Promising real-time fruit and vegetable quality detection technologies applicable to manipulator picking process

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Abstract: In recent years, worldwide research on fruit and vegetable quality detection technology includes machine vision, spectroscopy, acoustic vibration, tactile sensors, etc. These technologies have also been gradually applied to fruit and vegetable grading and sorting lines in recent years, greatly improving the income of farmers. There have been numerous reviews of these techniques. Most of the published research on fruit and vegetable quality detection technology is still carried out in the laboratory. The emphases have been on quality feature extraction, model establishment and experimental verification. The successful application in the fruit and vegetable sorting production line proves that these studies have high application potential and value, and we look forward to the performance of these sensing technologies in the fruit and vegetable picking field. Therefore, in this paper, based on the future highly automated fruit and vegetable picking mode, we will focus on three kinds of fruit and vegetable quality detection technologies including machine vision, tactile sensor and spectroscopy, to provide some reference for future research. Since there are currently limited cases of detecting quality during the fruit and vegetable picking, experiments performed on prototypes of manipulator, or devices such as Nanocilia sensors, portable spectrometers, etc., which are compact and convenient to mount on manipulator will be reviewed. Several tables and mosaics showing the performance of the three technologies in the detection of fruit and vegetable quality over the past five years have been listed. The performance of each sensing technology was relatively satisfactory in the laboratory in general. However, in the picking scenario, there are still many challenges to be solved. Different from industrial environments, agricultural scenarios are complex and changeable. Fragile and vulnerable agricultural products pose another challenge. The development of portable devices and nanomaterials have become important breakthroughs. Optical and tactile detection methods, as well as the integration of different quality detection methods, are expected to be the trends of research and development.

Keywords: fruit and vegetable quality detection, machine vision, spectroscopy, tactile sensors, picking scenario
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1 Introductions

Fruits and vegetables are increasing in production and consumption due to their good taste, appearance and health benefits. There are differences in the quality demands of fruits and vegetables among people with different consumption capacity. The demands for different grades of fruits and vegetables have led to the development of fruit and vegetable sorting and grading technologies. The emphases of sorting and grading technology have been in the non-destructive perception, extraction and evaluation of fruit and vegetable quality. In recent years, many commercial fruit and vegetable grading lines using these detection technologies have been put into production. These production lines are efficient but also require higher initial costs and maintenance costs[1]. Taking the current production process of some orchards as an example, after large-scale harvesting in the orchard, fruits are transported to the facility for further commercial processing such as storage, grading and packing. During these processes, some secondary damages will occur, such as bruises and infections from squeezing and bumping[2]. Especially with the current production process, low quality or diseased products can take up a lot of transportation and storage costs[3]. If the quality detection and grading can be completed in the orchard, the cost of indoor construction will be greatly reduced, and the loss caused by damage to fruits and vegetables can also be reduced. The quality parameters of the fruit can be used as the criterion for picking. The information and grading results can be used for yield monitoring and quality traceability, as well as provide guiding suggestions for regional farming[4]. Compared with the traditional labor-intensive fruit production mode, the integrated production mode of picking, quality detection and grading in the field in the future can greatly improve the efficiency of production. Figure 1 shows the comparison of traditional and future fruit production mode.

Judging from the research trends in recent years, the real-time detection of fruit and vegetable quality is becoming a research hotspot. Through the application of machine vision, spectroscopy, proximity sensors and chemistry sensors[5], fruit and vegetable quality parameters including external parameters and internal

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parameters can be detected[6]. Among these technologies, detection methods based on machine vision, spectroscopy and tactile sensors are more likely to be used in the process of picking[4,7,8]. Recognition and location are first needed, and machine vision is an effective tool to evaluate the external properties of fruits. With the development of portable devices in recent years, the combination of miniaturized spectroscopy devices and tactile sensors with end-effectors also has a broad development prospect. At the same time, the two technologies can also detect the internal quality of fruit and vegetable such as firmness and soluble solids content (SSC), which is a complement to the machine vision technology. Currently, most of the researches on fruit and vegetable quality detection technologies mounted on picking robots are conducted in the laboratory and are still in the testing phase, especially tactile and spectroscopic techniques. However, after reviewing numerous papers, the results of these studies were found to be promising. Most of the experimental results have a high correlation with the fruit and vegetable quality parameters detected by the sensing technology, that is, the sensing technology has a high potential to be applied to the future robotic picking process.

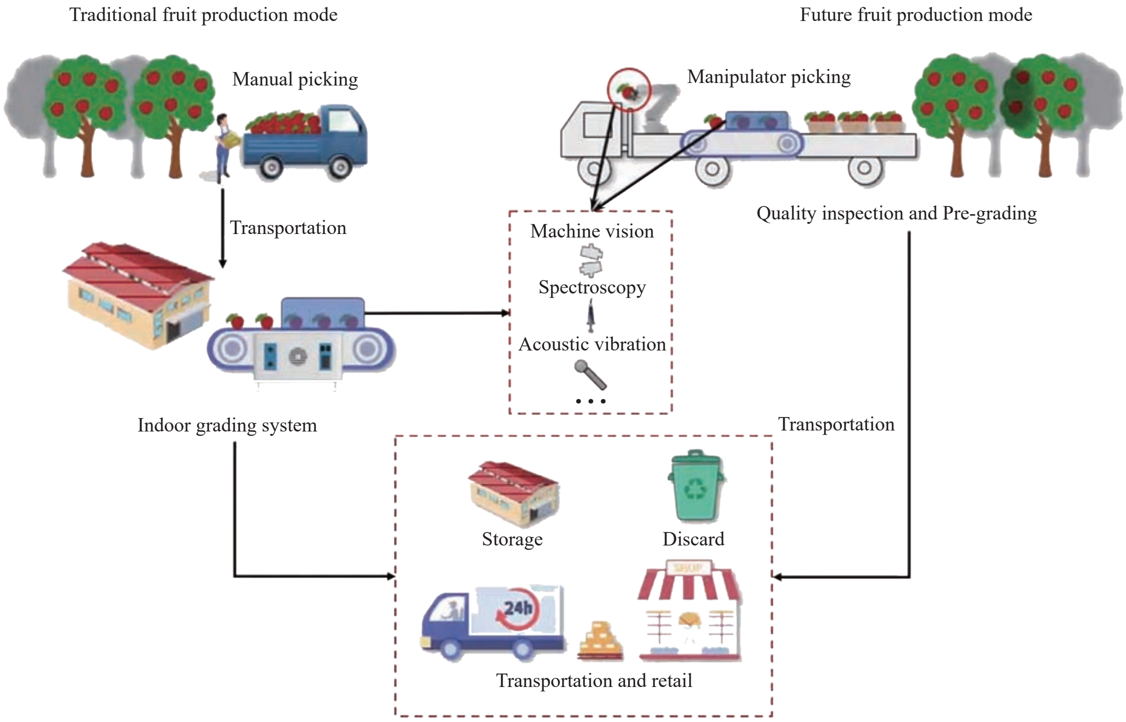


Figure 1 Labor-intensive traditional fruit production mode and future fruit production mode integrating infield picking, quality inspection and grading

This article provides a review of the research on fruit and vegetable quality detection using machine vision, tactile sensors and spectral sensors, with particular attention to the experiments performed on the prototype of the manipulator, as well as nanocilia sensors, portable spectrometers that are compact and convenient to mount on the manipulator. Over the past five years, the fruit and vegetable targets to which these techniques have been applied have varied. Most of the research has targeted fresh fruits, such as apples, blueberries, and bananas, which change color significantly after ripening, and mangoes and papayas, which change firmness significantly after ripening. There are also a few researches for Solanaceous vegetables like tomatoes and sweet peppers. Yet there are many challenges for these technologies to be applied in the picking infield. Different from the relatively closed and repetitive work environment and work requirements of industrial robots, the picking environment is often open and changeable[9]. This is a challenge for the stability of fruit and vegetable quality detection. Common challenges will be addressed in the discussion, and the challenges and possible solutions specific to each technology will be highlighted.

2 Detection method based on machine vision

2.1 Introduction of machine vision

The main quality parameters of most fruits and vegetables are related to the appearance (color, presence of epidermal wax, size and shape) and texture[6]. Machine vision is an effective tool to evaluate the optical properties of heterogeneous materials[10]. By using machine vision system, external characteristics such as shape, color, size, texture and defects can be detected and graded[7]. Besides, changes in appearance parameters have a profound impact on consumer acceptability. Therefore, machine vision technology has received early attention from researchers to detect the characteristics of produce.

In recent years, fruit and vegetable classification models based on traditional feature extraction combined with machine learning algorithm have good performance. However, the establishment of the model depends on the types of produce used for training and testing, and the data sets used to build the model are generally small, which will directly lead to the reduction of model robustness. In addition, the method based on hand-craft feature extraction is relatively time-consuming[11]. Deep learning technology deals well with the problems encountered by traditional machine learning algorithms. The model based on deep learning can automatically extract the relevant fruit features without intervention. Therefore, the bias in traditional feature extraction is avoided[12]. Gongal et al.[13] noted that the method of deep learning would be limited by hardware computing resources, but with the emergence of high-performance GPU and the update of deep learning framework such as Faster Regional Convolutional Neural Network (Faster R-CNN)[14], Single Shot multibox Detector (SSD)[15], and You Only Look Once (YOLO)[16], this problem has been gradually solved. Table 1 presents a summary of literature on the detection technology of fruit and vegetable quality using machine vision technology (traditional machine learning/deep learning) in the past five years.

Table 1 Summary of literature on the detection technology of fruit and vegetable quality using machine vision technology (traditional machine learning / deep learning) in the past five years

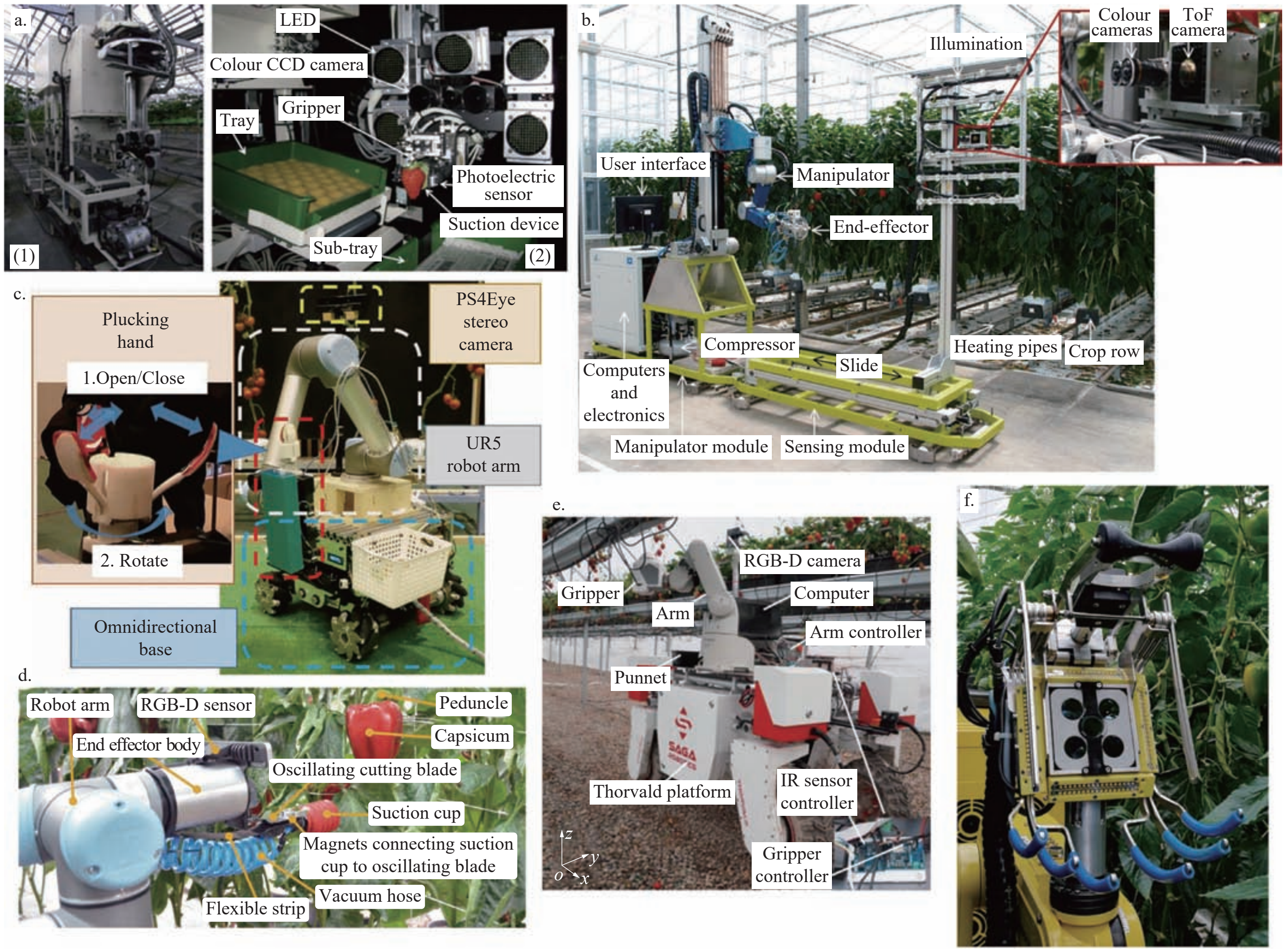
Types	Fruit species	Parameters	Methods/Classifier[a]	Accuracy	Reference
Traditional machine learning	Apple	Color, texture, shape	K-means, SVM	-	Dubey et al.[17]
		Defect, texture and size	SVM, MLP, KNN	89.20% (SVM) 86.60% (MLP) 85.80% (KNN)	Moallem et al.[18]
	Citus	Color	Distance transform and marker-controlled watershed algorithms	93.00%	Dorj et al.[19]
	Papaya	Color	RF	94.30%	Santos et al.[20]
	Orange	Surface defect	Sliding comparison window local segmentation algorithm	97.00%	Rong et al.[21]
	Mango	Size, shape, and surface defect	SVR	87.00%	Nandi et al.[22]
	Blueberry	Color	HOG, SVM, KNN	86.00%(young) 94.20%(intermediate) 96.00%(mature)	Tan et al.[23]
	Mandarin	Surface defects	ANN, RF	88.95%	Hadimani et al.[24]
		Texture, color, shape	ANN-HS, ANN-ABC, KNN	94.28% (ANN-HS), 96.70% (ANN-ABC), 70.90% (KNN)	Sabzi et al.[25]
	Tomato	Color	BPNN	99.31%	Wan et al.[26]
		Color	SVM, KNN, ANN	97.78%-99.81% (SVM) 93.78%-99.32% (KNN) 91.33%-99.32% (ANN)	de Luna et al.[27]
	Potato	Disease	SIFT-SVM, HOG-BOVW-BPNN, CNN	97.00%	Korchagin et al.[28]
Deep learning	Cassava	Disease	MobileNetV2	97.70%	Abayomi-Alli et al.[29]
	Apple	Surface lesion	CycleGAN, DenseNet-YOLO v3	-	Tian et al.[30]
		Bruise	CNN, SVM-VGG19, SVM-Inceptionv3	97.67%	Hu et al.[12]
	Tomato	Surface defects	ResNet50	91.70%	da Costa et al.[31]
	Banana	Color, texture, and surface defects	YOLO v3-SVM	96.40%	Zhu et al.[32]
	Papaya	Color	ResNet101, ResNet50, ResNet18, VGG19, VGG16, GoogleNet, AlexNet	100%(VGG19)	Behera et al.[33]
	Citrus	Surface defects	STA-CNN	98.00%	Zhang et al.[34]

Note: [a], Abbreviations: SVM, support vector machines; KNN, K-Nearest Neighbors; MLP, Multi-Layer Perceptron; RF, Random forests; SVR, support vector regression; HOG, histogram oriented gradients; BPNN, backpropagation neural network; ANN-HS, hybrid artificial neural network-harmony search; ANN-ABC, hybrid artificial neural network-artificial bee colony; SIFT, Scale Invariant Feature Transform; BOVW, Bag of Visual Words; STA-CNN, state transfer algorithm-convolutional neural network

2.2 Applications of machine vision

The size of the fruit and vegetable can be used as a standard for picking, and the weight prediction based on the size can also help estimate the yield of the orchard[35]. Qiao et al.[36] developed a mobile pepper grading robot to predict the weight of sweet pepper by processing the image information of a single sweet pepper, and got information about sweet peppers' size, color and fruit shape. Disease and insect damage can also be obtained by the use of the images from five cameras. With the application of depth cameras, imaging equipment is gradually streamlined and more efficient. Bac et al.[37] developed a sweet pepper harvesting robot based on a nine degrees of freedom manipulator in a complex environment, as shown in Figure 2b. The use of the depth camera helps to predict the size of the fruit, thus guiding the end-effector to open to an appropriate size. In a complex environment (light changes, occlusion, and dense obstacles), the harvest success rates of the two end effectors reached 26% and 33%. The Hsieh et al.[38] recorded the actual size information of tomatoes by Mask R-CNN and information from binocular vision depth camera. The average error of *XY* direction was 0.48 cm, and the average error of depth *Z* direction was 0.67 cm. Whether tomatoes can be harvested depends on their color. This color threshold is determined by experts and converted into HSV values.

In addition to characteristics such as size, the color of the fruit is the most commonly used criterion to distinguish between ripe and unripe produce. Hayashi et al.[39] realized strawberry picking based on a cylindrical coordinate manipulator in a field test, as shown in Figure 2a. The success rate of picking in the two separation modes reached 41.3% and 34.9%, respectively. The images were acquired by the color CCD camera and mature and immature pixels were distinguished by a hand-craft threshold. Xiong et al.[40] also used the color threshold method combined with the depth range of the target area to screen mature strawberries, as shown in Figure 2e. After optimizing the gripper, the robustness of grasping has been improved. The average harvest rate in the field experiment has increased to 53.6%, and the harvest time of a single strawberry has been shortened to 7.5 s. Lehnert et al.[41] harvested sweet peppers in the field combined with agronomy, as shown in Figure 2d. Based on the algorithm of color segmentation, the sweet pepper is picked after judging the ripeness, and the success rate can reach 58%.



Note: a. Strawberry-harvesting robot[39]; b. Components of the sweet pepper harvesting robot[37]; c. Tomato picking robot gets color extracted from 3D colored point cloud and picking based on threshold[42]; d. Sweet pepper harvesting robot[41]; e. Strawberry harvesting robot with optimized gripper[40]; f. Sweep pepper harvesting robot with cutting device, Fotonic F80 camera, LED illumination, and fruit catching device[43].

Figure 2 Fruit and vegetable harvesting manipulator with machine vision.

2.3 Challenges and possible solutions

1) The challenge of whole surface detection. Under the quasi-static detection condition of the picking process, it is difficult for the vision system to obtain the image of the back of the target. The defects on the back are often ignored, and these defective fruits and vegetables will cause subsequent waste of resources and hidden dangers to the health of others. In the current study, the priority of image collection on the back is after increasing the picking success rate and picking speed.

While this may result in complex path planning and significantly increase the time to process individual targets, the overall cost is worth it if the obvious defects on the backside of the target can be detected during the picking process. With the development of agronomy, the cultivation and growth patterns of fruit trees are becoming more suitable for mechanized picking, and the occlusion of branches and leaves will be relatively reduced. In other related research, the development of field fruit grading equipment has the potential to realize whole fruit surface inspection [44]. Compared with the indoor grading equipment, the classification performance and endurance have some disadvantages. However, compared to manipulator with limited resource and space, the use of multiple cameras to collect images[45], the use of mirrors to assist in obtaining multi-view images[46,47], and the use of rollers to rotate fruits have greater advantages in obtaining whole surface information[3]. Whole surface detection may present challenges such as distortion of the reflected image and replicated sampling of some surface regions. For qualitative problems such as surface defect determination, the above-mentioned challenges can be adapted by adjusting the rotation rate and the camera sampling frequency.

2) The challenge of unobvious defect detection. Defects in fruit and vegetable exhibit multiple patterns, including color, shape, texture, size, and position[4]. Common unobvious defects in fruits and vegetables include early bruises, physical damage, early decay, chills, and internal defects[2]. Bruises and chills are prone to occur in the process of transportation and storage after picking. Unobvious defects such as early decay, physical damage, and internal defects (including brown heart, disorders, watercore, black heart, and flesh browning) have chances to be detected during the process of picking. The crux of the problem lies in the insufficient ability of machine vision to obtain information based on the three visible light bands of RGB (Red, Green and Blue).

The combination of machine vision and spectroscopy technology can enhance the perception of machine vision. With the development of autonomous navigation and mobile robot platform, the miniaturization of hyperspectral imaging (HSI) and multispectral imaging (MSI) equipment and the improvement of computing and data storage capacity[48], some researchers have mounted spectral imaging equipment on the mobile platform to inspect the quality of fruit and vegetable in the orchard to obtain yield map and the best harvest time and other information. Wendel et al.[49] used hyperspectral imaging sensors mounted on unmanned ground vehicle (UGV) to predict dry matter (DM) content in mangoes remotely in the field to efficiently estimate and map mango ripeness. Benelli et al.[50] also used agricultural vehicles equipped with Vis/NIR hyperspectral imaging system to predict the soluble solid content (SSC) of grapes under natural light conditions to judge the ripeness of grapes. Table 2 presents a summary of literature on the detection technology of fruit quality using (mobile) spectral imaging (HSI/MSI) device in the past five years.

Table 2 Summary of literature on the detection technology of fruit quality using (mobile) spectral imaging (HSI/MSI) device in the past five years

Fruit species	Parameters	Types of spectral imaging	Methods/Classifier[a]	Performance	Reference
Peach	Chlorophyll	HSI	PLSDA	98.75%	Sun et al.[51]
Apple	SSC, anthocyanin	HSI	CARS-PLS	Rpre=0.9560 RMSEP=0.2528	Tian et al.[52]
Mango	Dry matter	HSI (mobile)	PLS, CNN	RCV2=0.58, RMSECV=1.17%w/w (PLS) RCV2=0.64, RMSECV=1.08%w/w (CNN)	Wendel et al.[49]
Strawberry	Ripeness	HSI	AlexNet-CNN	98.6%	Gao et al.[53]
Grape	SSC	HSI (mobile)	PLSDA	86%-91%	Benelli et al.[50]
Loquat	Defects	HSI	RF, XGBoost	97.5% (sound/defects) 96.7% (internal/external defects) 95.9% (purple spot, bruising, scars, flesh browning)	Munera et al.[54]

Note: [a], Abbreviations: PLSDA, partial least squares discriminant analysis; CARS, competitive adaptive reweighted sampling; RF, random forests; XGBoost, extreme gradient boosting

3 Detection method based on tactile sensors

3.1 Introduction of tactile sensors

Fruits such as kiwi and blueberry do not differ significantly in color between ripe and unripe individuals. Tactile sensors can complement machine vision by providing information at the time contact is made[55]. In previous research, tactile sensors are often used to determine the grasping force of the gripper for non-destructive grasping of fruit and vegetables. The relationship between the force on the surface of the target and the amount of deformation reflects the firmness, which provides a theoretical basis for the tactile sensor to detect the firmness of the fruit and vegetable when grasping it[56]. The combination of the manipulator and the tactile sensor is the foundation for the realization of flexible and precise grasping operation as well as firmness detection[57].

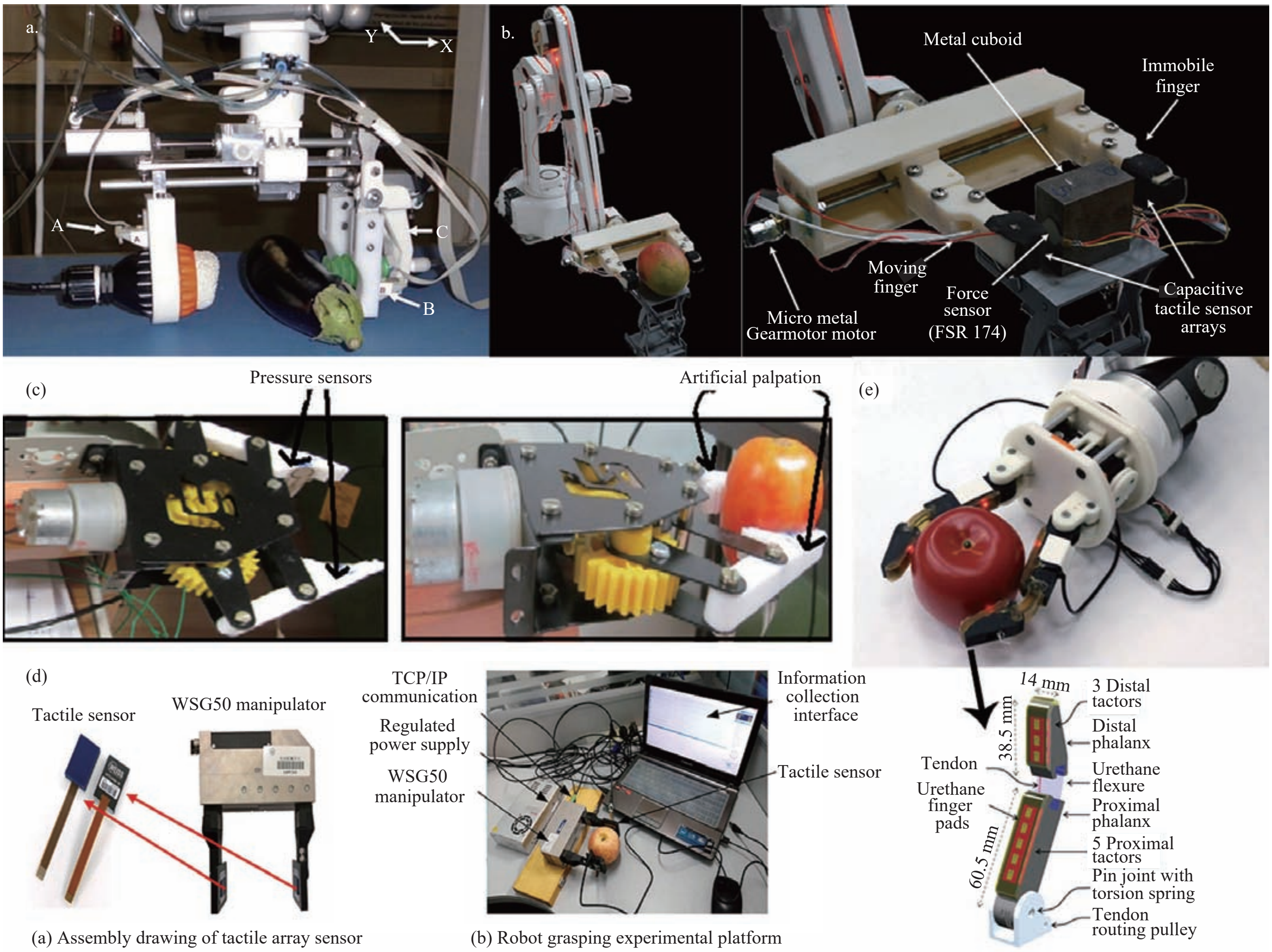
In previous studies, tactile sensors based on different principles have been proposed, mainly including optical (infrared or visible light)[58], piezoresistive[59], piezoelectric[60], capacitive[61], strain gauges[62] and accelerator[63]. Among them, capacitive tactile sensor arrays have higher sensitivity and dynamic characteristics, while piezoresistive tactile sensors are inexpensive. Table 3 shows the relative advantages and disadvantages of tactile sensors.

Table 3 The relative advantages and disadvantages of different tactile sensors

Types of tactile sensors	Advantages	Disadvantages
Optical	High sensitivity High spatial resolution High repeatability	Easy to wear Bulky Susceptibility to skin color and light
Piezoresistive	High spatial resolution Low cost Low susceptibility to noise interference	Hysteresis Low repeatability
Piezoelectric	High sensitivity High dynamic range	Poor static performance Poor spatial resolution
Capacitive	High sensitivity Good dynamic range Low susceptibility to temperature	Susceptibility to noise interference Complicated electronic design
Strain Gauges	Good sensing range High sensibility Low cost	Hysteresis Nonlinear response Susceptibility to temperature and humidity
Accelerator	Low cost High sensibility	Time-consuming Low repeatability

3.2 Applications of tactile sensors

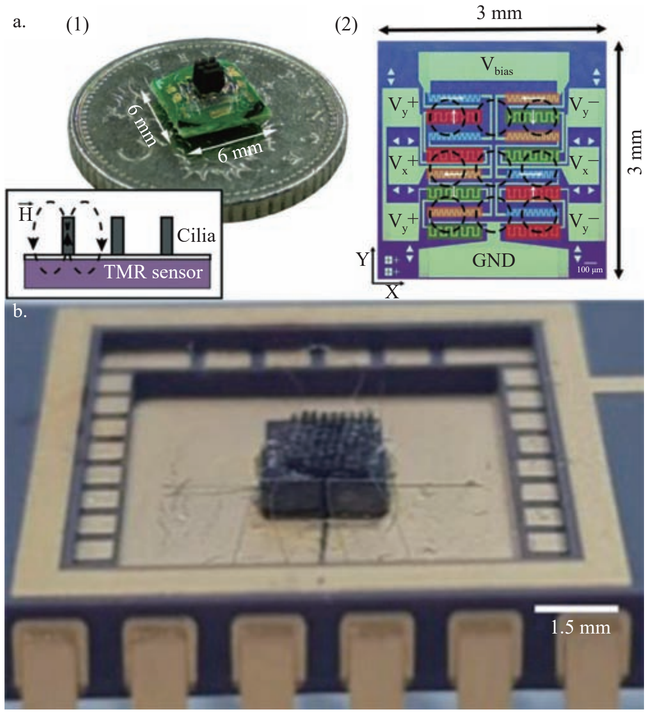
Combining the grasping action of the end effector and considering the fragile characteristics of the fruit and vegetable, most applications use piezoresistive, capacitive tactile sensors and accelerometers to evaluate the firmness of the target. Blanes et al.[64] embedded an accelerometer in a mechanical gripper to evaluate eggplant firmness and mango ripeness, as shown in Figure 3a. The non-destructive parameters extracted from the accelerometer constructed and validated partial least-squares (PLS) models, with a calibration regression coefficient of r=0.87 and a prediction performance (r=0.90). The firmness of the fruit is estimated by the deceleration time during the grasping action, the severity of the deceleration when the fruit comes into contact with the finger for the first time, and the highest peak deceleration[63]. Bandyopadhyaya et al.[65] installed two piezoresistive sensors containing ultra-thin flexible printed circuits on a two-finger mechanical gripper to detect and classify tomato firmness, as shown in Figure 3c. Eight features extracted from the data obtained from the sensors were used as classification criteria and modeled by two machine learning methods. It is concluded that the deterministic method (decision tree) (90%) is superior to the probabilistic method (® Bayes Classifier) (85%) in real-time implementation. Zhang et al.[66] established a manipulator with piezoresistive tactiles to detect the firmness of fruits, and compared the performance of PCA-KNN and PCA-SVM in an online test, as shown in Figure 3d. It is verified that the performance of PCA-SVM is better, and the accuracy of online detection can reach 90%. Distributed piezoresistive tactile sensor array increases the number of tactile sensing points and improves the sensitivity of online measurement. Spiers et al.[67] used an under-actuated two-finger manipulator to implement tactile object recognition and feature extraction techniques during the grasping process, as shown in Figure 3e. Each finger is equipped with eight tactile sensing units, and multiple target features including target size, stiffness, and posture are extracted with high classification accuracy. Zhou et al.[68] used tactile sensors with piezoelectric films and strain gauges to evaluate and classify the surface roughness of cucumbers, cantaloupes and apples with 93.737% accuracy. Scimeca et al.[69] used a custom mechanical gripper equipped with a capacitive tactile sensor array to palpate mangoes to assess their firmness, as shown in Figure 3b. The classification accuracy reached 88%. For the firmness of mangoes, the stiffness model established by the elastic deformation of mangoes was used in the experiment to represent the peel firmness value measured by the traditional penetrometer.



Note: a. Accelerator sensors mounted on gripper to assess the firmness of eggplant[64]; b. Capacitive tactile sensor array to assess the firmness of mango[69]; c. Piezoresistive flexible tactile sensor to classify the fimness of vegetables[65]; d. Distributed piezoresistive tactile sensor array on the two finger manipulator[66]; e. Under-actuated two-finger manipulator equipped with 8 tactile sensing units on each finger[67].

Figure 3 Robot grippers with tactile sensor

The (Magnetic nanocomposite) cilia tactile sensor is another kind of emerging tactile sensor in recent years, which is a bionic device developed by imitating the extremely sensitive cilia receptors found in nature. Cilia tactile sensors can transmit various mechanical forces and provide excellent sensing performance, mainly because they have a high aspect ratio and a high surface area to volume ratio, and can interact with the environment as much as possible[70]. The cilia of the cilia tactile sensor are often made of permanent magnetic materials, so there is no need for external magnetic field magnetization, which reduces the power consumption to the greatest extent and contributes to the integration of the system. In cases conducted in the laboratory, cilia sensors can assess the stage of fruit ripeness. Ribeiro et al.[71] used three different configurations of magnetic cilia (A: single cilia with a diameter of 400 μm and a height of 3 mm. B: nine cilia in a 3×3 array over the sensor, each with a diameter of 360 μm and a height of 1.6 mm. C: nine cilia in a 3×3 array over the sensor, each with a diameter of 400 μm and a height of 3 mm.) for nondestructive detection of Smoothness (S), Stiff®s (E) and ®ture (R) characteristics of apples and strawberries (with different surface roughness), as shown in Figure 4a. Since there is a paucity of publications on the correlation between fruit surface analysis and quality, experiments were conducted using a data-driven approach to test the classification performance of two supervised classification algorithms: *Random Forest* and *Gaussian Parsimonious Bayesian* methods. For the combination of features, experimental results demonstrate a significant improvement in model classification performance when stiffness and texture parameters are combined for evaluation. Fruits with smooth surfaces are more suitable for the cilia configuration with higher spatial resolution using type A, because more information can be conveyed, and the best classification accuracy obtained from the experiments reached 96%. Fruits with protrusions due to surface seeds like strawberries, where a larger contact area can average out the surface texture features, achieved an optimal classification accuracy of 83%. Carvalho et al.[72] proposed a cilia tactile sensor to qualitatively assess the ripening stages of blueberries and strawberries. The sensor is composed of up to 100 magnetized nanocomposite cilia, which are connected to a chip with a magnetoresistive sensor and adopt a full Wheatstone bridge structure. The average peak voltage provided by the contact between the cilia and the peel was confirmed to be related to the ripeness of the fruit, the cilia sensor is shown in Figure 4b.



Note: a (1) Cilia sensor, with a 3×3 cilia matrix configuration; (2) Microphotograph of the sensor die[71]. b. Optical image of the device wire bonded to a chip carrier, with the giant-magnetoresistive (GMR) sensor chip integrated with 100 artificial cilia[72].

Figure 4 Novel nano cilia tactile sensors

3.3 Challenges and possible solutions

1) The challenge of low repeatability. Almost all cases of tactile sensor detecting fruit and vegetable firmness are carried out in the laboratory. This is because the repeatability of the tactile sensor is not high enough, and this problem is caused by many factors. On the one hand, it is because of the biological specificity of the fruit and vegetable. Due to the uncertainty of the growth direction, the angle at which the end effector grabs the target cannot be completely consistent. The different grasping directions (parallel or perpendicular to the equatorial plane) have an impact on the firmness evaluation of fruit and vegetable. This is determined by the growth characteristics of fruit cells, because the firmness of the fruit reflects the ability of the cell wall to resist squeezing force on a microscopic level. The grasping test in the laboratory can ensure that the direction of grasping the same batch of target is as consistent as possible to avoid unnecessary singular data. On the other hand, various uncertain factors may appear in the environment when picking. Fruits may be mixed with branches and leaves when picking. Grasping damaged fruit may squeeze out the juice to contaminate the surface of the sensor. These conditions will test the robustness of the tactile sensor.

The high repeatability and high robustness of the sensing device are necessary conditions for fruit and vegetable quality detection in the picking field. In qualitative testing of fruit firmness indoors, the nanocilia sensor should detect the surface of the fruit multiple times to obtain data to eliminate accidental errors and improve the credibility of the results. In quantitative detection, tactile sensors capable of reflecting the force-deformation curve, such as piezoresistive type, are often used to reflect the toughness of the fruit skin to classify the fruit. The gripper should be grasped and tested in different poses and a global model should be established to improve the detection accuracy of fruit firmness in a complex outdoor environment. In the case of misdetection of fruit firmness caused by mixed obstacles and defects on the surface of the fruit, the combination with optical methods can greatly reduce these situations. When designing the structure of the end effector, the function of removing the branches and leaves that may be mixed during grasping should also be considered.

2) The challenge of high manufacturing cost of high spatial resolution and high sensitivity tactile sensors. Currently commercial distributed piezoresistive tactile sensors and distributed piezoresistive tactile sensors developed in the laboratory have very high spatial resolution (multi-contact array), sensitivity, and response frequency. At the same time, the sensor is integrated in the flexible film, which has good resistance to fracture and can adapt to the deformation during the grasping process. However, the manufacturing cost of these tactile sensors is generally high, and it is still unrealistic to be applied to the actual picking process at present.

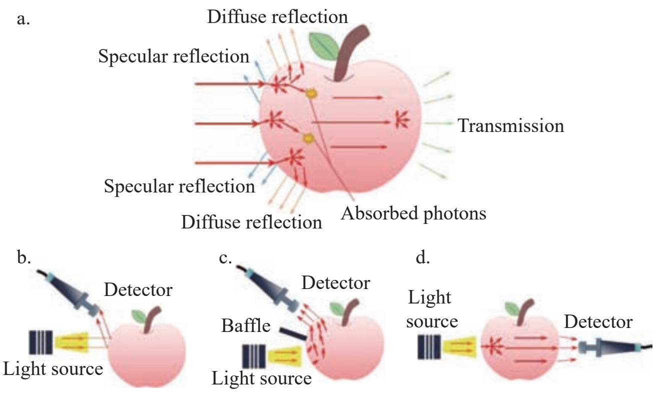
Modular design and production methods and the use of optical-based tactile sensors can reduce production costs. By converting the contact deformation signal into a high-resolution tactile image, the optical tactile sensor can achieve higher spatial resolution and sensitivity. In recent years, the research on optical tactile sensors mainly includes TacTip[73], Gelsight[74] and Gelslim[75]. Although they can achieve high spatial resolution and sensitivity, they are still large in size and not easy for the dexterous movement of the manipulator. At the same time, the gel surface is very easy to wear, which may lead to measurement uncertainty. Lambeta et al.[76] developed a new vision-based tactile sensor DIGIT based on GelSight. The components of DIGIT are modular, which enhances the versatility and interchangeability of parts. At the same time, DIGIT has a compact design and can be installed on multiple fingers at the end of the manipulator, greatly improving the tactile perception ability. The gel is also specially designed to be more resistant to wear. Combining with the latest manufacturing technology, mass production can further reduce the production cost of sensors.

4 Detection method based on spectroscopy

4.1 Introduction of spectroscopy

Machine vision technology can get the images of fruit and vegetable and obtain external quality information such as their color and size. Tactile sensors can perceive the texture of the surface and detect the firmness of the fruit and vegetable, but neither of the two technologies can detect internal qualities such as the sugar content and dry matter content of the fruit. Machine vision and spectroscopy are two important directions of optical technology. As another detection method based on optical principles, the spectroscopy method can obtain the internal chemical composition and part of the physical properties of the fruit and vegetable by detecting the reflection, transmission, and absorption information after the light source radiates the surface of the target[77], as shown in Figure 5.

As the more commonly used detection band in spectroscopy technology, visible light and near-infrared (Vis/NIR) radiation covers the 380-2500 nm wavelength range in the spectrum. First of all, the effective path of visible-near infrared spectroscopy ranges from millimeters to centimeters, which can effectively detect the internal quality of fruit and vegetable. Secondly, the main structure and functional group signals of almost all organic compounds can be detected in the Vis/NIR spectrum, and have a fairly stable



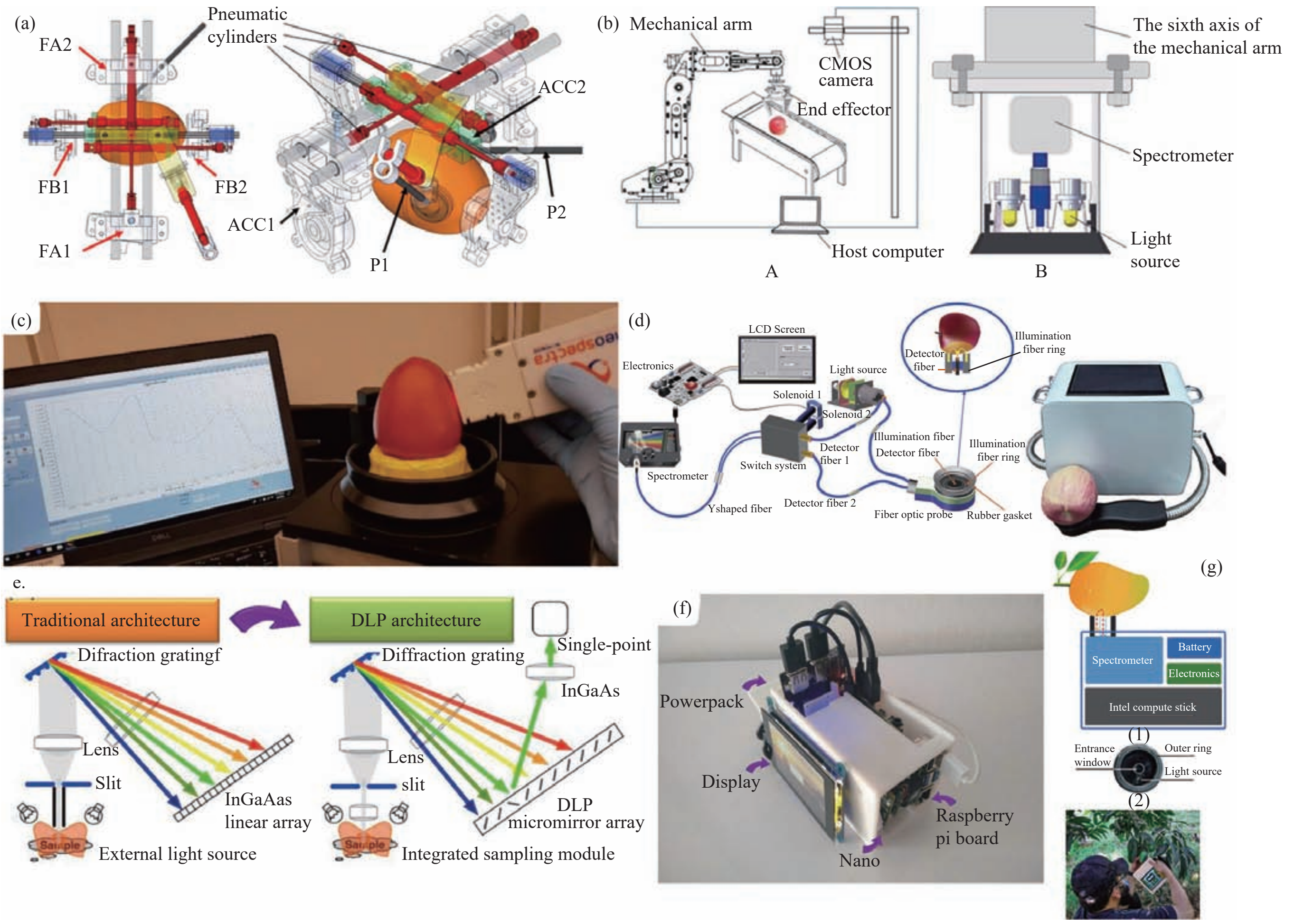
Note: Distribution of incident light in fruits (a) and different assessment modes based on specular reflection (b), diffuse reflection (c) and transmission (d)[78].

Figure 5 Working principle of spectroscopy equipment based on different light propagation modes.

spectrum. Therefore, the spectrum in the Vis/NIR range is usually used to analyze the content of organic compounds[77]. The visible light band is more sensitive to pigments (chlorophyll, carotenoids and anthocyanins), which can reflect the ripeness of fruit and vegetable. Near-infrared spectroscopy is more sensitive to C-H bonds and O-H bonds, and these chemical bonds are abundant in pectin, cellulose and hemicellulose in fruit cell walls. Therefore, part of the band information in the spectrum can reflect the firmness of the fruit and vegetable. In the Vis-NIR band detection mode, the three most commonly used detection modes are transmission, interactance, and reflection. Among them, the transmission mode and the interactance mode have better performance in the detection results than the reflection mode[79]. The interactance mode requires a smaller light intensity because the area where the information is received is attached to the fruit, thereby reducing energy consumption. The reflection mode has a relatively simple structure and is relatively easy to use. Compared with hyperspectral, visible and near-infrared spectroscopy contains more accurate band information, avoiding a large amount of data redundancy, which also provides a basis for practical operation of portable spectrometers.

4.2 Applications of spectroscopy sensors

At present, the quality detection of spectral information in the process of grasping by the manipulator is generally time-consuming. Cortés et al.[80] attached two accelerometers and two Vis-NIR spectrometer probes to the gripper to obtain the mechanical and optical properties of the fruit while grabbing the mango, as shown in Figure 6a. The prediction model established by the PLS regression of the two sets of spectral signals and the two sets of acceleration sensor signals has been verified to have the best prediction performance in all signal selection combinations. It takes



Note: a. Robot gripper with the accelerometers and the Vis-NIR spectrometer probes[80]; b. Schematic diagram of the system and the Vis/NIR module[81]; c. Portable NIR spectrometer, used to develop predictive models for non-destructive evaluation of tomato quality attributes[82]; d. Portable Vis/NIR spectrometer, used to meassure the soluble solid content (SSC) of apples[79]; e. Portable NIR spectrometer, used to meassure SSC of Korla fragrant pear, device schematic; f. Device appearance[83]; g. Portable NIR spectrometer, used to meassure dry matter (DM) of mangoes[84].

Figure 6 Applications in the process of picking and some portable devices nine seconds to process each mango, and further optimization is needed for the actual picking situation. Although it is not realistic in practical applications, it still demonstrates the advantages of fusion of multiple sensing technologies in modeling accuracy. Zhao et al.[81] detected the SSC of apples and classified with a portable spectrometer on the manipulator, as shown in Figure 6b. In independent verification, the classification accuracy rate was 90.0%, and the Rp and RMSEP values were 0.952 and 0.393%, respectively. It takes approximately 5.2 s for each apple to complete target detection, grabbing, internal quality detection and classification.

With the development of electronic equipment and the rapid improvement of computing power, palm-sized handheld/portable spectrometers have increasingly appeared in orchards for on-site detection of the internal and external quality of fruits. Figure 6 shows some handheld spectroscopic devices developed in recent years. Portable equipment is not only an effective tool for rapid on-site detection, but also has natural advantages when combined with manipulator picking due to its small size and light weight. Table 4 summarizes the applications of handheld/portable spectrometers in the past five years.

Table 4 Summarizes the applications of handheld/portable spectrometers in the past five years

Fruit species	Parameter[a]	Optical geometry	Wavelength	Statistical methods[b]	Performance[c]	References
Apple	Chlorophyll (Ripeness)	Absorption (UV fluorescence)	340-780 nm	–	–	Das et al.[85]
	SSC	Interactance	400-1000 nm	PLS	$R_p^2=0.690$ RMSEP=0.604% RPD=1.794	Fan et al.[79]
	SSC, Pulp firmness	Reflection	950-1650 nm	PLS	$R^2=0.91$ RMSECV=0.57	Pissard et al.[86]
Avocado	DM (Ripeness)	Reflection	940-1798 nm	PLS	$R^2=0.654$ RMSECV=2.62	Blakey[87]
	DM (Ripeness)	Interactance	310-1100 nm 908-1676 nm 740-1070 nm	PLS	$R^2=0.82$	Subedi et al.[88]
Mixed	Pesticide residues	Raman scattering	UV-Vis	–	–	Gong et al.[89]
	SSC	Diffuse reflection	650-1100 nm	PLS	RMSE=0.9% (Kiwifruits) RMSE=0.7% (Nectarines) RMSE=0.8% (Apricots)	Guo et al.[90]
Kiwi	SSC	Interactance	310-1100 nm	SVM	–	Sarkar et al.[91]
	SSC	Interactance	350-1100 nm	PLS	RMSE=0.93%	Yang, et al.[92]
Pear	Moisture & SSC	Reflection	400-1000nm 900-1700nm	SO-PLS	$R_p^2=0.67$ RMSEP=0.83	Mishra et al.[93]
	SSC	Reflection	900-1700 nm	RF-PLS	$R^2=0.966$, MRER=1.41%	Yu et al.[83]
Melon	SSC	Reflection	750-950 nm	CARS-PLS	$R_p^2=0.83$ RMSEP = 0.73 Brix	Li et al.[94]
Mango	Firmness	Reflection	400-1130 nm	iPLS	$R_p^2=0.75$ RMSEP=5.92 $Hz^2g^{2/3}$	Mishra et al.[95]
Tomato	SSC, TA	Reflection	1295-2611 nm	PLS	$R_p^2=0.86$(SSC) $R_p^2=0.79$(TA)	Borba et al.[82]
Orange	Acidity, TSS, Vitamin C	Reflection	610, 680, 730, 760, 810, 860 nm	BPNN	MAPE=6.95% (TSS) MAPE=11.5% (Vitamin C) MAPE=1.38% (Acidity)	Sulistyo et al.[96]

Note: a: Abbreviations: DM, dry matter; TA, titratable acidity; TSS, total soluble solids; b: Abbreviations: SO-PLS, sequential and orthogonalized partial leastsquares regression; RF-PLS, random frog partial least square regression; CARS-PLS, competitive adaptive reweighted sampling partial least square regression; iPLS, interval partial-least square; BPNN, backpropagation neural network; c: Abbreviations: R_p^2, the coefficient of determination of prediction; RMSEP, the root mean square error of prediction; RPD, the ratio of the standard deviation of the reference destructive SSC to the RMSEP; R^2, the coefficient of determination; RMSECV, the root mean square error of cross-validation; RMSE, the root mean square error; MRER, mean relative error rate; MAPE, mean absolute percentage error

4.3 Challenges and possible solutions

1) The challenge of extensive and overlapping spectral information. The data collected by spectroscopy often presents high-dimensional characteristics, and a large amount of band information contains extensive and overlapping absorption characteristics. It is difficult to interpret the raw absorption spectrum of fruits, and further wavelength selection and data processing methods are required[97]. In the NIR band, there are also short-wave near-infrared (SWNIR) (780-1100 nm) and long-wave near-infrared (LWNIR) (1100-526 nm). The common commercial portable spectrometers usually cover the Vis-SWNIR of 380-1100 nm or the 900-1700 nm of NIR. The narrow band range ensures the resolution and detection accuracy of the device. However, the third overtone signal in the SWNIR is weak and overlapping, which is not conducive to the construction and optimization of the model. The LWNIR has less overlap and stronger signal, but there is a problem of insufficient penetration depth[93].

Redundant band information and noise will complicate the model and reduce the calculation speed. In previous studies, many wavelength selection algorithms have been developed and used, and CARS is very effective in constructing characteristic wavelength models. In addition, the fusion of multiple wavelength selection strategies can achieve better performance. Yun et al.[98] made full use of the combination of variable combination population analysis (VCPA) with iterative retained information variables (IRIV) and genetic algorithm (GA) to obtain new models VCPA-GA and VCPA-IRIV with higher predictive power than the CARS model. In addition, two portable spectrometers with different wavelength ranges can effectively detect different spectral regions and then fuse complementary information[93]. It has also been verified that a higherprecision prediction model can be obtained. This is also a way to indirectly reduce the overlap of spectral information.

2) The challenge of establishing a highly robust model and calibration model transfer. For fresh fruits, a high degree of biological variability will cause the prediction model to fail. Biological variability is related to different fruit varieties, harvest seasons, storage conditions and fruit ripening stages[99,100]. Therefore, the models in the current portable spectroscopy device need to be adjusted or updated when they are applied to new environmental conditions. In the field test, there will be more than one portable device. Usually, the models developed by these devices are specific, and their calibration models may fail when transferred to other devices.

Recently, deep learning (DL) has performed better than PLS methods in predicting single fruit traits. This is due to the huge data set generated by the widespread use of low-cost spectrometers[101], and the robustness of the prediction model established by DL on the basis of large data sets is much higher than that of regression methods such as PLS, which can greatly improve the performance of portable devices. At present, there are some cases in which deep learning is used to improve spectrum prediction[101-104]. In addition, many new calibration model transfer strategies have also been verified to have certain application prospects. In previous studies, spectral response adjustment methods such as piecewise direct standardization (PDS), spectral space transformation (SST), and calibration model transformation based on canonical correlation analysis (CTCCA) have been proposed and achieved good results[105]. Slope/Bias correction (S/B) is suitable for many application environments by adjusting the final predicted value instead of correcting the spectral response. Li et al.[105] used the combination of PDS and S/B method to prove that PDS has better performance than SST and CTCCA. The high accuracy of R_p=0.926 and RMSEP=0.778% is achieved when predicting SSC.

5 Discussion

Robotics and sensing technologies are developing rapidly, and the agriculture is also enjoying dividends. Robot picking has always been a hot research direction in the agriculture field. The focus of the research starts from how to harvest fruits, and gradually develops to how to harvest fruits quickly and without damage, and then to detect the quality of fruits in future harvests. Therefore, the fruit and vegetable quality detection in the picking field has gradually been paid attention to. In recent years, the research on the non-destructive inspection technology of fruit and vegetable quality has also been in full swing. The more popular ones are optics-based technologies (Machine vision, Spectroscopy), acoustics-based technologies, tactile-based technologies, and chemical-based technologies (Artificial nose, Artificial tongue), etc. However, these technologies are generally still in the laboratory stage, and some of them are not suitable for picking scenes and are more suitable for indoor grading systems temporarily. Among the publications reviewed in this article, only a few cases have been successfully carried out outdoors, such as spectral imaging equipment mounted on UAVs and portable spectral equipment. Many experiments conducted indoors rely on powerful hardware devices and deep learning algorithms, and have achieved good results, but the tests in the picking scene need further follow-up.

The combination of picking patterns and agronomy to create controlled cultivation environments (including crop cultivation patterns and controlled artificial environmental light sources) is the direction in which many companies developing picking robots are currently working. We believe this is also the basis for the future realization of fruit and vegetable quality detection in picking scenarios. In the case of apples, for example, apple trees have gradually evolved from a tall, disorderly shape to various new growth patterns adapted to mechanized harvesting. The use of new canopy structures and layered harvesting strategies can effectively reduce the problems associated with branch shading[106]. In the picking period, both effectiveness and efficiency need to be considered. Therefore, the quality detection sensing technology combined with robotic picking in the future needs a combination of qualitative and quantitative detection to ensure effectiveness and efficiency. Compared with the two detection methods mentioned in the article based on optical principles, the tactile sensor receives relatively less interference from light and temperature. Tactile sensors can perform both qualitative and quantitative detection. Tactile sensors for quantitative analysis are highly accurate, but are less repeatable and susceptible to environmental disturbances. Vision-based tactile sensors are a breakthrough direction that can be made in recent years. In addition, cilia-based tactile sensors that can qualitatively analyze the surface quality of fruits and vegetables based on the research of nanomaterials are another promising research area. Two other optical based non-contact quality detection methods cause less damage to fruits and vegetables. RGB-based imaging is more sensitive to color and texture, and therefore has an advantage in detecting size, color, and surface defects. However, it performs poorly for defects that are not visible to the naked eye (e.g., bruises, early mold, etc.). Combining RGB bands with other bands of imaging techniques can enhance the information acquisition capability. Compared with hyperspectral imaging, multispectral imaging technology can acquire data faster and is more suitable for picking scenarios. Spectral technology can obtain information such as SSC of fruits and vegetables, however, it is influenced by external factors such as temperature and equipment, and the calibration of the spectrum needs to be further optimized. With the support of big data, researchers can share the collected data, including image data as well as spectral data. Through model training, deep learning detection models with higher robustness can be obtained for detecting external quality (size, color, surface defects, etc.) as well as internal quality (SSC, internal lesions, etc.) of fruits and vegetables. Also, the lightweight deep learning models researched in recent years help models to be deployed on edge devices with limited computational capability, which provides a research basis for quality detection during robotic picking. The development of portable devices provides new ideas for the integration of multiple sensing devices on manipulators and the design of manipulators. The integration of multi-sensor and multi-sensing modes in the future will also be an important guide for the development of quality detection technology.

6 Conclusions

In this study, we focused on reviewing the quality inspection techniques used in the fruit-picking process, and analyzed the techniques based on optical principles (Machine vision, Spectroscopy) and technologies based on tactile sensing. Starting from some existing application cases of various technologies, each chapter introduces the more prominent problems and challenges of this kind of sensing technology, and gives some possible solutions, some related technologies that have the potential to be applied in the future are also introduced in the article. In the discussion, we also discussed the current research status, some common challenges and future prospects.

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