systems in different fruit harvesting applications shown in Fig. 8. For each fruit, the advised cycle time for commercial viability is indicated by the area within the dotted rectangular region on each graph (Van Henten et al. 2009; Nguyen et al. 2014; Panasonic 2018; Hemming et al. 2014; Harrell 1987; Muscato et al. 2005; William et al. 2019; Tang et al. 2020). Among the analysed systems with cycle time reported, most applications cannot compete with human counterparts except for three systems by Octinion company (2020), HarvestCROO Robotics (2020), and Abundant Robotics (Courtney and Mullinax 2019).

Although cycle time provides a good metric for commercial viability, it alone alone cannot determine a system's commercial viability. Other factors like harvest success rate, fruit damage rate, robot costs and potential continuous operational time are equally important for commercial feasibility. In addition, different researchers may have different definitions of cycle time, achieving faster times when excluding fruit recognition time (Silwal et al. 2017) or fruit-to-fruit traversal time (Lehnert et al. 2017; Muscato et al. 2005), or slower times with the inclusion of mobile base traversal time (Williams et al. 2019). To indicate these alternate definitions, ++ or – marks are included in the comparison charts to indicate a shorter or longer than standard cycle time definition for a particular application.

Researchers and developers have also implemented multiple arms in a single robotic system as well as robot fleet concepts to further enhance cycle time and productivity. Xiong reduced the cycle time of their robot from 6.1s to 4.6 seconds per fruit when switching from single to dual arms (Xiong et al. 2019a). Agrobot (2020) and Advanced Farm (2020) mounted many independent picking systems on a single mobile base, and Harvest CROO's strawberry harvesting system equipped with 16 robotic heads and 16 arm-camera-gripper sets is able to pick 3 fruits every 10 seconds (Harvest CROO 2020). FFRobotics claimed that their 12-arms apple harvester can pick 10 times faster than human labours (FFRobotics 2019).

Damage rate

Ideally, fruit harvesting robots are expected to preserve the quality of the fruit during the picking cycle. This is very difficult for robots, as there are many opportunities to damage fruit when implementing pinching, clamping, or grasping actions with pulling, bending, and twisting motions (Bu et al. 2020).

Only 13 of the 47 reviewed applications had their damage rate reported. As shown in Fig. 9, 8 of the 13 applications presented a damage rate higher than or equal to 10%, and 5 claimed a damage rate equal to or lower than 5%. Only one system has verified its 5% damage rate with extensive field test data with 240 samples (Mu et al. 2020), while the rest have not made their field test data public.

Of the systems that report fruit damage, most focus on skin or flesh damage, which has the highest influence on fruit marketability. However, other forms of damage such as broken or removed stems can also affect its shelf life, respectively, as seen in apples, pears, cherries, and some types of plums (Paltrinieri 2002). Baeten et al (2008), no reported skin damage on apples harvested, but approximately 30% of them had stems removed.

Another form of damage a harvesting robot can inflict on are the trees and canopies that the fruit are attached to. Spur damage occurs when a fruit is extracted along with the branch or green matter it is attached to. If this contains a spur or bud, then this part of the tree will no longer yield any fruit, affecting the next season's harvest. Only one robot has recorded spur damage, recording 6.3% skin damage and 26% spur damage on harvested fruit (Silwal et al.

2017). Furthermore, tree damage can also come in the form of accidental contact with fruit during harvesting. This is particularly problematic if unripe fruits are damaged or knocked off the canopy, as it means the fruit cannot grow further and is permanently lost. Again, only one system has reported this kind of damage, where the reported 25% overall damage rate consisted of 15.3% drop rate and 6.7% knock off rate (Williams et al. 2019).

Relation between robot performance and commercial viability

The potential for commercialisation of a proposed harvesting robot is frequently mentioned in reported literature (Tibbets 2018; Williams et al. 2019; Nguyen et al. 2013; Hemming et al. 2014; Muscato et al. 2005; Van Henten et al. 2009). Although different thresholds for commercial viability have been cited, neither harvest success rate nor an outstanding cycle time by itself could secure the commercial success of a harvesting robot if the damage rate is unacceptably high. Hence, it is important to understand the determining criteria for the commercial viability of harvesting robots.

Economic factors should be considered, primarily cost and profit. If a robotic system can achieve comparable harvest success rate and damage rate as a human picker, then the threshold for commercial viability can be assessed by two the robot's annual cost and its efficiency. The overall annual cost of robots should be no higher than the yearly cost of human labour when picking the same amount of fruits, and the robot's daily picking amount should be no lower than a human counterpart. Alternatively, if a robot cannot compete with human labourers on either harvest success rate or damage rate, the harvest task could be shared by the robot and human pickers. In this case the annual profit of the farm after adopting the system should be equal or higher than the original annual profit. With such criteria, the relationship between a harvesting robot's performance and its commercial viability can be formulated. The effect of each performance indicator (harvest success rate, damage rate, cycle time) on the commercial viability can then be accurately assessed.

Synopsis of current research challenges in robotic harvesting

Significant efforts have been made to apply robots in fruit harvesting tasks in the past two decades, but very few of them have been proven reliable for commercial operation. In most cases, existing harvesting robots do not meet the requirements of low damage, high harvest rate and fast speed at the same time. Thus, most farms are still relying on human labours to perform harvesting tasks (Zhao et al. 2016a).

To gain a direct impression of the challenges and issues encountered in robotic harvesting development, we have compiled all data extracted from the 'issues to be improved' column of Table 1, and represented in Fig. 10. The reported challenges and issues have been categorised into four groups: environment control, system challenges, path planning, end-effector, and sensing challenges. The number reported to the right of each bar indicates the occurrences that the item has been cited as a challenge for their robot, and items marked with blue bars represent challenges and issues reported in less than 4 applications. From the chart, we observe that efficiency tends to be the most reported issue that needs improving in further development of the fruit harvesting robot, while end-effector adaptability, obstacle detection and handling, vision detection under occlusion, stem detection and fruit cluster handling can also be regarded as common challenges in the field.

Since this summary and statistical analysis is based on the information reported by literature, it is possible that some research challenges are underestimated or missed. Therefore, to develop a better understanding of the challenges and potential research directions of robotic fruit harvesting, a systematic review is conducted based on environmental challenges in harvesting versus customer requirements. Figure 11 shows a map diagram that links observed environmental complexities in harvesting to the left (marked in green), to meeting customer requirements on the right through a series of research challenges (marked in red) and associated potential research directions (marked in sky blue) which go to solve any of the four critical items linked to meeting customer requirements. Therefore, all issues and challenges discussed in the literature can be matched with its origin in the environment input and connected with potential research directions, which could eventually meet customer's demand. More critically, new insights for potential research topics (items in sky blue marked *) are formed in the process of completing this map diagram, which are topics that can drive harvesting robots further towards commercialisation.

Potential Research Directions

Based on our analysis on all robot applications of fruit harvesting which are suitable for our framework, we have identified the following frontier topics that can be significant drivers for harvesting robot commercialisation.

Occlusion mitigation

Occlusion is identified as one of the most significant issues of robotic harvesting, as it affects recognition and localisation accuracy of harvesting robots (Tang et al. 2020). Decreased recognition accuracy will result in lower harvest success rates and higher damage rates. Therefore, measures should be taken to mitigate occlusion from different aspects.

Cultivar training

Fruit trees are grown in a variety of shapes, but natural field-grown plants tend to be more unstructured than trained plants in a greenhouse or orchard in terms of size, foliage volume, and limb pattern (Fernández 2018). Before the emergence of harvesting robots in recent years, fruit growers had already started applying manipulation of the tree form or shape with the purpose of encouraging fruit production (Costes et al. 2010). For example, apple trees were pruned into a planar canopy to simplify manual or mechanised harvesting by providing better fruit accessibility (Nguyen et al. 2013). However, this practice also encouraged uniformity in fruit size, colour, and maturity (Hohimer et al. 2019). In 2019, apple growers in the US have presented their willingness to remove fruits adjacent to trellis wires and trunks to optimize fruit distribution for robot harvesting (Hohimer et al. 2019). There is also a recent push to build indoor farming systems, where compared with outdoor farming, indoor farms require much less space whilst securing much higher yields. For example, indoor tomato farms can have a yield ten times greater than outdoor farms (Shieber 2018). These significant advantages will lead to higher motivation of crop

growers to make the change, which will benefit robotic harvesting as indoor farms could be designed with trained cultivar systems best suit harvesting robots (Bac et al. 2014b). Thus, environment complexity could be significantly reduced in the future.

In the state-of-the-art, nearly all the harvesting robot systems that claimed to be commercial are designed exclusively for customised cultivation systems. In this case, trees and plants have been specifically trained to be well structured, providing the robot with a workspace of occlusion and obstacles. Further improvements to the workspace can be achieved by pruning, reducing occlusion further (Van Henten et al. 2002) and reducing cycle times (Edan et al. 1990).

Fruit and leaf thinning

Occlusion mitigation can be implemented by fruit and leaf thinning. Such operations are currently conducted mostly by human labour but will be gradually assisted by robots (Priva 2020).

Fruit thinning of annual bearing cultivars is widely practiced by growers to improve fruit size and quality (Dennis 2000). For robotic harvesting, fruit thinning can be implemented to avoid fruit clusters, as overlapping fruit pose a challenge on localisation of individual fruits (Jiao et al. 2020) while clustered fruit make the task of detachment significantly complicated (Bac et al. 2014b).

Leaf thinning or leaf removal through manual or mechanical means has been a common practice in modern viticulture to increase ventilation and sunlight exposure and thus improve fruit quality and production (Zhuang et al. 2014; Bogicevic 2015). Researchers have explored mechanical approaches to clear leaves temporarily for fruit extraction (Lee and Rosa 2006), However, As the soft robotic gripper becomes significantly popular for autonomous grasping application(Crooks et al. 2016; Wang et al. 2020), Zhou in (Kang et al. 2020a) developed an adaptive gripper that can reach through the canopy through the canopy and pushing away the leaves around the target fruit without damaging the canopy structure.

Fruit damage prevention

Mechanical damage during harvesting tends to result in substantial reduction of fruit quality (Li and Thomas 2014). Mechanical abrasions and bruising on fruit can accelerate water loss, increasing the chance of rotting fungi and bacteria to penetrate the fruit and causing rapid decay (Trimble 2021). Therefore, harvesting robot researchers should explore all possible measures to minimise fruit damage. Most existing studies only focused on avoiding mechanical bruises of target fruit, but damage could also occur to adjacent fruits due to direct robot contact or the unexpected detachment triggered by unintentional branch oscillation. Thus, the following points aim to reduce or prevent fruit damage.

Preserving target fruit

Target fruit can sometimes be surrounded by incompliant obstacles such as thick branches, trellis wires and sprinkler lines. Existing harvesting robots have difficulty picking these fruits without causing unexpected damage due to limited obstacle-sensing capabilities, difficulty locating and segmenting objects in unstructured areas, and lack of dexterity of robotic arm and end-effector. There are two potential methods of reducing fruit damage in these instances - handling or avoiding these scenarios effectively through sensors and software, or modifying the robot's hardware to reduce or eliminate fruit damage altogether.

In unstructured environments, machine vision is not effective due to the existence of leaves and other obstacles leading to partial or full occlusion. Additional sensing technologies such as tactile sensing can provide an alternative sense to assist the robot in planning. This can be effective in handling branch interference or collisions with trellis wires and other fruit.

The robot's gripper can also be modified to minimise the chance of damaging fruit. Applying soft material to the end effector surface minimises damage caused by direct contact between fruit and end-effector components (Komarnicki et al. 2017). However, the grasping of foreign objects such as branches can also damage fruit, regardless of the compliance of the gripper. To the knowledge of the authors, no solution to this problem has yet been found.

Preserving adjacent fruit

A frequently observed yet rarely mentioned form of fruit damage occurs during the grasping phase, where adjacent fruits are disturbed, this can potentially damage them in two ways - direct contact damage or indirect damage, causing the fruit to detach unintentionally. Precise environment modelling, robust path planning, and appropriate end-effector footprint optimisation can address these issues. Particular focus can be given to path optimisation in detaching fruit, as it is shown to be very effective in reducing fruit damage of this form (Nguyen 2012).

Sensing enhancement

Detection of fruits with similar colour to background

Most existing fruit recognition methods distinguish fruit from leaves and branches by analysing colour difference. However, this method is challenging in low lighting or low contrast environments (Kelso 2009), especially for fruits with less distinct colour from the background.

For the fruits with different colour with leaves, once they are exposed to low lighting or contrast environment, several measures can be taken to control the lighting condition for imaging in the orchard. Nighttime artificial lighting can be one effective solution as the illumination can be controlled from the lighting source. However, this will limit the operation time of the fruit picking robot. Gongal et al. (2015) reported the use of an over-the-row platform with the special tunul structure to control the lighting conditions. The way of controlling the lighting condition can be one potential solution as it can effectively control the lighting condition and guarantee the robot work in day and night.

For the fruits with similar colour compared with the background, spectral imaging can be used to improve recognition rates (Mao et al. 2020; Fernández et al. 2018; Li et al. 2017; Bao et al. 2016) to above 80% in most cases (Van Henten et al. 2002). The development of faster spectral imaging processing algorithms will save time and increase the feasibility of spectral imaging methods.

Researchers have also utilised morphology or texture features to distinguish the fruit from background with low contrast. Fruit recognition algorithms that utilised the shape features are universal for detecting the sphere fruit such as apples, tomatoes, and citrus (Zhao et al. 2016). The images taken in a natural outdoor environment have texture differences that can be utilised to distinguish fruit from its background. By using texture features and checking the intensity level of illumination distributed on the surface of the citrus and background objects, immature citrus fruits can be recognised. However, this method is highly affected by intense light. To improve reliability under all lighting conditions, some researchers used multiple features such as colour, morphology, and texture with data fusion approaches. This was applied successfully in reliable apple recognition (Rakun et al. 2011). Overall, utilising deep learning-based methods with multi-model sensors showed promising results and performance in fruit detection.

Exogenous disturbances

Exogenous disturbances of trees and canopies include lighting variation, wind, rain, and unintentional robot-plant contact. For the lighting variation, except for controlling the light condition of the environment, image quality enhancing can also be utilized like adjusting the intrinsic parameters for the cameras such as exposure, contrast. The imaging quality can be enhanced for better detection performance. Some of these disturbances can change the original pose of the fruit, which can reduce the accuracy of grasping if the positions of the fruit are not updated accordingly. To handle these disturbances, a combination resilient end-effector design, efficient vision servo and robust control technology should be implemented. From the vision aspect, a high frequency of detecting process can be implemented to refresh the detecting result to get real-time fruit distribution.

Ripeness and defect detection

In traditional agricultural practice, determining the proper harvest maturity of fruit largely relies on farmers' experience, as maturity dates of fruits grown on the same tree may vary at weekly intervals for a month or more (Paltrinieri 2002). Therefore, it is necessary to detect fruit ripeness when harvesting to maximise yield. The challenge in monitoring the ripeness of fruit for consumers lies in finding solutions that can provide non-destructive testing at minimal cost. The use of penetrometers and refractometers are two methods that are destructive to the fruit, either by breaking the skin (to measure sugar content) or causing bruising (to quantify firmness) (Torregrosa et al. 2009). Non-destructive methods such as the imaging, spectroscopy, and hyperspectral imaging are preferred, as they do not require physical contact with the fruit. Spectrometer-based approach splits light signals into a fruit and then measures the light that is emitted, absorbed, or scattered by the fruit for ripeness inference (Torregrosa et al. 2009). However, for both techniques based on colour imaging and spectroscopy are substantially determined by the occlusion and lighting conditions (Tan et al. 2018).

Tactile sensing can be an alternative solution for real time fruit ripeness detection, which has recently been applied to mangoes with an 88% accuracy in the lab (Scimeca et al. 2019).

Stem retention and stem length control

Proper handling methods during harvesting and post-harvest processes are critical for extending the shelf life of fruit (Shewfelt et al. 2014). For fruit varieties like apples, mangoes, citrus, and avocados, a pulled-out stem may act as an ideal entrance for fungi and bacteria to break into the fruit and lead to a rapid decay (Paltrinieri 2002). However very few applications in the literature have reliably solved the stem retention problem, due to the unpredictability of fruit growth orientation (Silwal et al. 2017). In addition to stem retention, stem length for specific fruit varieties is also important for extending shelf life, such as for mangoes (1.5 cm) and avocados (1 cm) (Paltrinieri 2002). For post-harvest handling of premium apple varieties with soft skins such as Honeycrisp and Fuji, stems must be clipped to avoid puncturing when stacking for storing (Hohimer et al. 2019). To address these challenges, further development of visual stem detection and tactile sensing are proposed (Gesellschaft 2018).

Optimising fruit detaching methods

Different fruits have different optimal detachment methods that consume least energy harvesting and produce minimal damage to the fruit, according to a report released by the Food and Agriculture Organization of The United Nations. For example, a *lift, twist and pull* series of movements are believed as the best picking method for tomatoes and passion fruit, as they grow a pedicel abscission zone (natural breakpoint) to shed ripe fruits naturally (Ito and Nakano 2015). While for fruits like apple, citrus, mango, and avocado which have woody stalks, the best way to remove them from the tree is to clip them, such that there remains a small section of stem attached to the fruit (Paltrinieri 2002).

Although these detachment methods have been proven and practiced by human workers all over the world, they are rarely implemented by robots on fruits like apples and oranges due to the difficulty of accurately detecting stems and stalks in a dense canopy (Silwal et al. 2017). Before a reliable stem detection technology is available, efforts to explore suboptimal detachment methods could also improve the efficiency of harvesting robots. Experimental investigation on apple picking patterns (Li et al. 2016) and tomato grasp types (Li et al. 2019) are good examples.

Other potential directions

Multiple end-effectors and swarms

Applying multiple end-effectors can significantly increase the harvest efficiency for individual robots, making it possible for robots to surpass human picking speed (Zhao et al. 2016a). FF Robotics has demonstrated that 12 arms can work simultaneously to pick apples with a productivity ten times higher than human pickers (Courtney and Mullinax 2019). Xiong has reduced the cycle time of strawberry harvesting from 6.1s to 4.6s by integrating two Cartesian arms

into their system (Xiong et al. 2019a). Swarms of harvesting robots can also work together to boost productivity by utilising rapid developing deep learning algorithms to enable training of interactive behaviour, such that the performance of robot swarms can be further enhanced with time (Shamshiri 2018).

Human - robot collaborative approaches

Before harvesting robots have developed sufficient intelligence to be able to perform fully autonomous harvesting tasks without human intervention or supervision, human-robot collaborative approaches can be an alternative research direction to be explored to bypass the technology bottleneck. Shamshiri illustrated a scenario of human-robot collaboration before robots can achieve a 100% harvest rate, where any remaining fruit missed by robot vision could be picked with humans intervening via a touchscreen interface (Shamshiri 2018).

Alternative technologies for versatile cross crop harvesting

Alternative solutions such as fruit picking drones (Tevel Aerobotics 2020; Saracco 2020), climbing robots (Megalingam et al. 2020), and continuum robots (Gao et al. 2021) have been demonstrated, but highlight the ingenuity of researchers and how one should not constrain harvesting robots to simply robotic arms on mobile bases. They also show how different types of robots and technologies can work for various crops.

Most crops share a similar harvesting process. Therefore, robots also tend to have similar capabilities, such as object detection, motion planning, target approaching and crop detaching with similar hardware. Only the task of crop detaching may require different end-effectors for different crops, which is a quick operation, therefore one specific robot can operate with multiple end-effectors and software packages to harvest multiple crops with similar growing environments. Cross crop harvesting has been attempted and demonstrated in tomato, strawberry, cucumber (ROOT AI 2020), oranges, apples (Barber 2020), melons, and peppers (Heater 2020). Furthermore, by extending crop detection technology to detect other objects like branches, stems, flowers or even trellis support wires, together with applying specialized end-effectors, current harvesting robots can be adapted to other agricultural tasks such as pruning, thinning, pollination, de-leafing (MetoMotion 2020; Wheat 2019).

Conclusion

We have conducted a comprehensive review of the state of the art of fruit harvesting robots, including the analysis and comparison of the 47 applications over the last 20 years, where the overall performance of each system and observed research trends have been presented. The performance indicators chosen for comparison are harvest success rate, harvesting speed, and damage rate, which are important performance indicators for a robot's commercial viability.

A close scrutinisation of the origin of the fruit damage in the robotic harvesting process has been performed. Although direct damage of harvested fruit is often the focus in existing literature, the indirect damage of the adjacent fruits is often overlooked. This paper analyses the potential source of indirect fruit damage, and potential prevention measures are proposed.

We conducted a systematic examination of the reasons behind the inadequate performance of existing harvesting robots. From this, a connected map of the challenges and corresponding research topics that link the environmental challenges of harvesting with customer requirements has been summarized for the first time in the literature. This map provided new insights to potential high-yield research directions, including vision systems to better identify obstacles and identify fruits with occlusions, fruit extraction optimisation to reduce stem and tree damage, and tactile sensing for stem and ripeness detection. These directions will help drive potential robotic harvesting systems closer towards commercialisation, and help solve the socio-economic problems that farmers face with seasonal fruit harvesting.

Declarations

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Conflicts of interest/Competing interests

The authors declare that they have no conflict of interest.

Availability of data and material

As per the regulations of our institute, we can share the data acquired in this research upon individual request until December 2021.

Code availability Not applicable

Authors' contributions

Mr. Hongyu Zhou contributed to collect and analyze the data of the existing applications and compete the major part of the writing, Mr. Xing Wang and Dr. Hanwen Kang contributed to the review of vision system, Mr. Xing Wang also contributed to the organisation and writing of future research directions of vision technology, Dr. Wesley Au contributed to the system analysis, data organisation and writing, Dr. Chao Chen provided significant contributions to this review as the lead.

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Figures

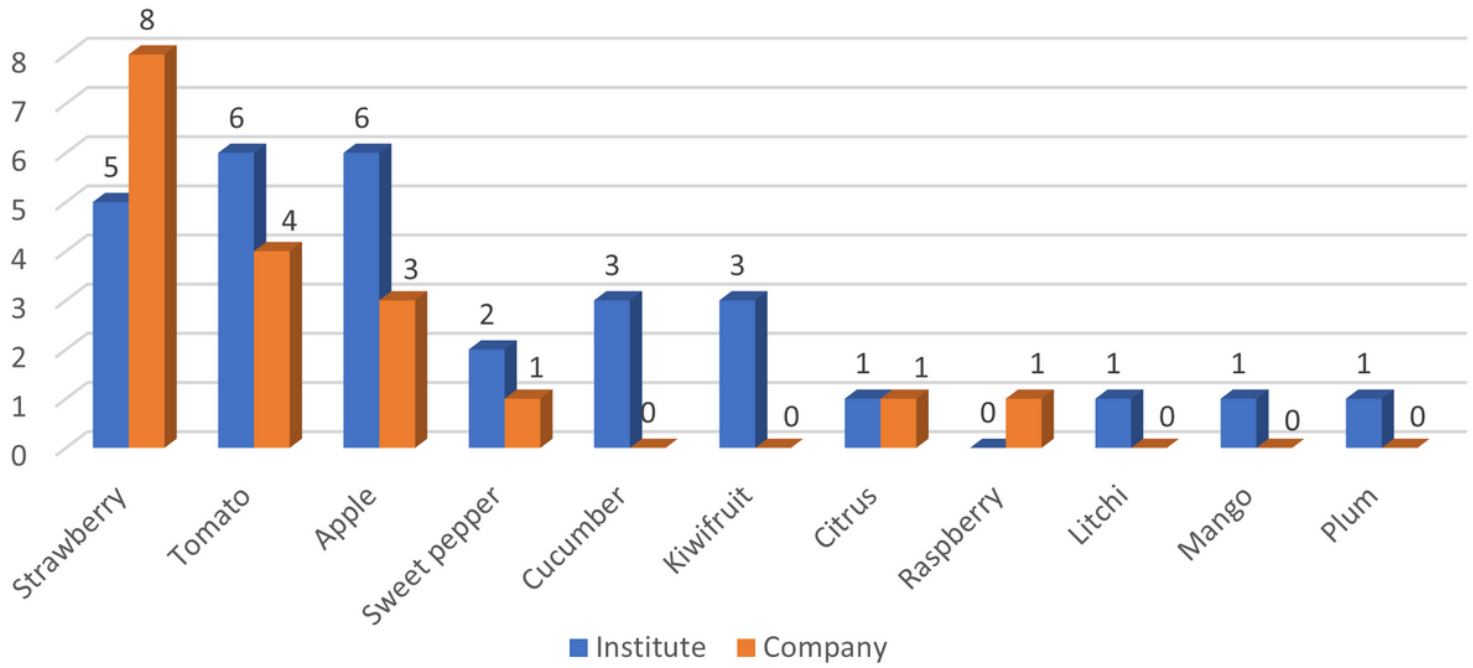


Figure 1

Number of robotic fruit harvesting systems by variety

Figure 2

Robotic harvesting applications sb-1. Feng,2012 sb-2. Hayashi, 2010 sb-3. Shibuya Seiki sb-4. DogTooth sb-5. Agrobot sb-6. Xiong 2019 sb-7. Tortuga sb-8. Traptic sb-9. Harvest CROO Sb-10. Octinion sb-11. Yamamoto,2014 sb-12. Advanced Farm tm-1. Kondo,2010 tm-2. Yaguchi, 2016 tm-3. Zhao,2016 tm-4. Wang, 2017 tm-5. Feng, 2018 tm-6. Panasonic tm-7. MetoMotion tm-8. Botian tm-9. ROOT AI ap-1. Abundant Robotics ap-2. FFRobotics ap-3. Ripe Robotics ap-4. Siwal, 2017 ap-5. Kang, 2020 ap-6. Baeten, 2008 ap-7. Zhao, 2011 ap-8. Nguyen, 2013 sp-1. Bac, 2017 sp-2. Lehnert, 2016 sp-3. SWEEPER kw-1. Scarfe, 2012 kw-2. Williams, 2019 kw-3. Mu, 2020 cc-1. Ven Henten 2002 cc-2. Ji, 2011 cc-3. IPK, 2018 ct-1. Muscato, 2005 ct-2. ENERGID, 2012 rb. Fieldwork Robotics lc. Xiong, 2018 pl. Brown, 2020 mg. Walsh, 2019. In Fig.2, “st”, “tm”, “ap”, “sp”, “cc”, “kw”, “ct”, “rb”, “lc”, “mg”, “pl” represent strawberry, tomato, apple, sweet pepper, cucumber, kiwifruit, citrus, raspberry, litchi, mango, and plum, respectively.

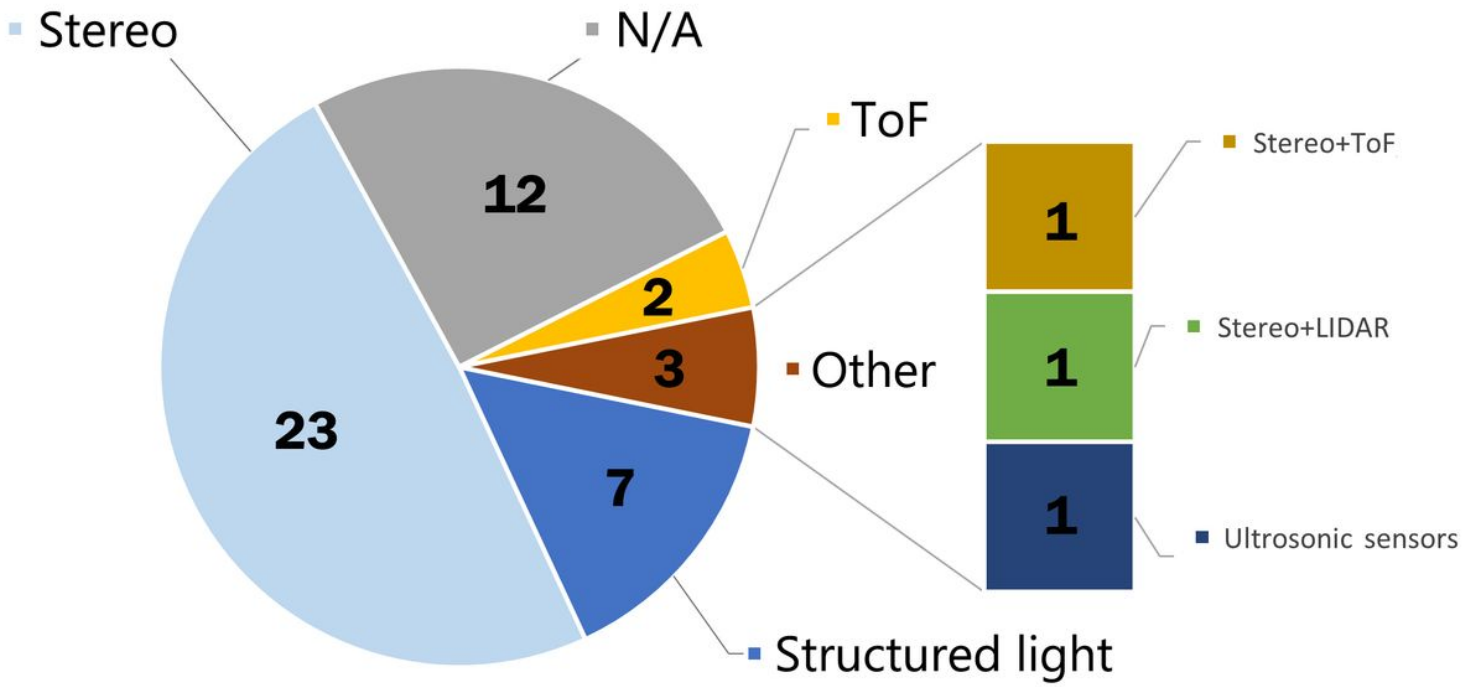


Figure 3

3D imaging techniques statistics

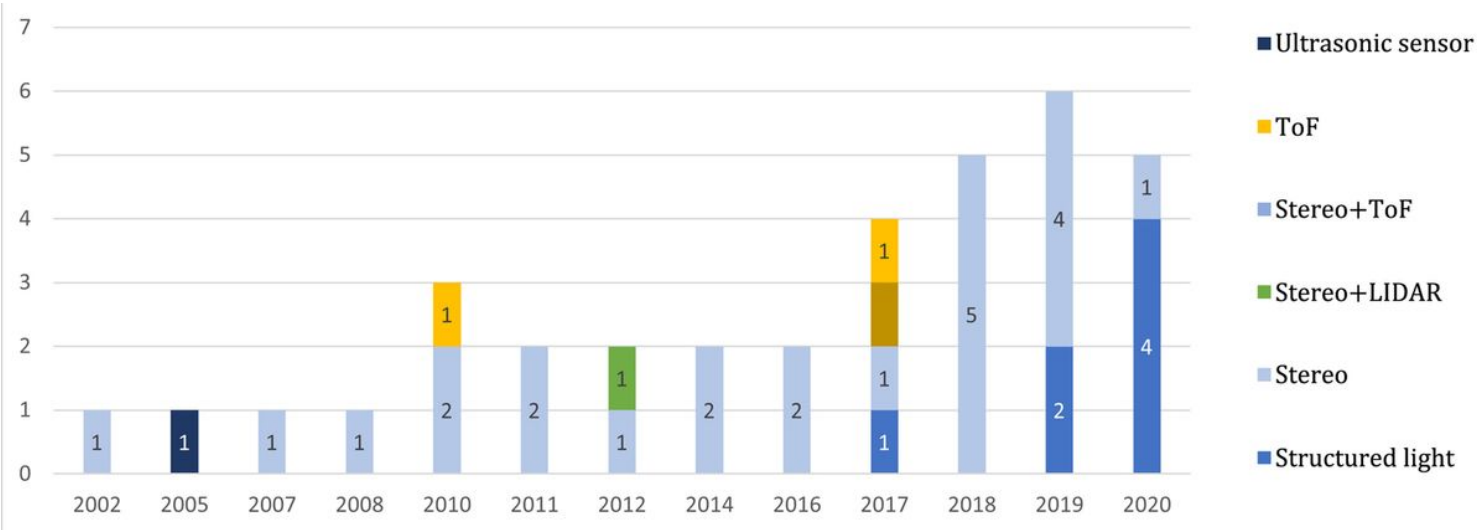
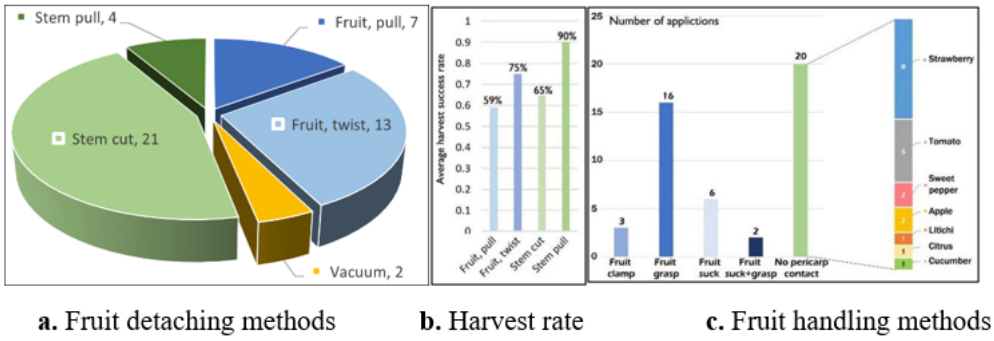


Figure 4

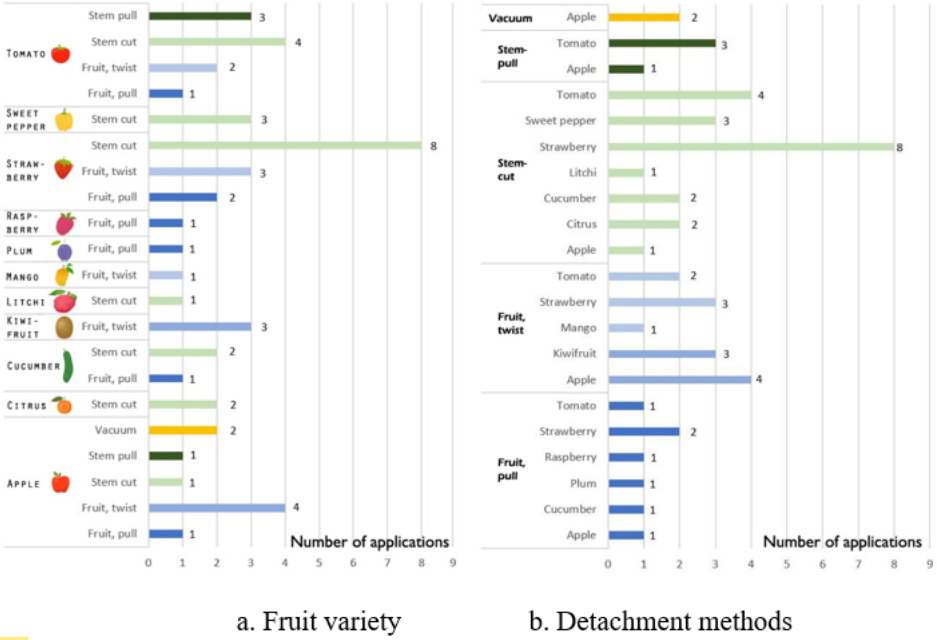
Visual sensors adopted each project published per year



a. Fruit detaching methods **b.** Harvest rate **c.** Fruit handling methods

Figure 5

Statistics of fruit detachment approaches



a. Fruit variety b. Detachment methods

Figure 6

Detachment methods utilised, where (a) is grouped by fruit variety and (b) is grouped by detachment method.

Figure 7

Harvest success rate by fruit and research group

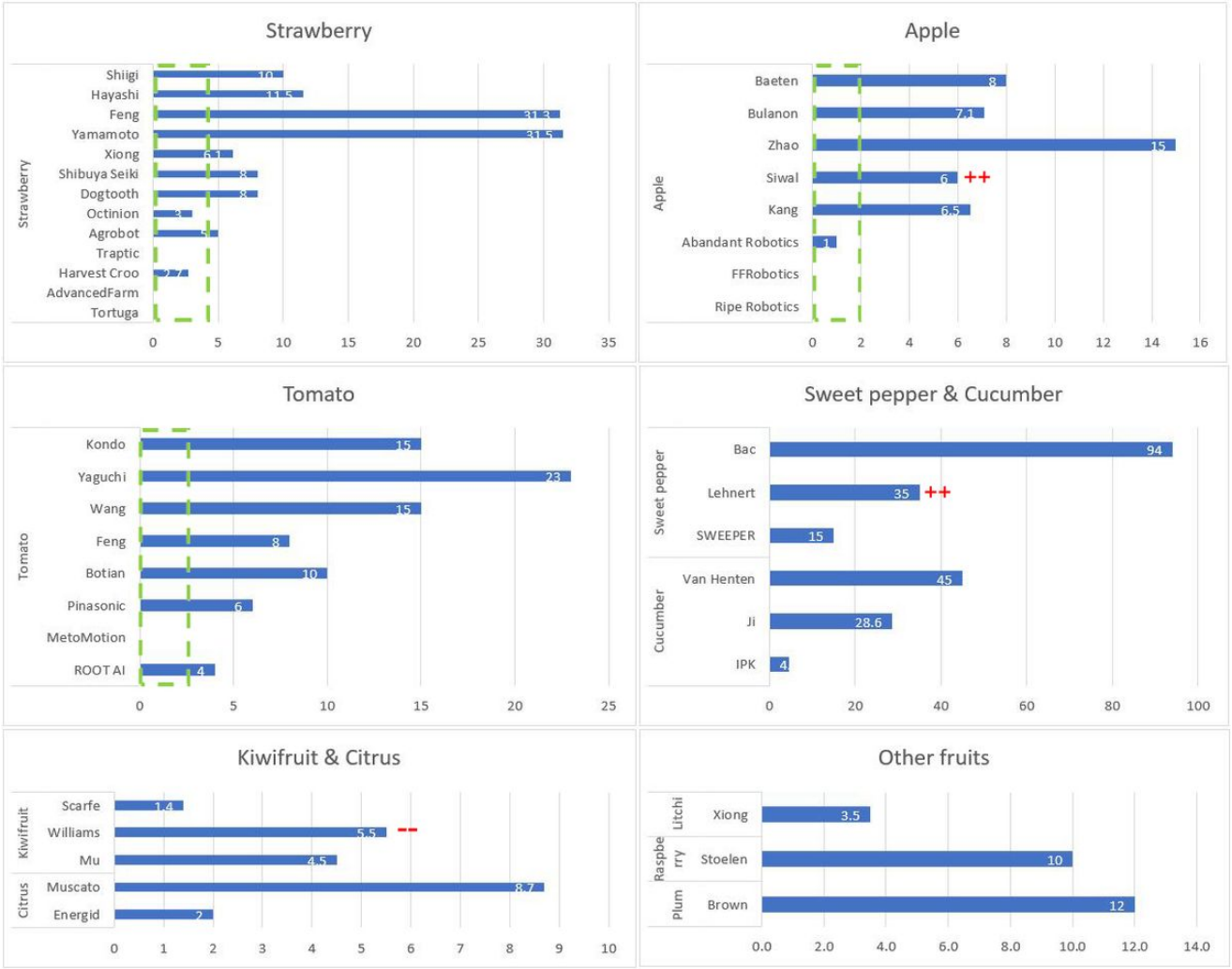


Figure 8

Picking time cost (seconds per arm per fruit) by fruit and research group

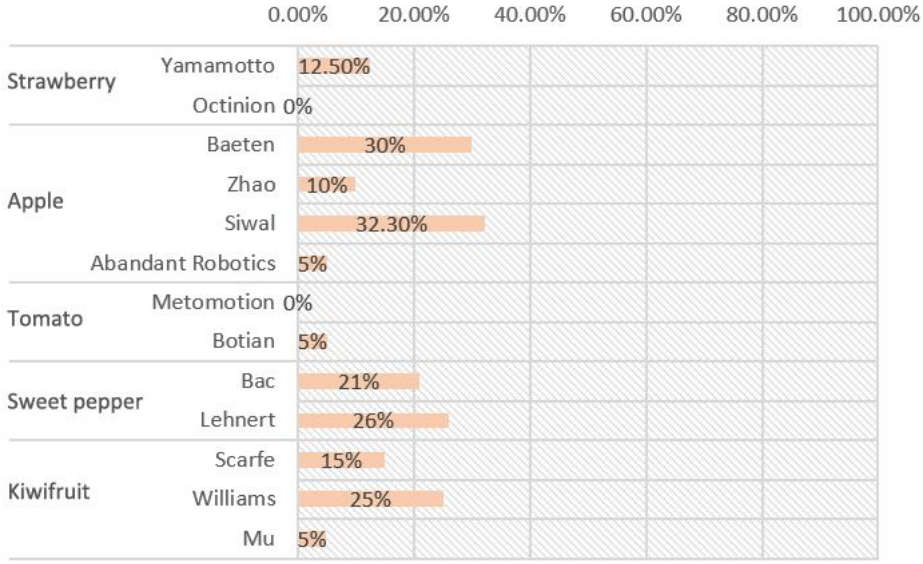


Figure 9

Damage rate comparison chart

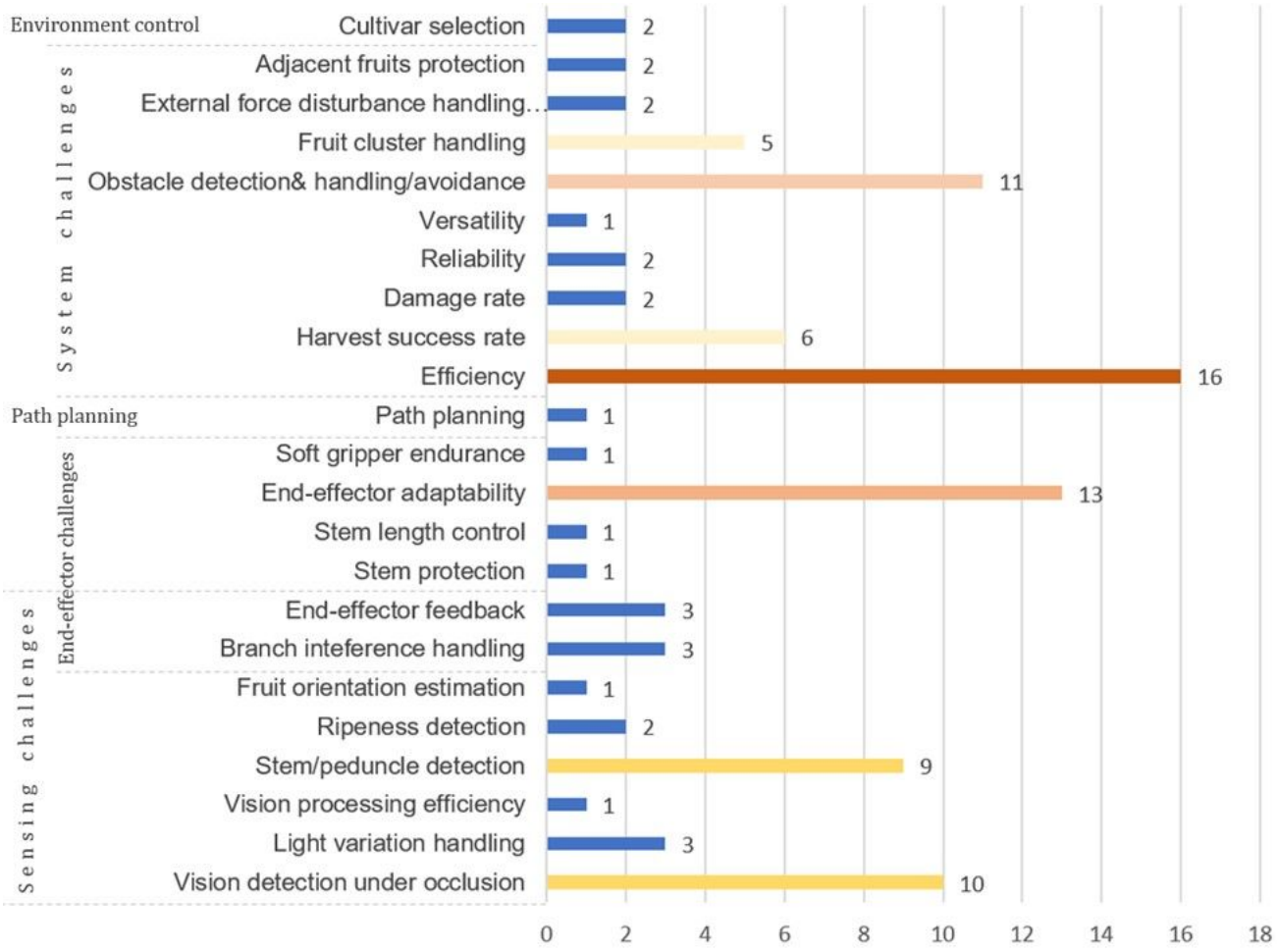


Figure 10

Robotic harvesting challenges reported in the literature

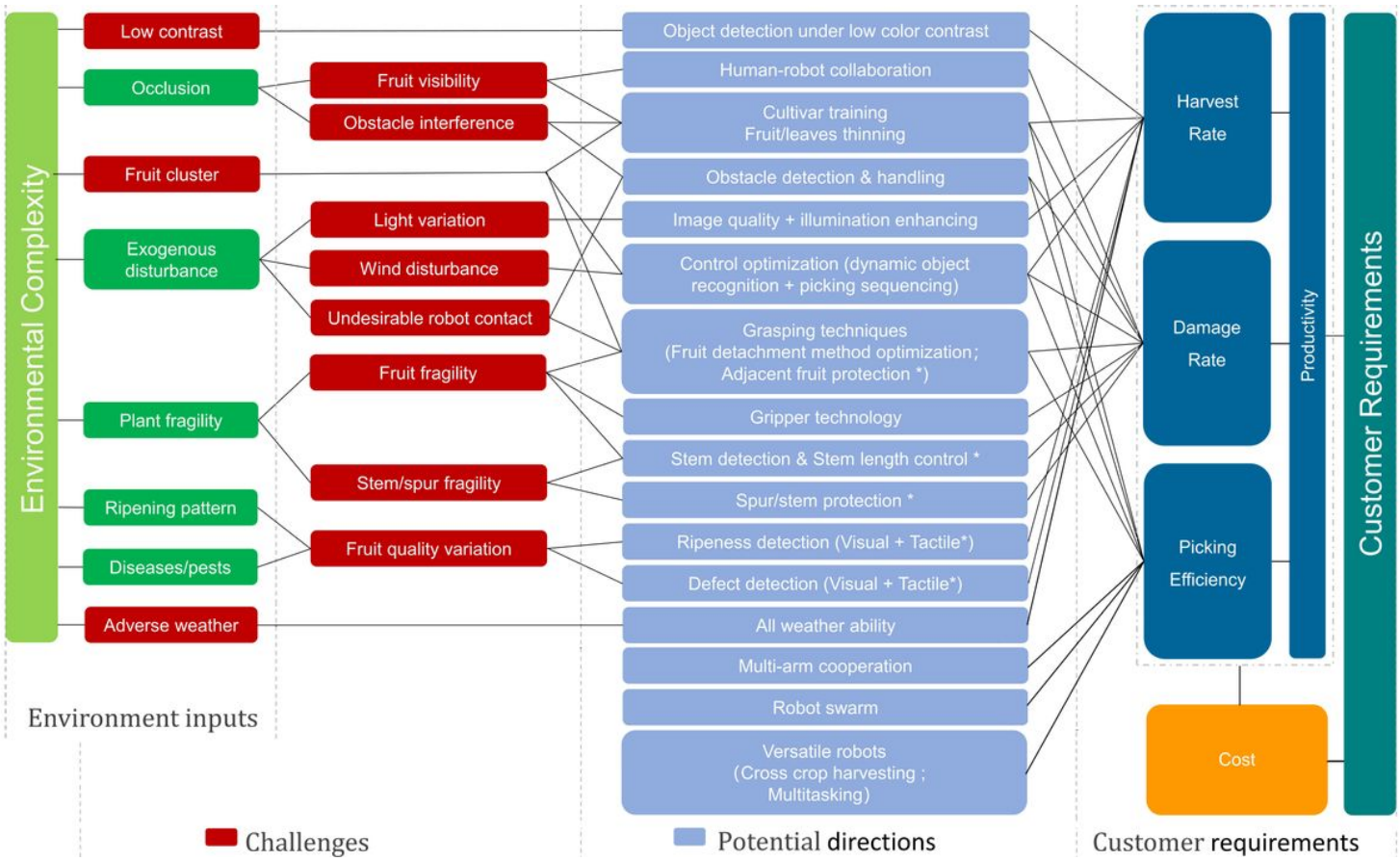


Figure 11

Harvesting robot development factors diagram

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixTable1ComparisonofFruitHarvestingRobots.xlsx