Review of rigid fruit and vegetable picking robots

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Abstract: The important indicators to measure the goodness of rigid fruit and vegetable picking robot have two aspects, the first is the reasonable structural design of the end-effector, and the second is having a high precision positioning recognition method. Many researchers have done a lot of work in these two aspects, and a variety of end-effector structures and advanced position recognition methods are constantly appearing in people's view. The working principle, structural characteristics, advantages and disadvantages of each end-effector are summarized to help us design better fruit and vegetable picking robot. The authors start from the rigid fruit and vegetable picking robot grasping methods, separation methods, and position recognition methods, firstly introduce three different grasping methods and the characteristics of the two separation methods, then introduce the under-driven picking robot developed on the basis of the traditional rigid picking robot, then explain the single special, multi-feature, and deep learning location position recognition methods currently used, and finally make a summary and outlook on the rigid fruit and vegetable picking robot from the structural development and position recognition methods.

Keywords: picking robot, end-effector, grasping methods, separation methods, under-driven, position recognition methods.
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1 Introduction

China is a populous country with a population of 1.41 billion[1] and an agricultural country with 1.21 million hm^2 of farmland[2]. Fruit and vegetables are essential daily nutritional supplements for everyone, and since 1994, China has ranked first in the world in fruit production[3], but fruit and vegetable picking usually requires a lot of labor, materials, and time. With the development of the economy, the labor force in some developing countries is gradually moving to the cities, resulting in a serious phenomenon of labor shortage in rural areas. In additional, the world's population is aging trend is becoming more and more serious, only China has 264 million old people, so the traditional fruit and vegetable picking is far from being able to meet the requirements of modern agricultural production. In order to improve labor productivity and reduce costs, picking robots are widely used in the field of fruit and vegetable production. Many domestic and foreign scholars and engineers have developed a variety of rigid fruit and vegetable picking robots, such as those for kiwi[4,5], cucumber[6,7], tomato[8-10], citrus[11,12], etc.

The end-effector, which is in direct contact with the fruit, is the core part of the whole rigid fruit and vegetable picking robot, which determines whether the performance of fruit and vegetable picking is excellent and universal and practical. In order to meet the requirements of picking tasks, the end-effector with different grasping and separation methods are widely used in the agricultural field. Three types of end-effectors with gripping, adsorption, and gripping and adsorption are widely used in the field of picking tomatoes[8,9], apples[13,14], strawberries[15-17], etc. After the end-effectors grasp the corresponding fruit, they then consider how to separate the fruit, and usually, the end of the picking robots are equipped with rigid or flexible separation elements, which have been widely used for picking kiwifruit[18], citrus[19], etc.

In a generalized analysis of relevant fruit and vegetable picking robots, it is found that many end-effectors can be applied to the corresponding fruit or vegetable picking, but many application examples show certain limitations in terms of picking efficiency, recognition accuracy, flexibility, and destruction rate, etc. These problems are usually caused by two aspects:

(1) Fruits or vegetables are particularly difficult to grasp because the skin is fragile and easily scratched, adhered, and damaged, so the robot should be more flexible, and therefore the design phase will present more complexity.

(2) The growth environment of fruits and vegetables as well as their morphological characteristics are different, and it can be very difficult to locate and identify fruits quickly, which in turn affects the picking efficiency. What's more, although many solutions have been proposed, experimented, and even some have been applied, it is not very clear for the future development.

Therefore, this study will systematically analyze the structural features and position recognition methods of fruit and vegetable picking robots, so that they can better make a perfect combination of advanced structures and good recognition methods in the future research process.

2 Grasping methods

In order to realize the function of "grasping", some end-effector with different grasping methods have been designed according to

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the characteristics of different grasping objects, which are adsorption type, clamping type and adsorption and clamping type.

2.1 Adsorption type

The suction type end-effector usually generates negative pressure to the suction cup to achieve the gripping of the target. This gripping method is widely used for fruits and vegetables with shapes similar to spheres or hemispheres because the gripping speed is fast and the damage to fruits and vegetables is relatively small. Although the force provided by the adsorption type of grasping is not very large, there are not many examples of its application to fruit picking, as shown in Figure 1, where Feng et al.[20] from the Beijing Agricultural Intelligent Equipment Center developed an end-effector that can be used for hanging wire cultivation of tomatoes, where the negative pressure airflow provided by the vacuum generator can suck the tomatoes hidden in the leaves, and by easily retracting the sleeve, the tomatoes will easily into the sleeve, and the success rate can reach 83.9%, but this harvesting method requires high light, and if the light is too weak, the success rate will decrease.

Figure 1 End-effector of hanging wire cultivated tomatoes

Li et al.[19] from Nanjing Agricultural University[21], also designed a robot capable of continuous fruit picking using adsorption gripping, as shown in Figure 2, which has good versatility and high picking efficiency and is suitable for picking spherical fruits such as apples.

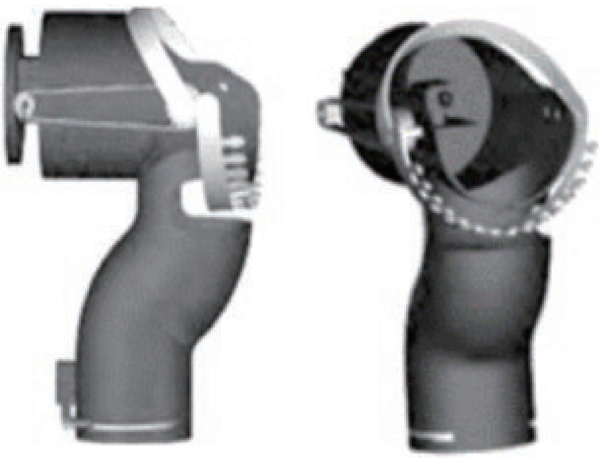


Figure 2 Apple picking robot (Front view and side view)

Arima et al.[17] in Japan designed a suction actuator for strawberry picking, as shown in Figure 3, using the suction force generated by the induced draft fan, the suction cups suck the fruit directly to the end actuator, and if this suction force is large enough, large fruits such as peaches will also be sucked and delivered to the collection device, but this picking method will suck the unripe strawberries together and It is not possible to judge the ripeness.

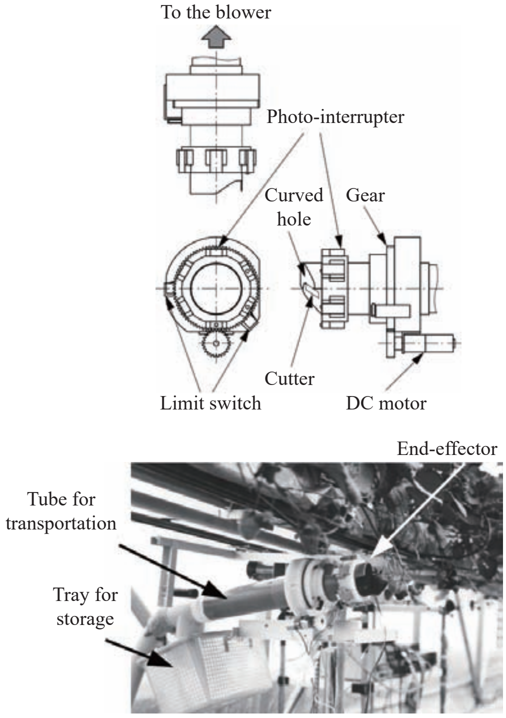


Figure 3 Structure design and picking experiment of hanging wire strawberry picking robot

2.2 Clamping type

In recent years, international scholars are also studying the end-effector of multi-finger structure different from the adsorption type, because the multi-finger structure can not only grasp objects with larger weight, but also grasp more stable, of course, the corresponding drive system will be more complex[22]. An apple picking robot was also developed by Ma et al.[23] at Jiangsu University, the piston rod of the cylinder is connected to the high side of the slide groove at the back end of the two fingers through the pin, and finally the linear motion of the guide rod is transformed into the swing of the two fingers around the rotary axis, thus forming the slide groove guide rod mechanism to realize the clamping of the apple, as shown in Figure 4. In addition, the inner side of the circular surface of the finger is covered with a sponge rubber layer to ensure that the gripping force is evenly distributed in the grip, and does not damage the apple.

Figure 4 Apple picking robot structure and its experiment

Davidson et al.[24] in the United States proposed a three-finger picking robot, as shown in Figure 5. The robot can imitate the behavioral characteristics of human hands and quickly pick the fruit by pulling and shaking these movements.

Kondo et al.[25] in Japan developed a tomato picking end-effector with upper and lower fingers, which first opens the upper and lower fingers to wrap the tomato if the presence of a tomato is detected, and then holds the stem with the lower finger and cuts the stem with the upper finger, and this end-effector is shown in Figure 6 below.

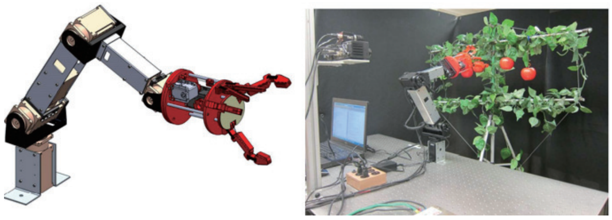


Figure 5 Three-finger structure of picking robot and its experiment

Figure 6 Tomato picking robot model and its application

2.3 Adsorption and clamping type

Taking into account the grasping characteristics of the above two approaches, picking robots with adsorption and gripping have likewise been studied by many scholars. This picking approach has a feature of first sucking the fruit with a suction element and then having fingers to grip the fruit. For example, Liu et al.[8,9] from Jiangsu University designed a tomato picking robot with an end-effector, as shown in Figure 7 below, which uses a vacuum suction cup device to pull the fruit to achieve a horizontal displacement of 35 mm after which the tomato will be gripped by the fingers, and it takes 3 s to complete a picking action, with a success rate of 92%, although the picking efficiency can be, the friction between the suction cup device and the tomatoes as well as the collision will damage the skin.

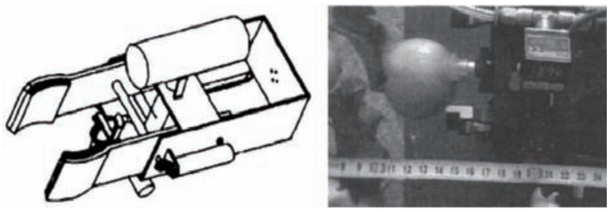


Figure 7 End-effector of tomato picking robot.

Xu et al.[26] of China Agricultural University designed a double V-finger navel orange picking robot end-effector, which mainly consists of three parts: adsorption mechanism, clamping mechanism and rotary cutting mechanism, using the adsorption mechanism to achieve rapid separation of fruit and fruit clusters, the clamping mechanism can carry out non-destructive and stable clamping of fruit, and the rotary cutting mechanism can quickly separate fruit from fruit stems. Although this method can pick navel oranges accurately and lossless, the control system is quite complicated, and Figure 8 below shows the structure of the end-effector and its picking experiment.

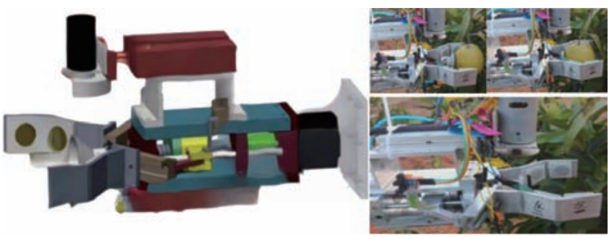


Figure 8 Structure of the end-effector.

American Chiu et al.[27] developed an end-effector for greenhouse cultivation of tomatoes, as shown in Figure 9, the center of the end-effector is a fruit adsorption device for fixing the fruit inside the end-effector, it is surrounded by four fingers and is filled with foam sponge inside to reduce damage to the fruit during bending and gripping. The experimental results showed that the average successful rate of suction attachment for each fruit was 95.3% and the average picking time was 74.6 s.

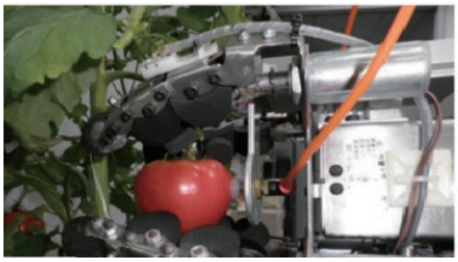


Figure 9 End-effector for greenhouse cultivation of tomatoes.

Monta et al.[10], Okayama University, Japan, designed an end-effector capable of harvesting tomato fruit in 1998, as shown in Figure 10 below. It consists of two parallel plate fingers and a suction cup that separates the fruit from the cluster under vacuum, and then by pulling the cable, the fingers are forced to bend, and when the tension reaches a certain level, the fruit is separated from the stalk.

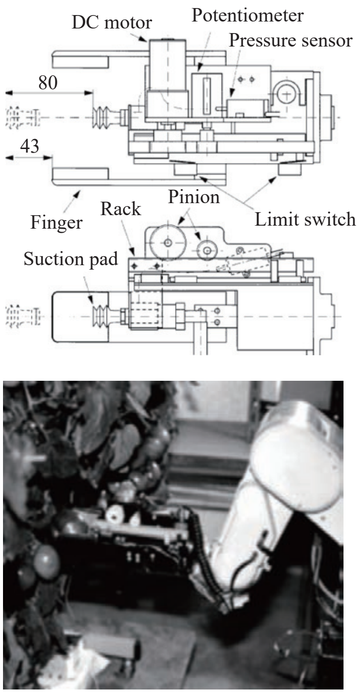


Figure 10 Structure diagram of the end-effector and its experiment of harvesting tomatoes.

3 Separation methods

The separation methods of fruits and vegetables are also important in the fruit and vegetable picking process, and it is an important indicator of the performance of the fruit and vegetable picking robot. Although some separation methods are briefly explained in some examples above, there is no systematic analysis of separation methods in fruit and vegetable picking robot. Fruit and vegetable separation methods can be divided into two types, the first is the rigid separation method and the second is the flexible separation method, which will be illustrated below with specific research examples for these two separation methods.

3.1 Rigid separation type

The rigid separation method is usually used by fruit and vegetable picking robots to cut the stems of fruits and vegetables after grasping the object using saws, scissors, lasers, etc. Using this cutting method, many components have been developed that can actively separate the fruit from the stem[28]. In Japan, an end-effector for picking eggplants was generated[29], as shown in Figure 11, which, after detecting the position of the object using ultrasonic sensors, reaches the corresponding position with the help of a mechanical arm, and mechanical fingers grip the fruit stem and cut it short using scissors.

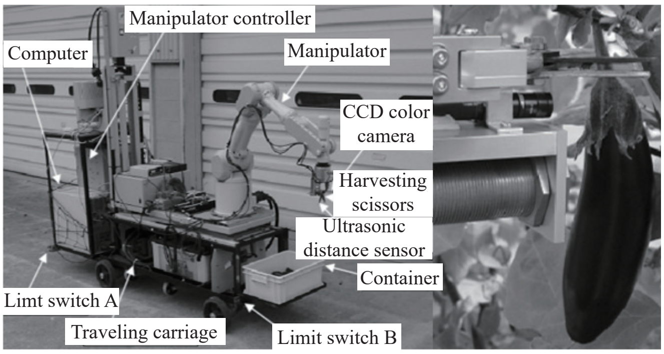


Figure 11 Eggplant harvesting robot whole machine structure and its experiment

Also using the mechanical cutting method, Xiong et al.[30] proposed a non-contact end-effector for picking strawberries, which consists of three active fingers, three passive fingers, and a cutting element, as shown in Figure 12, where six fingers will open and annex the strawberry at the same time. One of the cutting elements consists of two curved blades, which will cut the stem when the cutting element rotates rapidly, at which point the strawberry will fall into the container. If continuous picking is performed in this way, it is possible to achieve an average of only 7.5 s for single fruit picking.

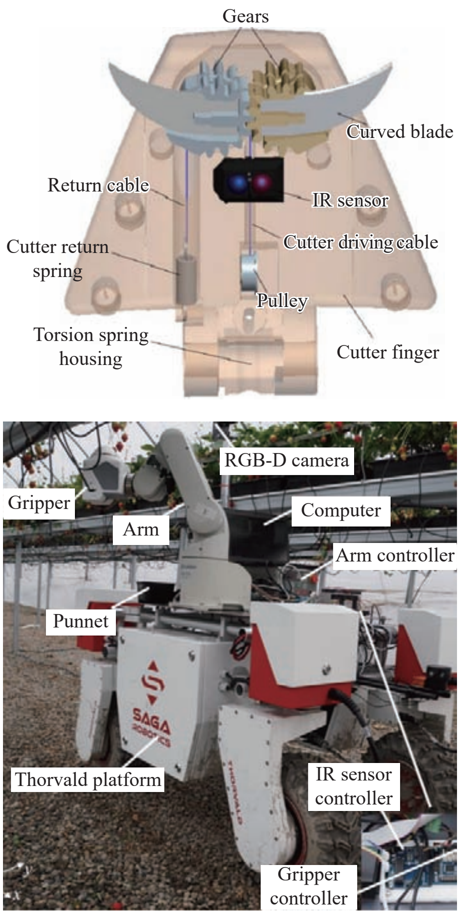


Figure 12 Strawberry picking robot cutting element structure and its whole machine experiment

Li[31] of Nanjing Agricultural University introduced a fruit catcher cut off by a tooth-like structure made by a blade, and the appearance of the whole fruit catcher looks like a tubular structure, as shown in Figure 2. As soon as the toothed fruit catcher is rotated, the fruit stalk will be cut off and subsequently, the apple will be entered into the fruit catcher, which can be seen that such an actuator has good versatility and high picking efficiency, and the damage rate is also low.

Using the bionic principle and mechanical cutting method, Fu of Chongqing University of Technology designed an end-effector applied to pick citrus[32], as shown in Figure 13. This effector contains a suction cup and a shearing element consisting of a hinged four-bar mechanism, and the fruit stalks of citrus can be cut by the upper and lower blades.

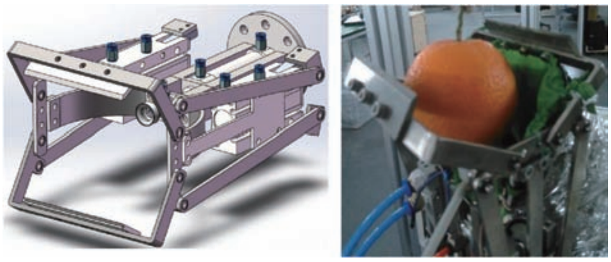


Figure 13 Citrus picking robot end-effector structure and its experiment

For round fruits such as apples and pears, Han of Beihua Institute of Aerospace Technology similarly established a picking actuator using mechanical cutting[33], with a stepper motor as the driving unit and a screw as the transmission mechanism, and the grasping and shearing behaviors will be driven by such a transmission mechanism so that the grasping and cutting behaviors are performed in an orderly and continuous manner, as shown in Figure 14.

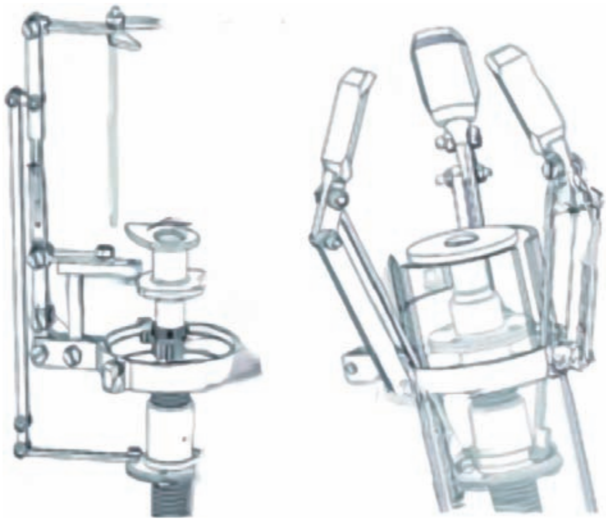


Figure 14 Round fruit picking robot cutting device and its whole machine

3.2 Flexible separation type

After a long period of manual fruit picking, it was found that there are some kinds of fruits that do not need the above-mentioned mechanical cutting methods at all and can be separated by pulling, folding, twisting, rotating and turning them, which are collectively called flexible separation.

Wang et al.[34,35] from Beijing University of Technology proposed a robot for picking tomatoes in a greenhouse environment, as shown in Figure 15 below. It uses a bionic form of one claw and three fingers, and the end-effector consists of a motor for the wrist, a finger motor, a rigid finger, a pressure sensor, a silicone finger sleeve, and a silicone wrist sleeve, and the fruit is twisted after it is grasped, and then the fruit is separated. Usually it takes 15 s to pick a tomato with a success rate of 86.7%, but it takes a lot of time to control the more tender fruits during the picking process because the grip of the hand grasp needs to be monitored so that the ripe tomatoes are not destroyed.

Figure 15 Tomato picking robot end-effector and its whole machine experiment

American scholars Schertz et al.[36,37] developed a citrus picking robot in the 1960s that also used a rotating wrist to cut the stem of the fruit and then into a rubber tube, and although this picking robot could pick citrus, it did not meet the different sizes of fruits, as shown in Figure 16 below.

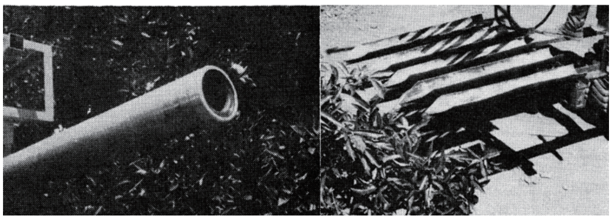


Figure 16 Vacuum twisting device and collector for citrus picking robot

Also using rotation, an apple picking robot with multiple robotic arms was proposed by FFROBOTICS, Israel, in 2020[38,39], with 4-12 robotic arms distributed on the left and right sides for simultaneous picking of multiple apples and using a three-finger structured gripper for grasping and separating the fruits, as shown in Figure 17 below.

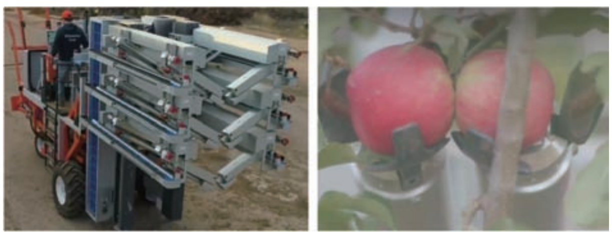


Figure 17 FFROBOTICS multi-arm picking robot structure and its experiment

4 Traditional picking robot summary

In order to give instructive suggestions for combining end-effector with excellent performance from conventional structures, the authors will summarize the above examples and make a simple comparison, as shown in Table 1.

Table 1 Comparison of end-effectors with different traditional configurations

Fruits	Separation methods	Grasping methods	Cycle time/s	Harvest success/%	Reference
Tomato	Pull	Sucking	24	83.9	China, Feng et al.[16]
Apple	Cut and bite	Sucking	4.5	82.15	China, Li et al.[21]
Strawberry	Cut	Sucking	-	-	Japan, Kondo et al.[17]
Apple	Pull	Clamping	2.3	-	China, Ma et al.[23]
Apple	Twist	Clamping	7	56	Amercia, Davidson[24]
Tomato	Cut	Clamping	15	90	Japan, Kondo et al.[25]
Eggplant	Cut	Clamping	64.1	62.5	Japan, Hayashi et al.[29]
Strawberry	Cut	Sucking	7.5	59	USA, Xiong et al.[30]
Citrus	Cut	Sucking	3	90	China, Fu[32]
Pear, apple, etc.	Cut	Clamping	-	-	China, Han et al.[33]
Tomato	Twist	Clamping	15	86.7	China, Wang, et al.[34,35]
Citrus	Twist	Sucking	-	-	Amercian, Schertz et al.[36,37]
Apple	Cut and twist	Sucking	-	2.7	Isreal, Ffrobotics Company[39]

From some examples we discussed above, we can see that the traditional rigid robot is usually used as a picking robot field, and in addition it has great deficiencies in size, weight, flexibility, and adaptability, including the cycle time for picking fruits, for example, it takes 45 s to pick a cucumber[40], 64.1 s to pick an eggplant[29], and 8.7 s to pick an orange[41] , therefore, in robots for orchard picking, there is a need to develop high-performance manipulators and intelligent control methods, such as image processing, recognition of target, and fast response.

The fruit picking process can be divided into two parts, i.e. “grasping” and “separation”. In order to describe the picking process of the fruit and vegetable picking robot and the structural characteristics of its effector, the authors created a flowchart describe the process, as shown in Figure 18.

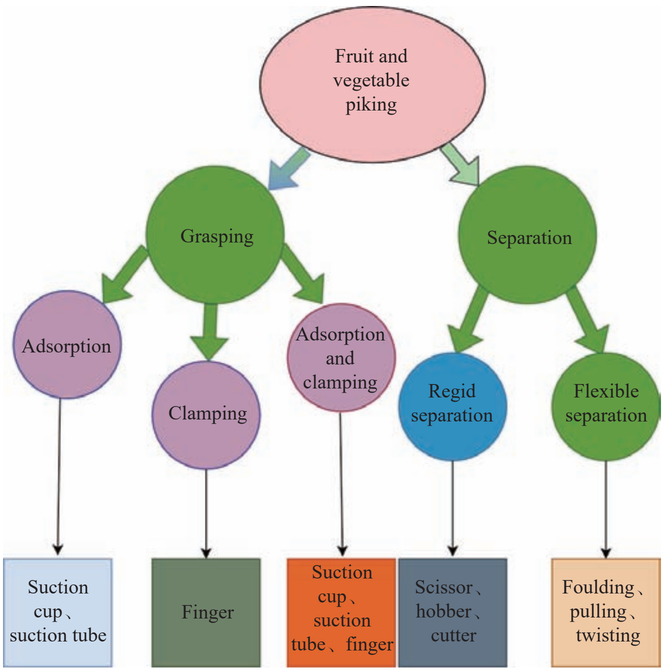


Figure 18 Fruit and vegetable picking.

5 Under-driven picking robot

Traditional rigid picking robot has some defects in grasping and separation methods, it is difficult to achieve versatility, and the structure is complicated, the flexibility is not high, the rate of damage to fruits and vegetables is also relatively large, the emergence of under-driven rigid robot will overcome these shortcomings, so as to achieve adaptive grasping and separation of fruits. The following will focus on the introduction of this type of manipulator.

If the number of drive elements in a robot is less than the number of degrees of freedom of the mechanism, then the robot can still function properly, and then the robot is called an under-driven picking robot. Under-driven robots have significant advantages over conventional fully driven picking robots

(1) Simple control system for under-driven robots.

(2) The under-driven robot is highly adaptable to grasp fruits and vegetables.

(3) The under-driven robot has good stability in grasping fruits and vegetables and low damage rate to fruits and vegetables.

Combining these characteristics, a variety of manipulators have been proposed by scholars at home and abroad. Sun of Sichuan Agricultural University designed a multi-degree-of-freedom end-effector[42], as shown in Figure 19 below, which controls the opening and closing of the finger by one motor, the whole structure is relatively simple and relatively easy to control, but the gripping force of this actuator is relatively small, which is not conducive to obtaining good versatility.

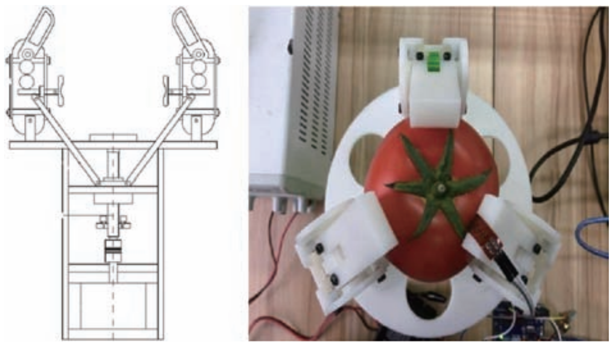


Figure 19 End-effectors for greenhouse tomato picking systems.

Li et al.[19] of Xi'an Engineering University designed an adaptive under-driven bionic end-effector, which imitates human fingers with three joints and can achieve adaptive grasping of objects of different sizes similar to human hands, as shown in Figure 20, in addition the carrying capacity of the manipulator is also relatively large, which is no problem for most fruit picking.

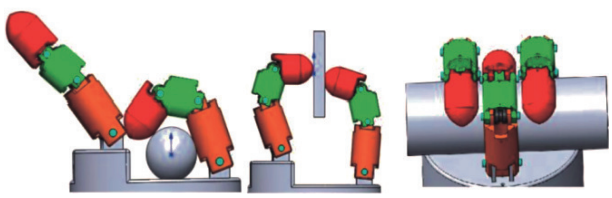


Figure 20 Adaptive under-driven bionic end-effector.

Sun et al.[43] of Wuhan University of Science and Technology proposed an under-driven end-effector with multi-mode grasping, as shown in Figure 21, which can perform flat-clamp, envelope-type stable grasping, and in by setting a finite slider, the manipulator can switch the grasping mode by itself according to the size of the grasped object.

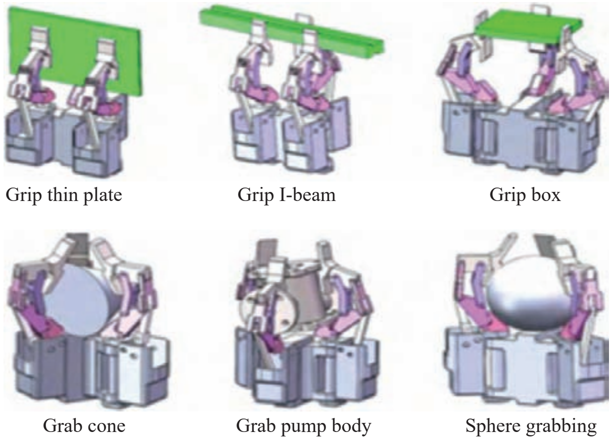


Figure 21 Under-driven end-effector for multi-mode gripping.

Abroad Jun et al.[44] proposed an under-driven robotic hand for grasping various types of tableware, as shown in Figure 22. The robotic hand can grasp the plate by inserting the claw into the edge of the stacked plate and closing the fingers. In practice, there is no shaking of the plate or any large acceleration, so it is most convenient to set the plate with it. In addition, the robotic hand can be installed in a fully automatic dishwasher.

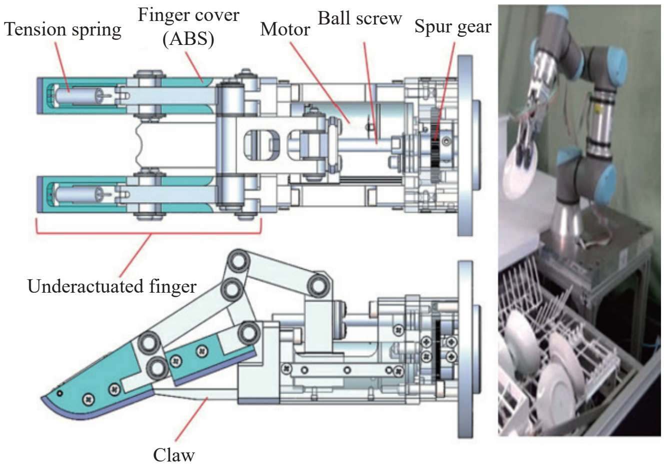


Figure 22 Under-driven end-effector structure and its experiment

Begoc, Italy, developed pneumatically driven under-driven manipulator[45], with two fingers, controlled by four cylinders, each finger has three joints, so it can control these six degrees of freedom by controlling pneumatic switches, which can be adaptive to grasp different types of objects, but due to the large size, it is also difficult to pick fruit, so the structure size needs further improvement, as shown in Figure 23. In addition to these, there are many under-driven robotic manipulators that can be used for picking fruits and vegetables that are worthy of reference, such as Dollar's SDM hand[46], Tegin's manipulator[47].

Figure 23 Pneumatically driven robotic wrapped grip and gripping grip.

6 Position recognition methods

In addition to the research on the structural characteristics of end-effector handling, the recognition of the position of fruits and vegetables is also the focus of research on the end-effector[48]. In recent years, many scholars have studied how to quickly identify the location of fruits so as to improve the efficiency and quality of fruit picking, which in turn can better promote the use and reduce the cost of picking. The authors summarized the positioning recognition methods of many scholars and found that fruit and vegetable position recognition methods can be divided into three types, single feature recognition method, multi-feature recognition method, and deep learning recognition method[49]. The specific features of these methods and their applications are described in the following section.

6.1 Single feature recognition method

The most common single feature recognition method is the recognition of the feature "color", which can be a very effective method if the color of the target object and the surrounding environment are very different. "Color" recognition mainly uses the color difference method and the intelligent learning method. The color difference method uses the color difference between different positions in the color space to recognize the target object. Combining the principle of this method, Zhao et al.[50] from Jiangsu University proposed a method for nighttime recognition of apple picking robots using an improved R-G color difference segmentation method, as shown in Figure 24, the result of segmenting apples is 83.7% at night without considering the obscuration and adhesion of fruits. Patel et al.[51] obtained a feasible identification method for ripe citrus using a component of the Lab color space with 98% accuracy. Although a variety of recognition methods can be developed using the color difference method, the flexibility and segmentation recognition rate are difficult to improve. Therefore many scholars propose an intelligent learning based approach, which is an intelligent algorithm that uses clustering, modeling and decision trees to discover the results in a given color space, rather than a simple threshold segmentation method, for example, Lv et al.[52] developed a method that can identify overlapping and occluded apple fruits in natural environments, which uses an improved RHT method to detect, for apple fruits in an overlapping state, the overlapping and adhering parts between apple fruits are separated by adding the segmented binary image to the edge image for processing. For apple fruits that are severely obscured by branches and leaves, the area-directed grouting method is used to recover apple fruits that are segmented into several parts by branches and leaves, and then feature extraction and recognition are performed on them. Figure 25 below shows the identification of different apple state features. Wei et al.[53] University of Chinese Academy of Sciences, using an improved Otsu adaptive thresholding algorithm, was able to recognize pomegranate, strawberry, tomato, and persimmon in natural environments with an extraction rate of more than 95%, however, segmenting images according to different thresholds reduces robustness and makes the results sensitive to the external environment, thus affecting detection accuracy. Thankfully, a multi-color recognition algorithm based on the double Otsu algorithm was proposed[54], and the following Figure 26 shows the image of its experimental results, which finally shows that the double Otsu algorithm takes less than 0.2 s for the recognition of ripe litchi with color targets thus improving the detection efficiency. In order to accurately identify grapes in vineyards, Luo et al.[55] developed a

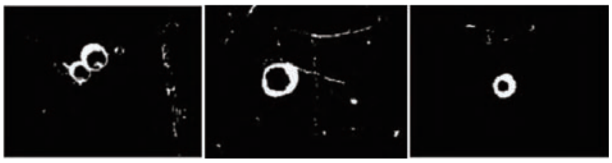
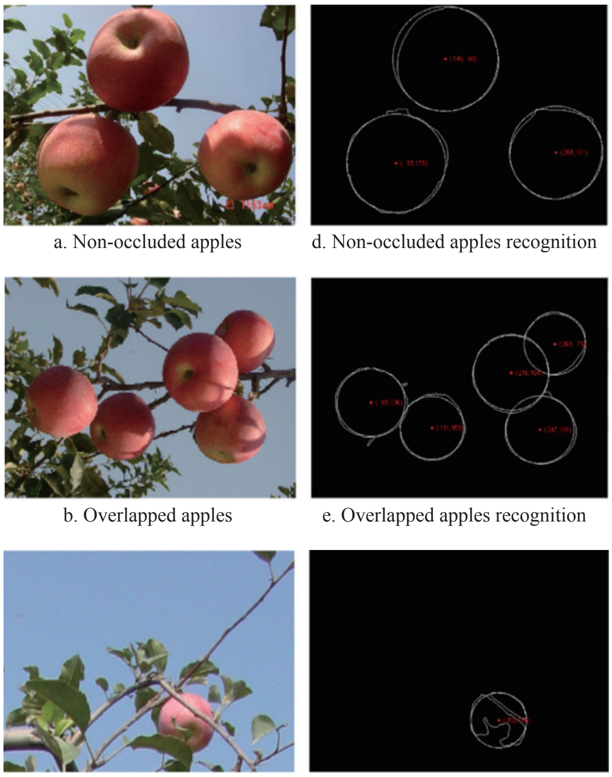


Figure 24 Improved R-G color segmentation

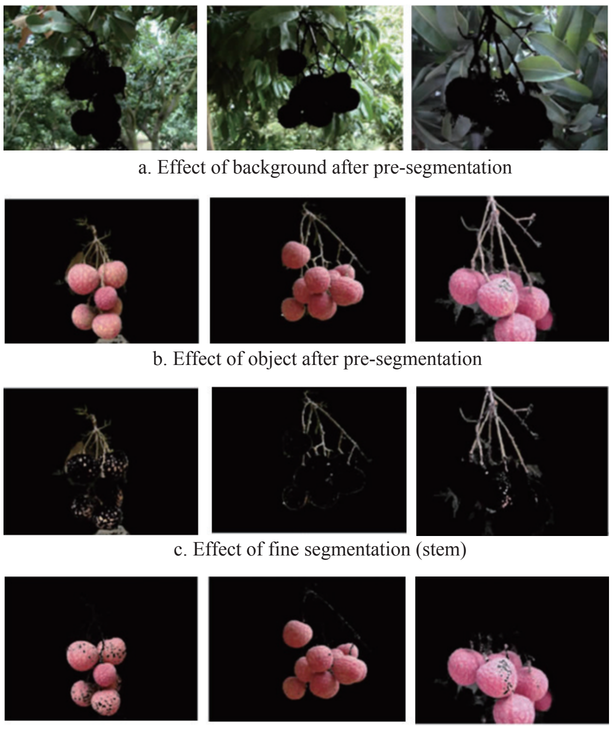


a. Non-occluded apples d. Non-occluded apples recognition

b. Overlapped apples e. Overlapped apples recognition

c. Occluded apples f. Occluded apples recognition

Figure 25 Recognition of different visual features of apple fruit



a. Effect of background after pre-segmentation

b. Effect of object after pre-segmentation

c. Effect of fine segmentation (stem)

d. Effect of fine segmentation (fruit)

Figure 26 Segmentation effects of double times Ostu algorithm on 3 pairs of lychee images method that combines the AdaBoost framework and multiple color components to automatically detect ripe grapes using a simple vision sensor, and the principle of the method is shown in Figure 27 below. Experimental results show that the method can be independent of weather conditions, foliage and light changes, etc., with an average detection rate of 93.74%.

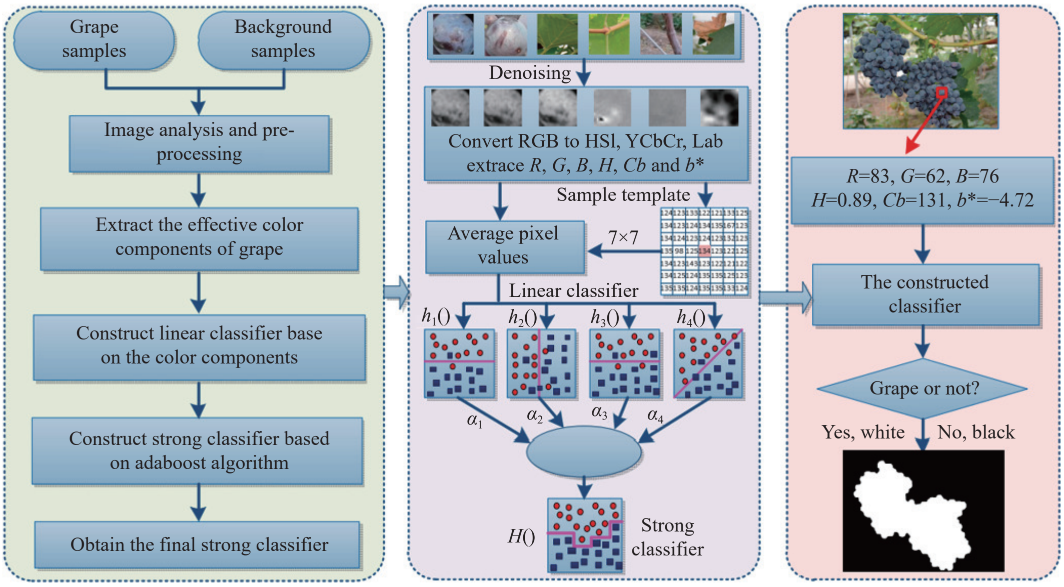


Figure 27 Approach Schematic

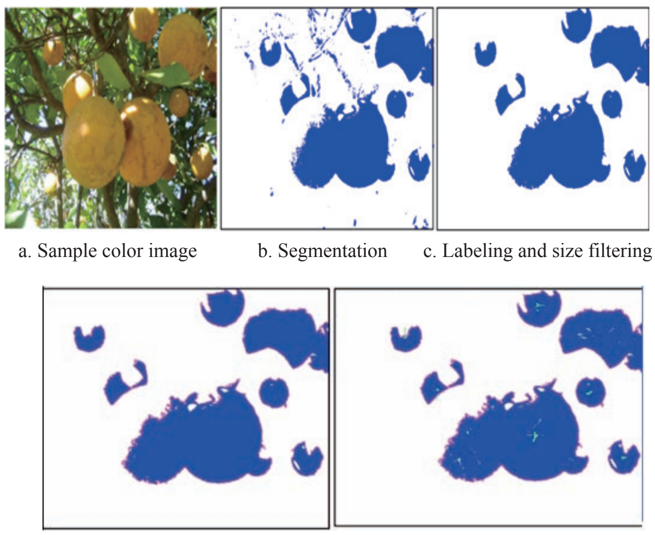
The specific application of a single feature, color, in fruit and vegetable localization recognition was discussed above, but in the detection process, it is affected by several environmental factors, including ripeness, color, variety, and illumination, etc. To avoid these problems, there are other methods to detect fruits and vegetables among the existing studies. From the image characteristics of some fruits, apples and oranges[55] have a more rounded appearance than their branches and leaves, while cucumbers are elongated and longer than their branches and leaves, and using this feature, the target contours of round or elongated fruits were successfully detected by the combination of Canny algorithm and Hough transform[56]. The boundary line between the position fruit and the image background was extracted by the edge detection algorithm, and accurate recognition of long-shaped fruits was achieved by this combination.

Although it is said that geometric features are not affected by light, many varieties of fruits will be blocked by some branches, leaves and bushes to find their location based on their shape, and in addition the shape size and other geometric parameters of the fruits will affect their recognition efficiency.

In addition to color and shape, texture features are also able to distinguish the location of fruits in color space, and texture features are not disturbed by color, so this method using texture features is usually used in cases where branches and fruits are similar in color, such as when green apples[57,58] and green citrus[59,60] are to be picked. Combining these three aspects, color, geometric features, and texture, the location of the fruit can be detected even when the fruit is unevenly lit and obscured. Kurtulmus et al.[61] used histogram-based separation to obtain color, texture, and shape information, and combined with extensive experiments, the recognition accuracy was 75.3%. To improve the accuracy, Chaivivatraku et al.[59] proposed a technique for green fruit detection based on texture analysis, also combined with circular Gabor texture feature recognition method, with a success rate of 90% .

6.2 Multi feature recognition methods

According to what is known in Section 6.1, single feature recognition methods have obvious shortcomings, so many scholars combine color, shape, and texture features for recognition to improve their success rate. Hannan et al.[62] proposed a machine vision algorithm for recognizing citrus fruits, where color threshold segmentation and edge perimeter were integrated to detect citrus, and Figure 28 below shows their processing method for recognizing citrus, which was able to reach 90% success rate. Patel et al.[63] proposed an algorithm that includes features such as intensity, color, orientation, and edge to detect different fruit images on trees taken at different locations with 90% detection accuracy. Liu et al.[64] introduced an image processing algorithm that combines color and texture information and uses the support vector machine principle by separating and counting the fruit in the image bunches to improve fruit detection, and in experiments conducted on two varieties of red grapes (Syrah and Cabernet Sauvignon) showed detection efficiencies of 88% and 91.6%, respectively. Han et al.[65] proposed a fast normalized correlation (FNCC)-based machine vision algorithm that combines three features, color, shape, and texture, and a validation dataset of 59 images successfully detected



a. Sample color image b. Segmentation c. Labeling and size filtering

d. Perimeter extraction e. Circle detection

Figure 28 Sample image processing for fruit detection

84.4% of the fruits. An example of fruit identification using this method of FNCC is shown in Figure 29 below.

a. b.

c. d.

Figure 29 An example of FNCC fruit potential position detection

6.3 Deep Learning Methods

In the above examples, it can be well demonstrated that the multi-feature recognition algorithm significantly improves the accuracy and robustness of fruit recognition, but it does not well eliminate the effects of occlusion, lighting, and fruit clustering, and the fitting accuracy and the ability to handle complex scenes are limited. To be able to solve these problems, deep learning algorithms have been proposed, which have been widely applied to detect, localize, and segment fruits in images. Sa et al.[66] fine-tuned the VGG16 network based on a pre-trained ImageNet model to build a vision-based fruit detection system. Xiong et al.[67] from South China Agricultural University used Faster R-CNN method for visual detection of green citrus on trees based on deep learning techniques, but the comprehensive recognition rate was only 77.45%. Zhou et al.[68] from Shenyang Agricultural University proposed a deep convolutional neural network-based tomato major organ classification and recognition method for fast and accurate detection of different tomato organs, and established 10 tomato organ network models based on VGGnet and adjusted by result optimization. After detection and recognition tests on tomato plants, the average detection success rates of flowers, fruits and stems were 84.48%, 81.64% and 53.94%, which were better than R-CNN and Fast R-CNN in terms of detection speed and accuracy. Xue et al.[69] improved the YOLOv2 recognition method and calculated a new Tiny-yolo network structure with dense connections to achieve network The success rate reached 97.02% with the multiplexing and fusion of multi-layer features to improve the detection accuracy. Liu et al.[70] of Chongqing University of Technology proposed an advanced deep convolutional neural network (CNN) vision system including YOLOv3, ResNet50 and ResNet152 networks, which can distinguish not only citrus fruits but also leaves, branches and fruits that are obscured by branches or leaves. The recognition ability of the three CNNs was confirmed among the experiments, with ResNet152 having the highest recognition accuracy of 95.35% for normal citrus in natural environment, 97.86% for overlapping citrus fruits, and 85.12% for citrus leaves and branches. Li et al.[71] proposed a fast recognition method for ripe strawberries based on a deep learning approach, which uses the Otsu algorithm to separate the target from the background, and then uses the valid image region specified by the minimum external rectangle labeling method to train CaffeNet for automatic target recognition, and the following Figure 30 shows the recognition graph for strawberry experiments, and the experimental results show that the average recognition rate of CaffeNet for ripe strawberries can reach 95%, which is 11% higher than that of SVM.

Single strawberry

Fruit overlap

Leaf sheltering

Many goals

a. Original image b. Segmentation image

Figure 30 Target segmentation

The deep learning method has great advantages over traditional recognition methods for the recognition of covered and overlapping fruits, but this method requires a sufficient training set and is computationally intensive, time-consuming, and costly.

The above introduction of three position recognition methods found that almost all of them have shortcomings in accuracy, efficiency, and versatility. To facilitate the selection and improvement of the corresponding methods, Table 2 compares these methods.

7 Conclusions and outlook

7.1 Conclusions and challenges

This paper mainly reviews rigid fruit and vegetable picking robots in the agricultural field, especially in the structural design of end-effector and positioning methods have been introduced a lot. In the related field of research, there are still some problems to be solved, which are reflected in the following aspects.

(1) Rigid fruit and vegetable picking robots use hard materials, which can cause certain damage when gripping or adsorbing fruits, and in addition the gripping and adsorption forces are not easy to control and the damage rate is large.

(2) Rigid robots usually lack flexibility and cannot perceive the magnitude of the force, and thus it is difficult to grasp the fruit

Table 2 Comparison of different positioning recognition methods

Methods	Advantages	Disadvantages	Applicable fields
Color feature	Distinguish between fruit and background	Influenced by differences in maturity, color, variety, background, and external light	Fruits with obvious color difference from the background, such as apples, tomatoes, citrus, oranges, etc.
Texture feature	Fruits separated from the background	It is affected by changing lighting conditions, fruit occlusion, and similar backgrounds	Fruits that are similar in color to the branches and leaves, such as green citrus and green apples
Shape feature	Obtain profile information of fruit targets; Insensitive to light	Affected by branches, leaves, shape, size, and other geometric parameters	Round and long fruits, such as tomatoes and cucumbers
Multi-features	Compensate for the limitations of single features; Improve accuracy and robustness	Affected by occlusion, lighting conditions, and fruit shape	Suitable for most fruits
Deep learning	Resolving overlapping and closed difficulties; Achieve good robustness and versatility	Adequate training sets are required; Long training time; The amount of computation is large and the cost is high	Fruit detection in complex environments

adaptively.

(3) The picking process of fruit and vegetable can be divided into grasping and separating. Specifically, the picking robot firstly absorbs or clamps the fruits, and then separates them by pulling and rotating, so the picking efficiency will be reduced by tedious movements, uncoordinated mechanisms, and complicated control.

(4) The combination of rigid fruit and vegetable picking robots and agronomy is not common. Most of the fruit picking robots are still in the research stage, with long picking cycles and low efficiency, and few end-effectors that can really be used in large numbers for fruit and vegetable picking.

7.2 Outlook

With the continuous development of variable stiffness technology, new materials, rigid fruit and vegetable picking robot can make great improvements on the basis of these technologies. In addition, combined with the above summary of rigid fruit and vegetable picking robot poor adaptability, high cost of recognition of position, low efficiency and other problems, the following recommendations can be made.

(1) It can combine flexible materials, variable stiffness technology, and bionic principle to improve the characteristics of rigid fruit and vegetable picking robot with high stiffness, high damage rate, poor flexibility, and low adaptability.

(2) Improve its multifunctionality. At present, almost all rigid fruit and vegetable picking robot function is relatively single, can only pick a single fruit, cannot be extended by replacing the actuator, increase the positioning function module, so through the research and design of open structure and control system, agricultural robot can achieve better development.

(3) The end-effector can develop a new drive system by combining its biomechanical characteristics when operating similar objects, optimizing and improving its drive principle and structural characteristics to ensure the quality of operation while reducing its development costs.

(4) The cost of the positioning recognition system should be reduced and the accuracy and stability should be improved so that an intelligent picking robot is just around the corner.

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