TECHNOLOGICAL DEVELOPMENT OF ROBOTIC APPLE HARVESTERS: A REVIEW
/
苹果收获机器人技术发展综述

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ABSTRACT

Apple harvesting in orchards is a challenging task due to its dependence on manual labour. In addition, the reduction in skilled farmers and increasing employee costs have popularized mechanical harvesting. As a highly optimal apple picking method, apple harvesting robots integrate machine vision, image processing, robot kinematics, and multi-sensor fusion. This article reviews the vision system and mechanical structure of apple harvesters and evaluates the performance of robotic apple harvester prototypes from 2010 to 2018. Moreover, horticultural adaptability is also discussed in order to facilitate the expansion of orchard structures suitable for mechanized operations. We find that to solve the difficulties faced by apple harvesters, the development of mechanized apple harvesting and modern orchard structure applications must be accelerated. Furthermore, research into anthropomorphic control strategies has the potential to optimize picking patterns, while improvements in environment reconstruction and semantic segmentation can improve harvesting efficiency. Finally, the challenges and strategies based on the development status of robotic apple harvester are also analysed. The review is intended to assist researchers in structure design, sensor choice and adaptability improvement of agricultural machinery and horticulture, and to influence the direction of the development of robotic apple harvester.

摘要

苹果收获是一项极具挑战性的工作，并具有劳动密集型的特点。劳动力减少和劳动力成本的增加促进了机械化收获的发展。作为一种高度优化的收获方法，苹果收获机器人集成了机器视觉、图像处理、机器人运动学以及多传感器融合。本文对苹果收获机器人的视觉系统和机械结构进行了综述，并对 2010 至 2018 年间的苹果收获机器人的样机性能进行了评估。此外讨论了苹果收获机器人的园艺适应性，以促进果园结构适应机械化作业的发展。为解决苹果收获机器人所面临的困难，除园艺与农机适应性之外，拟人化的控制策略具有优化采摘方法的潜力，而环境重建技术和语义分割的应用可能提高采摘效率。最后，根据苹果收获机器人的发展现状，分析了其面临的挑战和策略。本文旨在为研究人员在机器人的结构设计、传感器选择以及园艺适应性改进方面提高参考，并对苹果收获机器人的发展方向产生一定影响。

INTRODUCTION

Apple is one of the most valuable agriculture products across the globe. According to the United States Department of Agriculture (USDA), global fresh apple production between 2018-2019 was approximately 68.7 million tons (*USDA, 2019*). As the world's biggest apple producer, according to China Agricultural Yearbook of 2016, the apple planting area in China covered 2.32 million hectares, accounting for 17.9% of the global total planting area. Furthermore, apple production reached 43.882 million metric tons, accounting for 24.2% of the total. Since the 20th century, the development of agricultural mechanization technology has fundamentally changed modern agriculture, allowing for the mechanization of farming to harvesting in the main food crops (e.g. wheat and corn). However, the harvest of fresh fruit, such as apple, pear and peach, which is easily prone to bruising and damage, remains as a complicated task for farmers (*Bac et al., 2014*).

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In particular, apple harvesting is highly labour intensive, with manual labour making up 35-40% of the total orchard production process during harvest (*Sanders, 2005*), and approximately 25% of labour cost used during the harvest process (*Gallardo and Brady, 2015*).

The 21st century has seen a reduction in the agriculture-related workforce, placing a serious challenge in many countries. Mechanization has the potential to overcome this obstacle faced by the fruit industry (*Fennimore and Doohan, 2008*).

Robotic and platform-assisted mechanical apple harvesting technology focuses on semi-automatic harvesting technology (also known as bulk technology) (*Zhang et al., 2016; De Kleine and Karkee, 2015*). For the application of this type of technology, a worker is initially required to drive the machine to the target location, whereby the machine then generates external excitation in order to detach the apples from the limbs. This basic principle can be employed for both single tree vibration harvesting (*McHugh et al., 1981*) and over-the-row continuous harvesting (*Monroe, 1982; Peterson, 1982a*). However, harvesting machines based on the shake-and-catch (*Peterson et al., 1985*), combing principle (*Le Flufy, 1983*), rod press (*Peterson, 1982b*), and air jet (*Berlage, 1973*) approaches are easily damaged and thus cannot be used for the harvest of fresh apples. Apple harvesting robots integrate machine vision, image processing, robot kinematics, and multi-sensor fusion. Relevant research on the identification, picking and placing of the fruit in order to reduce the damage rate and improve efficiency is still in the laboratory and orchard trial phase. Platform-assisted harvesting concepts integrate the working platform, conveyor and fruit collecting systems (*Peterson and Miller, 1996*). In contrast to manual harvesting, where climbing a ladder is required, workers are placed on a platform in order to pick apples from trees, depositing them in an automatic fruit delivery mechanism that subsequently delivers the fruit to fruit-collecting boxes. Although commercial platform-assisted products are available, they are expensive and require workers of high quality.

Apple harvesting robots have been the focus of research for over three decades. Despite this, commercial apple harvesting robot systems are unavailable on the market. This is attributed to high manufacturing costs, low harvesting efficiency and poor horticultural adaptability to environment complexity. Thus, we aim to review the state of apple harvesters in terms of their vision system and mechanical structure, as well as the performance of robotic apple harvester prototypes, from 2010 to 2018. Furthermore, we also investigate the theme of horticultural adaptability, thus facilitating the expansion of orchard structures for mechanized operations. Finally, we evaluate the current development status of apple harvesting robots, and predict possible trends and challenges for the future.

VISION SYSTEM

Machine vision systems are widely employed in agricultural robotics applications, including yield estimation, path planning and vision-based control. Previous studies have achieved fruit grasping by driving the robot to the target position (*Barth et al., 2016*). The visual system simultaneously recognizes the fruit and acquires depth information. Depth information can be determined directly via time-of-flight (TOF) methods, including the deployment of laser range finders and 3D-cameras, or indirectly using colour images, such as monocular and binocular depth. Recent reviews on recognition algorithms present a comprehensive evaluation of such methods (*Wang et al., 2017*). In the current paper, we focus on the hardware requirements and their performances of the following four methods.

Laser range finder

A laser range finder is able to perform scene reconstruction through horizontal and vertical scanning. (*Jiménez et al., 2000b*) developed a laser-based computer vision system for the picking of spherical fruit by a harvesting robot. More specifically, the contour, crown, convex and reflectance primitives generated by the range and reflectance information were applied to determine the 3D position, radius and surface reflectivity of the fruit. The study was able to achieve a 100% and 74% detection rate of the red and green fruit, respectively. This system proved to perform well under scenarios with shadows, occlusions, and overlaps. However, the scanning speed (20s) and processing time (60s) limited its application (*Jimenez et al., 1999; Jiménez et al., 2000a*).

Liu et al. (2010) designed a three-dimensional vision sensor based on reflectance spectra variations across Fuji apple tree components. Laser reflection at the wavelengths of 685 nm and 830 nm were used to distinguish apples from branches and leaves, with depth information determined from the reflection at 830nm.

Experimental results indicated a stable output signal of the system, ranging from 150 mm to 750 mm, and a maximum error of 13 mm.

Furthermore, previous work has integrated machine vision and laser ranging sensors into a fruit detection system based on an apple picking robot. This real-time system employs CCD camera image feedback to drive the robotic arm, such that the camera mounted on the end-effector was aligned with the target fruit in 2D space, and the laser measured the fruit centre. The detection accuracy of this system lies within 3 mm (*Bulanon and Kataoka, 2010*).

Monocular camera scheme

Parrish et al. (1977) presented a camera model that mapped plane coordinates to spatial coordinates via a perspective transformation that calculates location information in natural scenes. More specifically, a single-camera moving with the end-effector (eye-in-hand) can locate the fruit (*Zhao et al., 2011*). The location process is similar to that of laser ranging sensors in that the setting position is based on information derived from the image, while the distance between the target fruit and the camera is determined via the camera parameters and geometrical relationships. Triangulation is then used to calculate the additional distance to the target apple, and is updated in real-time as the camera approaches the target apple (*Baeten et al., 2008*).

Binocular vision system

Binocular visual localization calculates the parallax of image pairs that can be potentially matched together. The distance to objects from the camera is converted using relative camera locations and orientations, and built-in parameters of the cameras. Therefore, calibration is necessary prior to fruit recognition.

Li et al. (2016a) used a Bumblebee2 binocular camera mounted on the manipulator of the system to detect apples in a single tree canopy. Limited by the vision of the camera, the robotic arm moved in front of the canopy, stopping to collect images in order to localize all apples. At least six images were required to cover the region of the canopy to be harvested.

Binocular vision imaging sensors can also be applied in global vision systems. (*Si et al., 2015*) used two complementary metal-oxide semiconductor (CMOS) cameras to implement a recognition algorithm, with distance estimation errors observed to be less than 20 mm in the range of 400-1500 mm. In order to overcome lighting issues, (*Hohimer et al., 2019*) fused stereo image pairs at five exposure values collected via a Bumblebee XB3 industrial stereo vision imaging sensor to form a single image.

Ji et al. (2017a) constructed an experimental platform with an MV-VS220 binocular stereo vision system in order to locate branches. The platform was based on skeleton feature extraction, and was able to avoid branch obstacles during apple picking with the harvesting robot manipulator. Errors of just 1.5 mm were associated with distances of 1000 mm between the object and binocular camera.

Wang et al. (2013) integrated two high-resolution monocular Nikon D300s cameras with wide-angle lenses into an autonomous orchard vehicle for yield estimation. The global location of apples was calculated from image sequences taken by the two cameras at either side of the tree row. Each single apple was matched in the different images, merged and subsequently registered on the global map. However, navigation system errors and stereo triangulation bias led to inaccurate position information.

3D-camera system

A 3D-camera is a type of time-of-flight detector, whereby the lens collects the reflected light and images it onto the sensor or focal plane array. Such a camera is able to detect the intensity, distance and 3D coordinates of the fruit (*Gongal et al., 2015*). Previous research has implemented a 3D-camera as the single sensor for a vision system. Features of the target were extracted from 3D point clouds, and were subsequently used to reconstruct the fruits, such that apples could be separated from branches and leaves. (*Nguyen et al., 2016*) used the colour feature to test a Kinect sensor system, resulting in 100% and 80% detection rates for fully and partially visible apples, respectively. Location errors were reported to be less than 10 mm, with a 50 ms processing time per apple. (*Tao and Zhou, 2017*) evaluated five features for the recognition of apples, branches and leaves, observing that a support-vector machine, optimized by a genetic algorithm (GA) and trained using Colour-FPFH (combined colour features with Fast Point Feature Histogram), was associated with a high recognition accuracy and performance.

Wang et al. (2012) tested a vision system consisting of a Kinect sensor positioned on the manipulator and a camera mounted under the gripper allowing for long-distance observations to locate targets as the

system approached them. Kinect sensor errors for distances of 240 cm and 150 cm were reported as 4.9 cm and 2.4 cm, respectively.

Gongal et al. (2016) constructed a sensor system consisting of a PMD CamCube 3D camera, a Prosilica GigE colour camera and a LED light mounted on an over-the-row platform with a tunnel structure. Apples were identified in 2D images, while distances and coordinates were determined by intersecting the 2D and 3D images. The system was able to achieve a detection rate of 87.0% for repeated apples.

As a stage summary, there is a characteristic that the vision sensor could move with the manipulator or be fixed on the platform to provide a global view. As two different ways of visual servo, the "eye-in-hand" configuration is referred to as the end-point closed-loop, while the additional configuration is referred to as the end-point open-loop. In particular, open-loop servo control falls into the category of position-based visual servos (PBVS), whereby the robot pose is calculated by the target position. Hence, the accuracy of this "looking then moving" system depends on the precision of the robot kinematic model as well as the calibration of the camera. Moreover, closed loop servo control is a type of image-based visual servo (IBVS), employing continuous images to estimate current robot pose by comparing the current image to the desired image. This avoids the requirement of a complex camera calibration process (*Zhao et al., 2016*). Closed-loop control is considered to be more accurate than open-loop control, yet the former requires a longer operation time due to the highly non-linear image features of the camera pose (*Corke, 2013*). Despite high data acquisition and processing speeds, as a relatively new product, the vulnerability of the 3D camera to light and heat limits its adaptability to daytime operation.

MECHANICAL STRUCTURE
Manipulator

A robotic arm is typically employed as the manipulator in robotic apple harvesters. The manipulator generally consists of several links and joints, including revolute (R) and prismatic (P), which have one degree of freedom (DOF). In addition, the Denavit–Hartenberg (D-H) parameters can be used to describe the forward kinematics of the manipulator (*Denavit and Hartenberg, 1955*). Moreover, the control of the manipulator is closely related to inverse kinematics, that is, the desired pose of the end effector is solved for each joint pose, which consequently completes the path planning.

The working reachability of the robot arm is affected by the degrees of freedom. The number of joints of the underactuated robot arm is generally less than six, thus the pose of the end effector is limited. Moreover, although a redundant robot arm (excessive number of joints) can theoretically reach the desired position in any Cartesian coordinate system, due to conditions such as joint limitation and singularity, this is not always true in real applications (*Corke, 2013*).

Hence, the forward and inverse kinematics of the manipulator are usually pre-verified via simulations. Robotic apple harvester simulations performed by the Washington State University determined apple fruit reachability rates of 69.9%, 77.6% and 81.8% for robotic arms with 5-DOF，7-DOF and 8-DOF, respectively (*Wang et al., 2018; Hohimer et al., 2019*). (*Bloch et al., 2018*) developed a methodology to optimize robot systems according to tree shape.

Simulated results indicate the optimal frames of a 3-DOF robotic arm for Central Leader, Tall Spindle, and Y-trellis apple trees to be RRR, RRR, and RRP, respectively. (*Vougioukas et al., 2016*) evaluated linear fruit reachability (LFR) via simulation tools and concluded that more than 90% of fruits were reachable with the employment of suitable approach angles following three "harvesting passes". (*Nguyen et al., 2013*) applied nine algorithms including RRT, RRTConnect, KPIECE, BKPIECE, LBKPIECE, SBL and EST to a 9-DOF robotic arm in Gazebo for motion planning. All algorithms were able to perform tasks within 5s due to the high DOF, with RRTConnect as the most efficient algorithm, independent of running and planning time.

End-effector

The end-effector is a crucial component of the detachment of the fruit from the tree by the robotic apple harvester. This is usually performed via vacuum gripping or grasping, with the aim of mimicking the functionality of the human hand. (*Napier, 1956*) classified the end-effector grasp into the power grasp and precision grasp based on human grasp taxonomy. The power grasp results in a large contact surface when the fingers and palm envelop the object, while just the finger and thumb tips are used to hold the object in the precision grasp (*Rodriguez et al., 2013*). In general, the power grasp is appropriate for a large load, whereas the precision grasp is always applied to smaller loads (*Feix et al., 2014*).

The shape and size of the target object determine grasping postures and the choice of grasp type (*Lee and Jung, 2014*). Power and precision grasp can be adapted to prismatic- and circular-shaped objects, the general shapes of most fruit and vegetables. For prismatic (i.e. long) shapes, the thumb is used such that the object is picked up like two virtual fingers, while for circular (i.e. radially symmetric) shapes, all fingers are used, picking the object like three virtual fingers (*Rodriguez et al., 2013*). (*Cutkosky, 1989*) analyzed 16 grasp types used in manufacturing and proposed the spherical power grasp robot hand for sphere objects. Table 1 reports the gripper characteristics of robotic apple harvesters.

Table 1

Summary of apple harvesting robot gripper characteristics

References	Grasp classification	Major structure	Accessory	Transmission system
(*Setiawan et al., 2004*)	Power grasp	Cylinder cup with rubber bladders inside	NA	Pneumatics
(*Bulanon and Kataoka, 2010*)	Precision grasp	Two parallel rigid fingers	NA	DC motor
(*Zhao et al., 2011*)	Power grasp	Two angular spoon-shaped fingers	electric cutting knife	NA
(*Gu et al., 2012*)	Precision grasp	Two parallel rigid fingers	NA	NA
(*Davidson and Mo, 2014*)	Power grasp	Three 2-joint fingers and a palm	NA	Tendons and reset spring
(Davidson and Mo, 2015); (*Silwal et al., 2017*)	Power grasp	Three 2-joint fingers and a palm	a stem gripper	Tendons driven by DC motor
(*Quan et al., 2017*)	Power grasp	Six 3-joint fingers	NA	Tendons driven by servo motor
(*Hohimer et al., 2019*)	Power grasp	Three pneumatic fingers	NA	Pneumatics

Cutkosky additionally pointed out that the power grasp is more suited for apple picking (*Cutkosky, 1989*). Furthermore, the robustness of the gripper increases with the number of fingers. In particular, for precision grasp, the two finger grippers tend to require accessories during the grasping and picking process, such as a cutting knife and suction pad. This is attributed to the lack of necessary force to break the joint between the stem and branch (*Kataoka et al., 1998*).

Detecting the apple stem and detaching the fruit is an alternative strategy for precision grasping, yet it requires a complex algorithm and an uncontrolled environment (*Bulanon and Kataoka, 2010*).

Direct contact force detection is widely used in the controller of grippers with stiff fingers using press sensors to avoid the occurrence of surface bruises in real-time (*Zhao et al., 2011; Ji et al., 2015; Ji et al., 2017b*). A simpler and more effective way to eliminate the effects of fruit size and environmental changes is to embed elastomeric materials on the surface of the fingers. However, the soft pneumatic gripper is currently the most compliant end-effecter in fruit protecting, providing adequate grasp force and avoiding bruise. The flexible gripper with simple structure and easy control should be the focus of further research.

ROBOTIC APPLE HARVESTER PERFORMANCE

Despite the development of the robotic apple harvester MAGALI over three decades ago (*D'Esnon et al., 1987*), there are no commercial robotic systems available for apple picking. A substantial amount of research on individual harvesting system components has been performed due to their relative independence, yet work on the whole system performance is limited. Table 2 reports robotic apple harvesters tested during 2010-2018, with the corresponding prototype photos presented in Figure 1. The areas of concern include the structure configuration and test metrics.
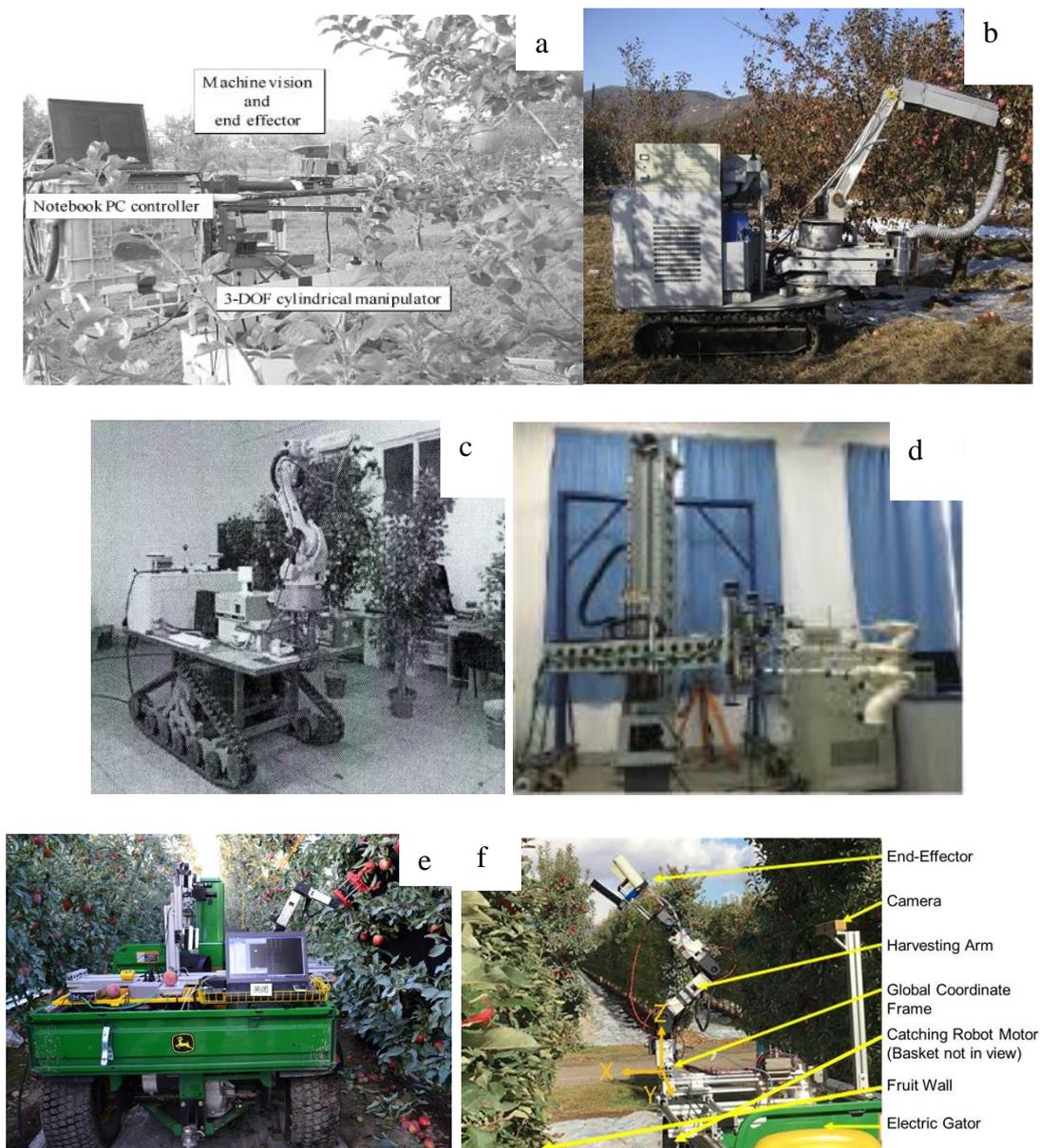
Fig. 1 - Six robotic apple harvester prototypes tested during 2010-2018

(a) Apple harvesting robot from (*Bulanon and Kataoka, 2010*); (b) mobile fruit robot designed by (*Zhao et al., 2011*), reprinted with permission from Elsevier; (c) intelligent mobile fruit robot reported by (*Gu et al., 2012*); (d) apple harvesting robot manipulator with multiple end-effectors (*Li et al., 2016a*); (e) robotic apple harvester tested in Washington State University (*Silwal et al., 2017*), reprinted with permission from Wiley; and (f) robotic system with soft pneumatic gripper (*Hohimer et al., 2019*).
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Table 2

Robotic apple harvester configuration characteristics and performance metrics

References	Servo method	Sensors	Manipulator	End-effector	Picking method	Localization time/ success rate	Picking time per fruit [s]	Success rate [%]
Baeten et al., 2008	Closed-loop	Monocular CMOS camera	6-DOF	Soft suction gripper	Vacuum suction	NA/ approximately 80%	8-10	80
Bulanon and Kataoka, 2010	Closed-loop	CCD camera and laser range finder	4-DOF	2-parallel-finger peduncle holder	Stem bending	NA/100%	7.1	90
Zhao et al., 2011	Closed-loop	Monocular CCD camera	5-DOF	Gripper shaped like 2 angular spoons with	Stem cutting	NA	15.4	77

References	Servo method	Sensors	Manipulator	End-effector	Picking method	Localization time/ success rate	Picking time per fruit [s]	Success rate [%]
				a cutting knife				
Gu et al., 2012	Closed-loop	Binocular camera	Industry robotic arm	2-parallel-finger gripper	Fruit grasping	NA/81.73%	9.5	86.92
Li et al., 2016a	Open-loop	Binocular camera	One main robotic arm (3-DOF) with three accompanying arms (2-DOF)	collectors with cutting devices connected to conveying pipes	Stem cutting	NA	NA	82.14
Silwal et al., 2017	Open-loop	CCD camera and 3D camera	7-DOF	3-finger gripper	Fruit grasping	1.5s/NA	6	84
Hohimer et al., 2019	Open-loop	Binocular camera	5-DOF	Pneumatic 3-finger gripper	Fruit grasping	NA	7.3±0.78 s[*]	67

*This time accounts for the entire picking process, from apple identification to storage bin.

The picking method determines the mechanical structure hence the design of the robotic harvester is embodied in the structural characteristics of the system. Previous work employed a laser ranging sensor as a camera collaborator to measure the distance to the target fruit and to confirm the end-effector's reaching working space. This is followed by the tripping and twisting of the stem by the end-effector when the required distance is reached. Though the system presented high localization and harvesting success rates, the localization time was not reported, and an ideal environment was also required (*Bulanon and Kataoka, 2010*). The robot systems reported by (*Zhao et al., 2011*) and (*Gu et al., 2012*) employ an end-point closed-loop visual servo for navigation in a traditional orchard. Field tests faced obstructions when approaching the detected fruit and light interference. (*Li et al., 2016a*) presented a regionalization strategy for parallel harvesting that can extend design ideas. Spatial interference is one of the difficulties in the synchronization control of multi-manipulator system. The partitioned fruit tree picking strategy could reduce control difficulty and improve efficiency.

Researchers from Washington State University developed the 7-DOF robotic apple harvester designed for V-trellis fruiting walls. They were able to maintain the end-effector speed at 0.15 m/s as it approached the target apple, which it subsequently detected and detached from the branch (*Silwal et al., 2017*). (*Hohimer et al., 2019*) further developed the robotic apple harvester system by designing a new tendon-driven end-effecter prototype to replace the pneumatic gripper to avoid bruising. The kinematic model was also applied to reduce backtracking and translation, and an inexpensive vision sensor was employed to reduce costs. Field tests indicated that clustered apples, calibration and position errors caused by the harvesting system and the branch pendulum phenomenon were the main reasons leading to picking failure.

(*Baeten et al., 2008*) evaluated the AFPM robotic harvester with vacuum suctioning, demonstrating that stem-pull apples accounted for 30% of all picked apples, which proved to reduce storage time (*Janisiewicz and Peterson, 2004*). Recently, a new automated vacuum harvester system has been presented in Agricultural Robotics (*Vougioukas, 2018*), including a global vision sensor, a delta robot with a vacuum gripper connected to running piping and a fruit bin positioned on the mobile platform. Other technical details were not reported by the authors.

HARVESTING METHODS AND HORTICULTURAL ADAPTABILITY

The adaptability of agricultural machinery and horticulture is crucial for the development and popularization of agricultural machinery. Compared to traditional orchards, factors such as complex fruit tree structures, fruit clusters, fruit shape and size differences across varieties, as well as sensitivity to mechanical damage, exert high adaptability requirements for picking machinery (*Robinson, 2008*).

At the early development stage of mechanized apple harvesting, (*Tennes and Brown, 1985*) determined the shake-and-catch method to be highly suitable for high-yield, structured trees, and also suggested that the orchard structure should be adapted to the harvester structure. Following on from this, semi-automatic harvesters for the narrow hedgerow systems, with the Y-trellis, T-trellis, and double-layer T-trellis structure, were developed (Figure 2). Table 3 compares these harvesters.
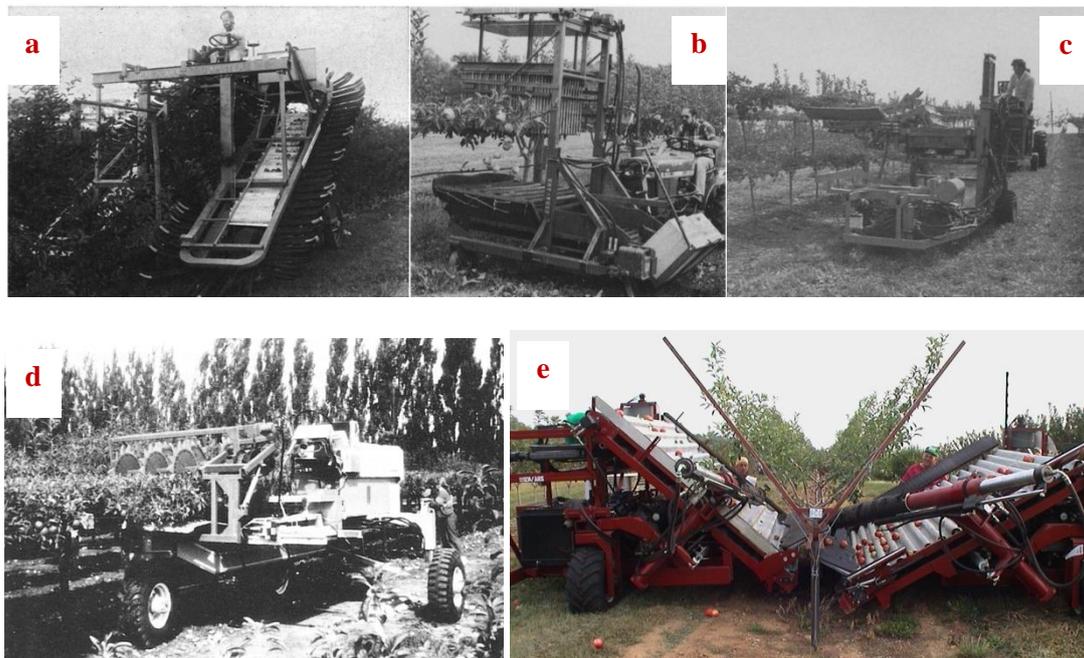
Fig. 2 - Five typical mechanized apple harvesting prototypes for different tree shapes
(a) Combine principle harvester for narrow hedgerow systems (*Le Flufy, 1982a,b; Le Flufy, 1983*), reprinted with permission from Elsevier; (b) harvester with rod press fruit removal mechanism for T-trellis canopies (*Peterson and Kornecki, 1987*). Copyright 1987 ASABE. Used with permission; (c) catch-shake harvester for double-T trellis (Domigan et al., 1988), reprinted with permission from Elsevier; (d) self-propelled NZAEI (New Zealand Agricultural Engineering Institute) machine with shaking units for T-trellis (*Láng, 1989*), reprinted with permission from Elsevier; and (e) two-sided scaffold-shaking harvester for trees trained to Y-trellis (*Peterson and Wolford, 2003*), Copyright 2003 ASABE. Used with permission

Table 3

Comparison of semi-automatic apple harvesters for typical tree structures

Reference	Tree shape	Harvest method	Damage rate*
LeFlufy, 1982a,b; 1983	Narrow hedgerow system	Combine principle (Figure 2a)	23%[a]
Peterson and Kornecki, 1987	T-trellis	Rod press mechanism (Figure 2b)	15%[b]
Domigan et al., 1988	Double "T" trellis	Shake and catch harvest (Figure 2c)	3%[c]
Láng, 1989	T-trellis	Canopy shake harvest (Figure 2d)	15%-31%[d]
Peterson and Wolford, 2003	Y-trellis	Fruiting wall shaking harvest (Figure 2e)	9.9%-33.1%[e]
(a) Damaged fruit is defined as any fruit exhibiting broken skin (i.e. a cut or a puncture) or bruising greater than 1 cm^2, assessed at least 3 d after harvesting. (b) Graded by the 1964 USDA grade standards. (c) Apple graded into not "fancy and extra fancy" (1987). (d) New Zealand Standard, issued by the Apple and Pear Board. Apple graded into "Bruised". (e) USDA fresh market standards. Apple graded into "Bruised" and "Cuts and Punctures".			

The emergence of apple harvesting robots also placed new demands on the orchard structure, as the obstruction by branches and leaves results in difficulties in fruit recognition and localization. Thus, scholars have attempted to eliminate the influence of fruit occlusion by improving the visual system hardware and upgrading algorithms, subsequently enhancing recognition and positioning accuracy (*Silwal et al., 2014; Wang et al., 2016; Niu et al., 2017*).

However, thus far, the occlusion of branches has not been entirely eliminated. (*Robinson et al., 2013*) reported seven simple, narrow, accessible, and productive (SNAP) canopies suitable for assisted-platform operations and high tree densities (900-2200 trees/acre), projected to attain very high yields (1500 bu/acre), as shown in Figure 3.

The apple picking robot developed by (*Silwal et al., 2017*) has been demonstrated as a feasible system for the V-trellis fruiting wall. Here, the branches are fixed on the trellis wire, allowing for the fruit to be distributed along the same wire, significantly avoiding the occlusion by branches and leaves, and consequently, improving the recognition efficiency and accuracy. This indicates that the modern orchard structure should evolve with the development of different harvesting methods.

Due to limited land resource availability and the need to simplify technology and save labour, most new orchards in China are densely planted dwarfed orchards. This increases the yield per unit and also improves fruit quality. In order to increase the bearing capacity of the fruit trees, spindle-shaped trees with fewer branches are widely promoted. However, the early cultivation and management costs of the fruit tree wall have restricted its development. Therefore, changes in fruiting wall or V-trellis require further comprehensive evaluation in terms of their economic applicability.
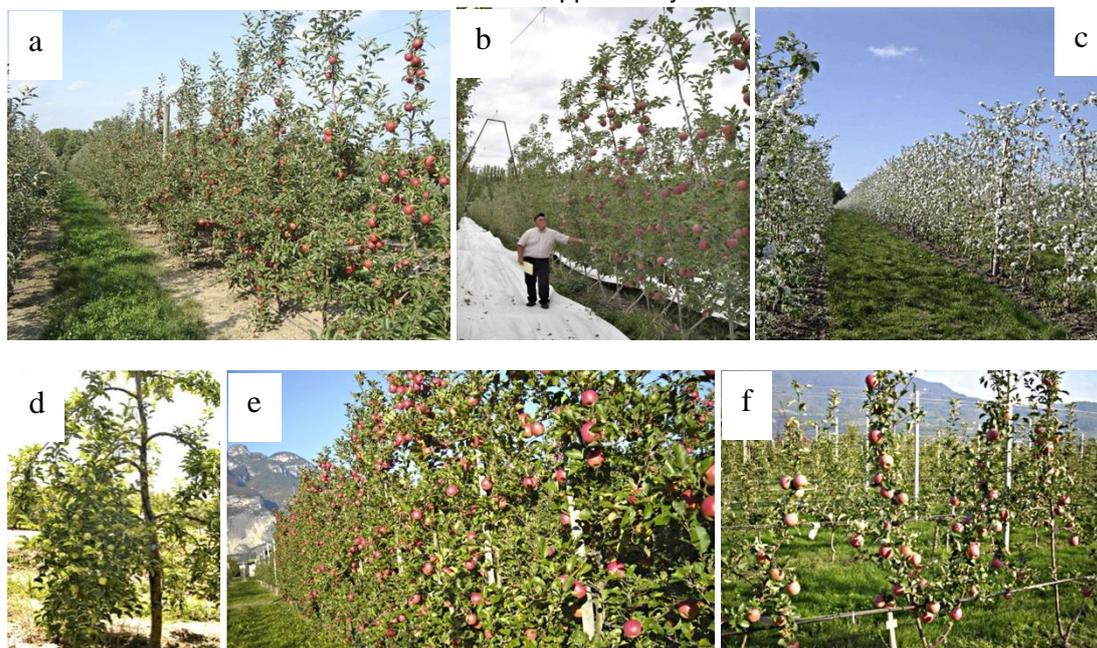
Fig.3 - Six leading global orchard systems:
(a) Tall spindle; (b) V-trellis; (c) super spindle; (d) solaxe; (e) fruiting wall; and (f) bi-axis
(*Robinson et al., 2013*)

DISCUSSION

Analysis and summary

The robotic apple harvester system had developed rapidly over the recent years. Much of the research in robotic apple harvesting presented in the previous sections is still in the course of development and can thus not be fully reviewed. The performance gains of apple robotic harvesters resulted in two factors: "simplifying the task" and "enhancing the robot".

Modern cultivation systems have been able to reduce the computational scale of fruit recognition and also avoid obstacles during the recognition and grasping process compared to traditional orchards. Therefore, position-based look-and-move becomes the main method of visual servo in apple picking. The eye-to-hand model improves harvesting efficiency and allows for the accurate estimation of the localization time, yet high-performance cameras are required. Moreover, eye-in-hand robots boast autonomous navigation and fruit detection capabilities to deal with complex environments. The localization of fruit within an independent tree using the image-based vision servo (IBVS) control method requires multiple successive iterations, while scanning surrounding canopies is necessary when searching for potential targets. This may explain the missing data in the "Localization time" column in Table 2. In addition to the temporal factor, the failure to detect target apples due to branch obstacles in the canopy also impacts the performance evaluation of the harvesting robots.

The simplification of the apple harvesting task calls for a robot-friendly orchard environment, while enhancements in robot performance depend on technological improvements and the update of hardware. Vision sensors developed from RGB cameras and laser range finders, and 3D cameras enhance sensor output and improve performances. Furthermore, commercial sensors involved in the previously mentioned robotic harvesters have undergone substantial updates, for example Bumblebee 2 to Bumblebee XB3. Numerous sensor technologies provide more choices for the design and development of robots, and highlight the potential of multi-sensor fusion.

Challenges and strategies

High robot manufacturing and maintenance costs, insufficient speeds and the complexity of agricultural environments have limited the promotion of harvesting robots. Traditional orchards have been unable to adapt to the requirements of the modern fruit industry because of mechanical adaptability. Tall fruiting walls with simple narrow canopies at an optimum planting density is the trend for future orchards. Despite the proved advantages of such an orchard design, the economic gain from yield improvements may take at least three years to materialize following orchards remould. If the evolution of orchards is to be popularized, issues relating to initial investment and loss compensation should be prioritized.

Early apple harvesters applied the "optimum technique" (*Nguyen et al., 2012; Tong et al., 2014*) or "standard method" (*Davidson et al., 2016*), whereby the orientation and stem of the fruit are initially detected, followed by cutting of the stem. Since the gripper was only required to limit the movement of the fruit, a small force was necessary to support. Ensuring minimum damage was prioritized, which consequently increased picking time due to too many necessary moving steps. Compared to the apple harvesting robot reported by (*Zhao et al., 2011*), (*Silwal et al., 2017*) attempted to detach apples by grasping them directly via a three-finger end-effecter, demonstrating the potential to reduce picking time. In terms of direct grasping, the harvesting effect is largely determined by the motion characteristics of the manipulator picking patterns of the robotic apple harvester. Several anthropomorphic methods have been explored to develop control strategies. (*Davidson et al., 2016*) used a sensing glove to evaluate four picking techniques and determined that the optimum picking method (i.e. with the lowest stem loss rate) depended on the apple variety. (*Li et al., 2016b*) evaluated four three-finger examples to measure the detachment angle, movements, and patterns of stem bending using sensing glove, and presented that pull with a bending moment could reduce the required grasping pressure for fruit detachment. These results appeared to have been applied to the control of their robotic apple harvesters, and yet they are associated with unexpected circumstances resulting in picking failure (e.g. pendulum apples with long branches) (*Hohimer et al., 2019*). Additional research in anthropomorphic methods can help to overcome these common picking failures.

As shown in figure 1, all prototypes are the serial structure apple harvesting robot, whereby a working cycle is completed after reaching a working position. In this case, the visual system recognizes and obtains the 3D coordinates of the fruit, determines the picking order according to the relative position of the fruit from the end effector and completes the inverse of the Kinematics solution of the mechanical arm. Following this, the actuator completes the fruit picking and confirms whether the picking has been successful. Finally, it moves to the next working position, continuing the cycle. However, the vision system enters the idle state following the completion of the fruit position feedback, providing for room for potential efficiency improvements. Fruit detection and separation in orchards requires multi-sensor fusion. Environment reconstruction is a rapidly-developing technology based on machine vision, and is used widely in horticulture phenotyping and yield evaluation. This technology can be potentially applied to fruit harvesting. Double-side views of orchard rows were matched using global features and semantic information in order to reconstruct 3D row models and the spatial distribution of the fruit (*Yao et al., 2010; Dong et al., 2020*). A possible solution of efficiency improvement is to divide the serial robot into two separate components: a visual recognition robot and a picking robot. The visual recognition robot detects the position of the fruit and determines their location on a fruit map. Fruit maps make the visual system redundant in the harvesting robot system, while only eye-in-hand cameras are required to compensate for position errors. According to the fruit map, the path planning of the picking robot is performed and the robot is driven to complete the picking action. This is expected to achieve continuous positional movement and fruit grabbing. However, it is worth noting that the accuracy of the fruit positioning, the positioning error of the visual robot and environmental changes may lead to the "blind" picking robot missing the target. Thus, a "hand eye" can be included in order to correct this error. An exceptional equipment performance usually means high prices; thus, farmers have to

decide between performance and cost. For researchers, if function implementation and promotion are the main goals, then the application of cheap equipment to achieve acceptable performance levels for farmers should be the next step for consideration.

CONCLUSIONS

We have presented a comprehensive review of the robot harvesting techniques published during 2010-2018. Based on our analysis of these strategies, we determine the development of harvesting robots to be a function of the modern orchard structure, anthropomorphic research, and environmental reconstruction. In particular, the development of constructed orchards should be popularized as this orchard system can be easily adapted to the mechanization requirements of robotic harvesters. In addition, further anthropomorphic foundation testing should be performed on direct grasping to optimize the control strategy of the robot during the harvesting process. Lastly, we propose that the application of environmental reconstruction during harvesting can promote the efficiency of robotic harvesters. Robotic fruit harvesting has proven to be a highly challenging task due to environmental complexities, sensor reliability, and robot stability. In order to improve the accuracy and efficiency of harvest mechanization applications in fruit, the orchard structure and environment, harvesting robot, and horticultural technology must all be optimized accordingly.

Overall, the review is intended to assist researchers in structure design, sensor choice and adaptability improvement of agricultural machinery and horticulture, and to influence the direction of the development of robotic apple harvester. As the proposed solution of efficiency improvement, the eye-hand separated harvesting system requires multi-sensor fusion. The accuracy of fruit map depends on semantic mapping for orchard environments, which is still difficult due to technical limitations and the complexity of the orchard. Therefore, semantic segmentation and environmental reconstruction are important directions for agricultural robots to enhance their environmental awareness and precise operation.

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