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Review

A review of key techniques of vision-based control for harvesting robot

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ABSTRACT

Although there is a rapid development of agricultural robotic technologies, a lack of access to robust fruit recognition and precision picking capabilities has limited the commercial application of harvesting robots. On the other hand, recent advances in key techniques in vision-based control have improved this situation. These techniques include vision information acquisition strategies, fruit recognition algorithms, and eye-hand coordination methods. In a fruit or vegetable harvesting robot, vision control is employed to solve two major problems in detecting objects in tree canopies and picking objects using visual information. This paper presents a review on these key vision control techniques and their potential applications in fruit or vegetable harvesting robots. The challenges and feature trends of applying these vision control techniques in harvesting robots are also described and discussed in the review.

Contents

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1. Introduction

With the development of modern agriculture, the application of robotic and intelligent machines in agriculture has followed several trends in technology advancements. Firstly, increasing cost and decreasing supply of skilled labor force are becoming a huge challenge to the agriculture industry. Traditional farming is highly labor intensive and contains many menial and tedious tasks, it is one of the last industries to use robots (Sistler, 1987). Secondly, food safety is an important issue that requires the use of reliable robotic machines to reduce the risk of contaminations (Edan et al., 2009). Thirdly, sustainable agriculture, which provides enough food while not harming the environment, also needs robotic systems to improve productivity at low cost (Grift et al., 2008). It is evident that wide application of robots can offer a significant benefit to agriculture.

The emergence of agricultural robots is accompanied with other industries such as manufacturing and mining that have embraced the robotic revolution. Agricultural robots are perceptive and intelligent machines which are programmed to perform a variety of agricultural tasks such as transplanting, cultivating, spraying, trimming and harvesting (Edan et al., 2009). Considering the economic benefit, high harvesting costs have led the harvesting robot as a research focus (Hayashi et al., 2005). Harvesting robots are designed to sense the complex agricultural environment by various sensors and use that information, together with a goal, to perform the harvesting actions (Edan and Gaines, 1994). Although harvesting robot holds ample promise for the future, currently the overall performance of harvesting robot is often insufficient to compete with manual operation (Grift et al., 2008). The bottleneck to promote the application of harvesting robot lies on the performance of vision-based control.

The use of visual information for the control of robotic manipulator is called vision-based control, which began with the work of Shirai and Inoue (1973). The progress of vision control in that era was hindered largely by various technological issues, in particular, extracting information form vision sensors (Corke and Hager, 1998). Since 1990, there has been a marked rise in the interest in this field of vision control, largely fueled by the increasing computing power of personal computers. After that, vision-based control for harvesting robot had ushered in the era of rapid development. Although numerous research results have been reported on development of vision control technology for robotic harvesting, the low successful rate of fruit recognition and inefficiency of eye-hand coordination are the main factors to limit the performance of harvesting robot. Thus, a review of this research field is necessary to promote further developments of vision-based control technology for harvesting robot.

This article provides a review of the past and current research and development of vision-based control for harvesting robot. It is aimed to introduce an up-date account of useful methods found in literature to provide solutions to the two key issues: (a) the recognition of target fruit; (b) eye-hand coordination control. The remaining of this paper is organized as follows. In Section 2, a general background to vision-based control is introduced. Representative vision schemes for harvesting robots are presented in Section 3. In Section 4, approaches adopted for fruit target recognitions are discussed. A review of eye-hand coordination techniques is given in Section 5. Section 6 presents some examples of fruit or vegetable harvesting robots. Challenges and future trends for harvesting robots are discussed in Section 7. A conclusion is drawn in Section 8.

2. Vision-based control for harvesting robot

2.1. The concept of vision-based control for harvesting robot

Vision-based control for harvesting robot is a framework by which the robot accomplishes the fruit picking task under the guidance of visual information. This framework is constructed with two objectives; fruit recognition and eye-hand coordination (Hashimoto, 2003). Automatic fruit recognition for harvesting robot means identifying and locating the fruit in a natural complex scene. These two tasks are the foundation of picking operation. Eye-hand coordination for harvesting robot is concerned with the interaction between the robot visual perception of the workspace and it actuators (Goncalves and Torres, 2010).

2.2. The role of vision-based control in harvesting robot

The idea of robotic harvesting was firstly proposed by Schertz and Brown (1968) in 1960s for citrus harvesting. Compared with the traditional mechanical harvesting approaches using shaker or air blast, robotic harvesting is a precision harvesting approach. Typical fruit or vegetable harvesting robots are built with manipulators, end-effectors, vision systems, and motion systems (Edan et al., 2009). Among these, vision-based control plays an important role of autonomous harvesting. On the contrary to industrial robots which are simple, repetitive, well-defined and known a priori, harvesting robots need to work in an unstructured, uncertain, and varying environment. Vision-based control for harvesting robots is designed to solve the follow difficult problems. Firstly, the manipulated objects of harvesting robots are natural objects which have a high degree of variety in fruit size, shape, color, texture and hardness as a result of environmental and genetic differences. Secondly, the workspace is complex and loosely structured with large variations in illumination and degree of object occlusion. Thirdly, the random location of target fruits requires picking to operate in a three-dimensional continuously changing track. Thus, vision-based control is an attractive approach to meet these challenges.

3. Vision schemes for harvesting robot

Fruit or vegetable detection for harvesting robot is conducted by various visual sensors. According to the principle of imaging, the visual sensors used to recognize objects are classified into two-dimension (2D) visual imaging sensors and three-dimension (3D) visual imaging sensors. The 2D images acquired can indicate morphological features of the target fruit such as color, shape and texture. Three-dimensional visual image sensors provide 3D coordinate maps of the entire scene which can give the shape and spatial location of the fruit object. The vision scheme also has relationship with the recognition process. As shown in Fig. 1, for identifying different kinds of objects, it is needed to select available visual sensors cooperating with a certain recognition algorithm.

The review of recognition algorithms such as color based analysis, edge detection, K-means clustering, and Bayes classification is given in Section 4. The follow sub-sections contain a critical review of visual sensors used in the past for fruit detection in harvesting robot. The applications, principles, advantages and limitations of various vision schemes for harvesting robots are summarized in Table 1.

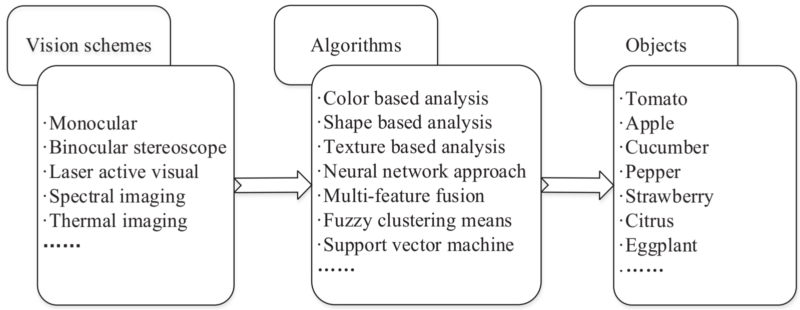

Fig. 1. Various vision schemes and recognition algorithms for different kinds of fruits (Li et al., 2011a,b).

Table 1
The classification of applications, principles, advantages and limitations of various vision schemes for harvesting robots.

Vision scheme	Applications and principles	Advantages	Limitations
Monocular	Identifying target fruits by color, shape, and texture feature	Monocular vision system is the simplest and lowest cost	Only provides 2D information, light change influences the imaging results
Binocular stereo	Identifying fruits using color shape, and texture features; positing target fruits through the principle of triangulation	The binocular stereo is the most common approach to obtain the 3D position of detected fruit	Sensor calibration is required, image matching is very time consuming; errors in 3D measurement is unavoidable
Laser active visual	Identifying fruits using 3D shape feature; positing target fruits through 3D reconstruction approach	It is an alternative to obtain the 3D position in the condition of light changing and background clustering	Vision system is required for geo-referencing, complex and large image data are needed. The imaging processing is also a challenge
Thermal imaging	Identifying target fruits using the differences of infrared radiation between target fruit and background	It is available to detect target fruit in varying illumination condition, especially at night	Sensor calibration and atmospheric correction are required, high computation consumption for image processing
Spectral imaging	Identifying target fruits using features extracted from invisible wavelengths	It can detect the green color or overlapped fruits	Imaging processing is very time consuming, the sensor cost is high

3.1. Monocular camera scheme

Monocular scheme is a machine vision system consisting of a single camera, which was used in some earliest studies for detecting fruit (Jimenez et al., 2000a,b). The cameras with Charged Coupled Device (CCD) sensors or Complementary Metal Oxide Semiconductor (CMOS) sensors are widely used in monocular schemes. In the MAGALI project, a B/W camera was applied to detect the fruits based on geometric feature (d'Esnon et al., 1987). In later years, the B/W camera was replaced with a color camera to enhance the color contrast between red apples and green leaves. Slaughter and Harrell (1987) also used a digital color camera with a filter of 675 nm wavelength to amplify the contrast between oranges and background. The author reported a detection accuracy of 75%. Zhao et al. (2005) used a color camera to identify apples based on color and texture features and reported an accuracy of 90%. Baeten et al. (2008) developed a monocular vision system combining a camera and a high frequency light source to detect apples in outdoor environment. The author recognized that high frequency light could reduce the illumination influence. There are other vision systems for harvesting robot with several cameras forming a redundancy monocular system. Edan et al. (2000) developed a multiple monocular cameras system which was constructed with two B/W CCD cameras to detect and locate melons in the field. The two B/W cameras mounted on the platform and griper could acquire far scene images and near scene images. The author reported that the use of multiple monocular cameras could improve the recognition accuracy. The major disadvantage of monocular scheme is that images captured by the visual sensor are sensitive to illumination conditions (see Table 2).

3.2. Binocular stereovision scheme

The Binocular stereovision scheme is designed with two cameras separated in a certain distance with an angle between them, and they capture the same scene in two images. The three-dimensional map of fruit object can be obtained through triangulation (Sun et al., 2011). Buemi et al. (1995, 1996) used a color stereoscopic vision system consisting of two micro cameras in a tomato harvesting robot named Agrobot. The stereovision system mounted on the robot head could be used to navigate and identify the ripe tomato. Shinsuke and Koichi (2005) installed a parallel stereovision system of two cameras in a sweet pepper picking robot. The stereovision system controlled by a camera positioning system could move to a desired location to capture images of sweet peppers. Yang et al. (2007) developed an improved stereovision system based on the Color Layer Growing (CLG) algorithm to reconstruct the 3D model of fruit object. Fruit objects with stereo and self-occlusion in a strong sunlight condition could be detected and located by the improved stereovision system. Xiang et al. (2014) also studied a clustered tomato recognition method based on depth map acquired by a binocular stereo camera. The recognition accuracy of clustered tomatoes was 87.9% at an acquisition distance of 300–500 mm. Li et al. (2011a,b) developed a stereovision system, with optical filters, which was an attempt to capture different waveband images. The recognition test results indicated that the polarizer filtered data is slightly better than neutral density filtered data, and much better than the original image data. Si et al. (2015) also used a stereo camera to detect and locate mature apples in tree canopies. As shown in Fig. 2, the stereo camera was mounted on the slide bar in parallel with a distance of

Table 2
The comparison of different single feature analysis approaches.

Features	Fruits	Application situations	Accuracy	Limitations	Reference
Color	Tomato	Artificial light condition	96.36%	It is not available to the green color fruit such as cucumber	Arefi et al. (2011)
	Strawberry	Uncontrolled environment	>95%		Wei et al. (2014)
Shape	Apple	Uncontrolled environment	94%	The contour loss is less than 1/2	Kelman and Linker (2014)
	Peach	Uncontrolled environment	90%		Xie et al. (2011)
Texture	Pineapple	Field	85%	High computation cost, occlusion is a big challenge	Chaivivatrakul and Dailey (2014)
	Bitter melon	Single objects	100%		

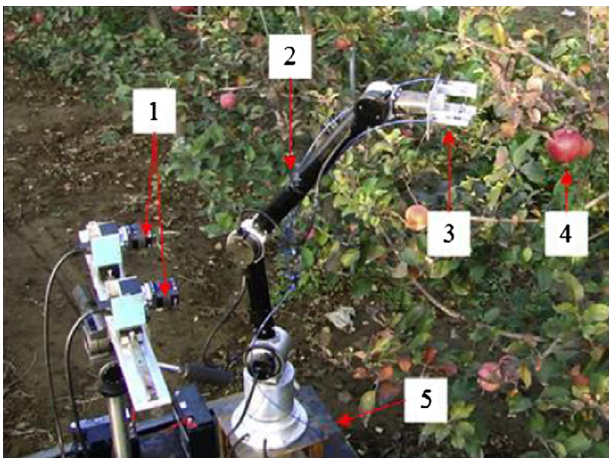

Fig. 2. Fruit harvesting robot with a binocular stereoscope. (1) Binocular stereoscope, (2) Manipulator, (3) End-effector, (4) Fruit object, (5) mobile platform (Si et al., 2015).

200 mm between the centers of the two camera lens. The author reported that over 89.5% of apples were successfully recognized and the errors were less than 20 mm when the measuring distance was between 400 mm and 1500 mm. The disadvantage of stereovision scheme is its complexity and long computation time due to stereo matching (Hannan and Burks, 2004).

3.3. Laser active visual scheme

Although there are several techniques to obtain depth information, but considering some desirable features of the sensed image, the laser active visual is a better choice. The 3D shape of fruit object is measured by scanning the laser beams and the fruit can be distinguished from other obstacles according to different spectral-reflections. The laser active visual scheme for fruit detection is illustrated in Fig. 3 (Gotou et al., 2003). Both laser beams scan the fruit object simultaneously and the locations of fruit objects and obstacles are recognized through image processing. An infrared laser range-finder was installed in an orange harvesting robot named Agribot working in non-structured environments, Jimenez et al. (2000a,b). The output of the infrared laser range finder includes 3D position, radius, and surface reflectivity of fruit object. Tankgaki et al. (2008) designed a machine vision system equipped with red and infrared laser scanning devices to detect cherry on the tree, which could prevent the influence of the sunlight. Yin et al. (2009a,b) used a laser active visual sensor to measure the turned angles of robot arm and distance between target tomato and end-effector. Zhang et al. (2015) developed a novel apple stem recognition system using the 3D reconstruction technique combined with near-infrared and linear-array structured lighting. The author reported that 97.5% overall recognition accuracy for the 100 samples was obtained by the proposed system and method. Even though the accuracy of laser active visual system is promising, the complexity of the system often limits its practical application.

3.4. Thermal imaging scheme

Thermal imaging is also called infrared thermograph which is the visualization of infrared radiation (Li et al., 2014). Because of the physical structure and characteristic, leaves accumulate less heat and radiate faster than fruits, the temperature distributions of the plant canopy with fruit can be applied for fruit detection (Vadivambal and Jayas, 2001). Xu and Ying (2004) used a thermal camera to identify the citrus in a tree canopy. From the analysis result shown in Fig. 4, the temperature distribution along line AB

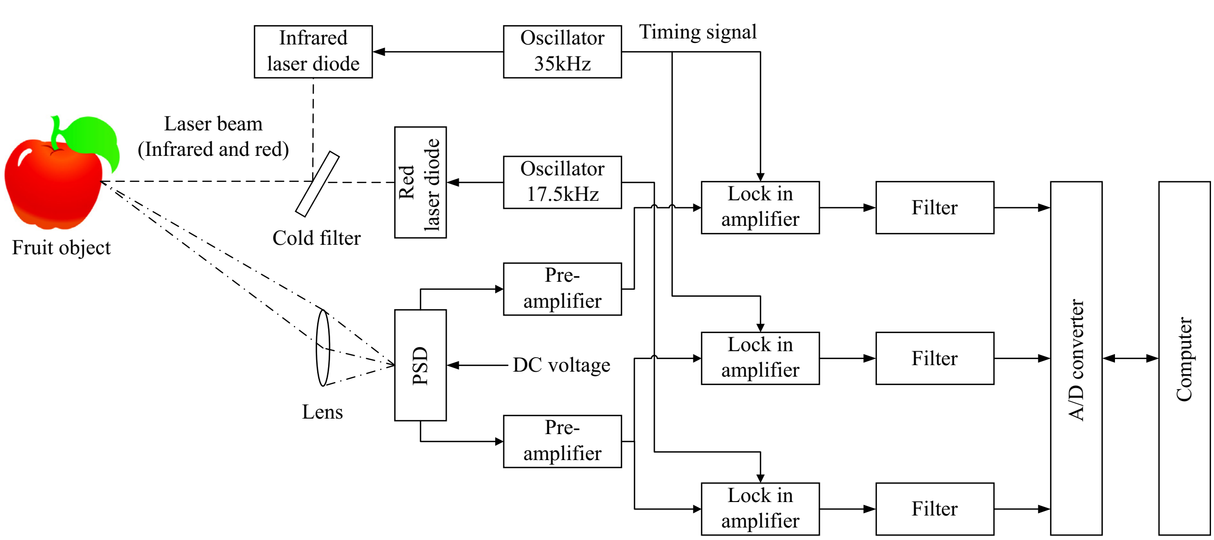

Fig. 3. A scheme of the laser active visual system for fruit recognition (Gotou et al., 2003).

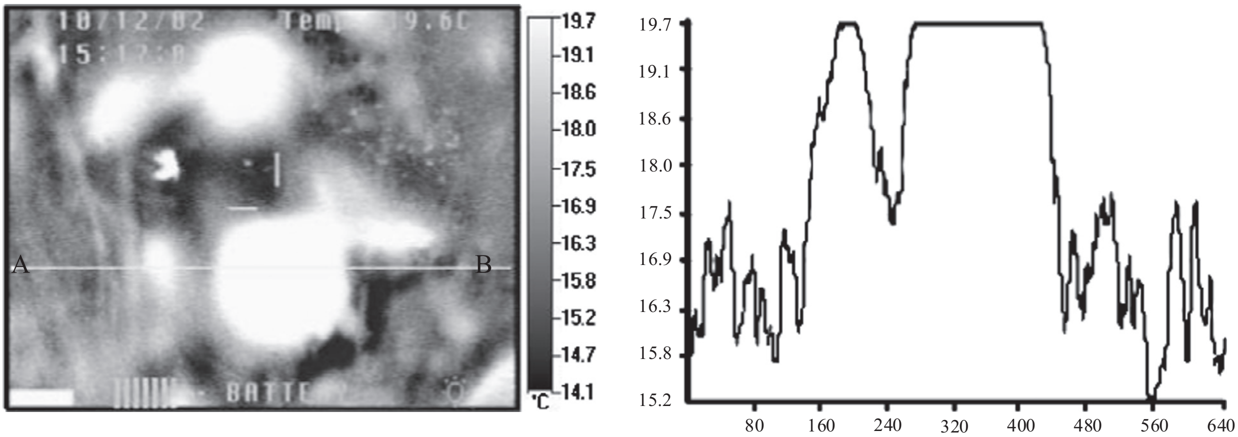

Fig. 4. The typical test results of thermal image for citrus recognition.

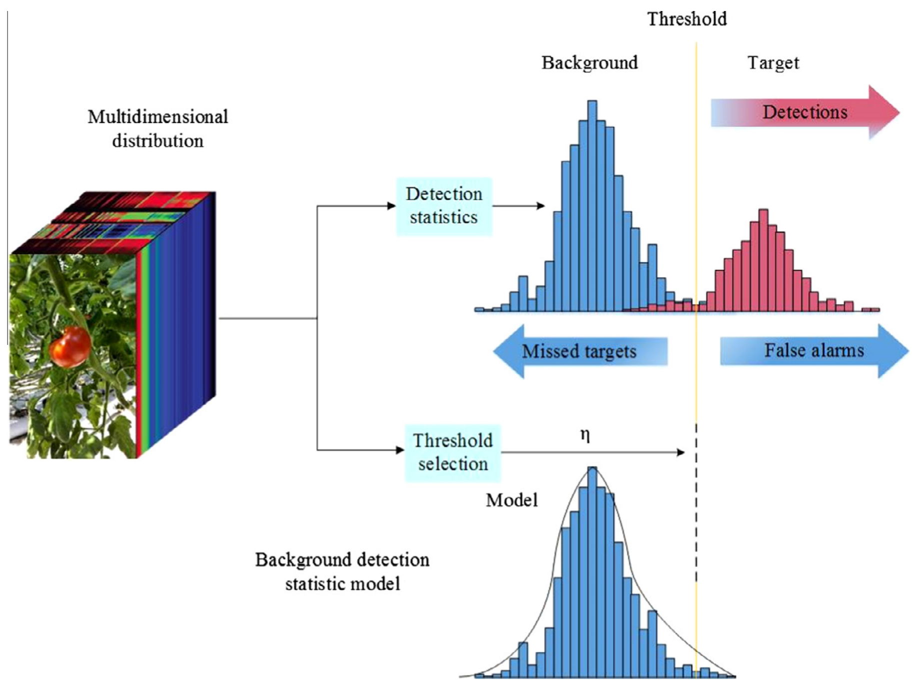

Fig. 5. The model of fruit object detection using hyperspectral image.

across the citrus area, leaves and others showed that the temperature difference between citrus and other objects was more than 1 °C. Bulanon et al. (2008) also used a thermal infrared camera to detect the citrus in day and night. The fruits were successfully segmented in the thermal images using image processing techniques according to the largest temperature difference. Based on prior research, Bulanon et al. (2009) proposed an improved fruit detection approach combined with a thermal image and a visible image. Results showed that the performance of the image fusion approach was better than using the thermal image alone. Even though thermal imaging has advantages on detecting fruits even when fruit and background color are similar, the accuracy of recognition using thermal imaging is affected by the shadow of the tree canopy (Stajnko et al., 2004).

3.5. Spectral imaging scheme

The spectral camera is developed to integrate both spectroscopic and imaging techniques into one system to obtain a set of monochromatic images at a continuum of wavelengths (Zhang et al., 2014). With recent development of spectral imaging, the spectral cameras have been used to recognize fruits. The model of fruit object detection using multispectral image is shown in Fig. 5 (Manolakis et al., 2003). A monochromatic near-infrared camera, equipped with three different optical band pass filters (1064, 1150 and 1572 nm), was used to identify in-field green citrus by Kane and Lee (2007). The author reported an average correct pixel identification of 84.5%. Safren et al. (2007) used a hyperspectral camera to detect green apples. The hyperspectral imaging was capable of giving a wealth of information both in the visible and the near-infrared (NIR) regions and thus offered the potential to detect the green apples. Okamoto and Lee (2009) also proposed a green citrus recognition method using a hyperspectral camera of 369–1042 nm to solve the detection problem arising from similar color between fruits and natural scenes. The test results reflected that 80–89% of the citrus in the foreground of the validation set were identified correctly. By comparing the spectral reflectance difference of cucumber plant (fruit, leaf and flower) from visible to infrared (350–1200 nm), sensitive bands of fruit information were obtained by statistical variance analysis (Yuan et al., 2011).

4. Recognition approaches for harvesting robot

The recognition algorithm is a key factor affecting the performance of a vision recognition system. Numerous literatures reported that various recognition algorithms have been employed for robotic harvesting of fruits. Those recognition approaches can be classified into single feature analysis approaches, multiple features fusion analysis approaches and pattern recognition approaches.

4.1. Single feature analysis approaches

Color is one of the most prominent features used to distinguish the mature fruit from the complex natural background. In the studies of color-based segmentation for fruit recognition, the image pixels are categorized into two groups according to the threshold which decides whether a pixel belongs to the fruit object or to the background. However, the accuracy of segmentation using color feature is sensitive to varing illumination conditions. For alleviating the influence of varying illumination, several color spaces such as HIS, L*a*b*, and LCD are used to extracting color features (Huang and He, 2012; Yin et al., 2009a,b). Arefi et al. (2011) developed a ripe tomato recognition algorithm using a combination of RGB, HSI, and YIQ color spaces and fruit morphological features. The authors argued that the total accuracy was 96.36% when the proposed approach was adopted in a greenhouse with artificial illumination. Mao et al. (2009) employed a Drg-Drb color indexing to segment apples from background and an accuracy of 90% was achieved. Wei et al. (2014) also proposed a fruit recognition method based on an improved OSTU threshold algorithm using a new color feature in the OHTA color space. The OHTA color space was transform from the RGB color model through linear conversion and the extraction accuracy was more than 95%. When the fruits and leaves have similar colors, color-based segmentation methods are not available for recognizing fruits (Reis et al., 2012).

Fruit recognition algorithms based on extracting geometric features are universal for detecting spherical fruit such as tomatoes, apples, and citrus (Liu et al., 2007; Xie et al., 2010). Because of independent color features, the shape-based analysis approach is not affected by varying illuminations. Whittaker et al. (1987) proposed a modified Circular Hough Transform algorithm for locating mature tomatoes which were partially hidden from obstacles. The authors recommended that this shape-based analysis algorithm could be valid for situations in which the perimeter of the fruit is partially obscured by leaves or by overlapped tomatoes. Xie et al. (2007, 2011) also put forward a concave spots searching algorithm based on Hough Transform to improve the accuracy of strawberry recognition. The authors argued that the proposed strawberry recognition method is effective both for single fruit and complex situation when the strawberry contour loss is less than 1/2. Kelman and Linker (2014) also proposed a localization algorithm of mature apples in trees using convexity. Together with the removing 99.8% of the edges initially identified by Canny detector, 94% of the visible apples were correctly detected.

The images captured in natural outdoor conditions have some texture differences which can be used to facilitate separation of fruits from their background. Thus, texture feature plays an important role in fruit recognition especially when the fruits are clustered or occluded (Zhao et al., 2005; Kurtulmus et al., 2011a,b; Rakun et al., 2011). To use color, texture, and shape information by histogram based separation, circular Gabor texture features and eigen-fruit approaches were implemented in the fruit recognition algorithm by Kurtulmus et al. (2011a,b). Notice that the application of texture features are always combined with color features and/or geometric features.

4.2. Multiple features fusion approaches

In order to increase recognition reliability in uncontrolled environments caused by uneven illumination conditions, partly occluded surfaces and similar background features, some researchers apply multiple features (color, geometry, and texture) fusion algorithms to recognize fruits. Hannan et al. (2009) also developed a machine vision algorithm consisted of color-based segmentation and perimeter-based detection. Yin et al. (2009a,b) proposed a ripe tomato recognition method which is combined with the tomato's shape features and the color features. With the color features extracted from the L*a*b* color space and the shape feature acquired by a laser ranging sensor, the recognition and localization system for tomato harvesting robot could be used to handle the situations of tomato overlapping and sheltering. Zhao et al. (2005) proposed a texture based edge detection algorithm combined with color properties analysis to recognize on-tree apples. The authors presented that 90% of apples were correctly detected using the recognition approach. Colors, intensity, edge and orientations as the features of the target were considered by Patel et al. (2011) to develop an improved multiple features based algorithm for fruit detection. The authors reported that the detection efficiency was achieved up to 90% using the optimal weights of different features. Lu et al. (2014) also developed a novel method based on fusing the segmentation results of chromatic aberration map (CAM) and luminance map (LM) to recognize the citrus in a tree canopy. Rakun et al. (2011) comprehensively considered three distinct features; color, texture and 3D shape of the fruit object for overcoming low recognition reliability in uncontrolled environments. They

Table 3
The major types of multi-modal images recognition algorithms.

Features	Fruits	Vision scheme	Accuracy	Reference
Color + Geometry	Tomato	Camera and Laser ranging sensor	NR	Yin et al. (2009a,b)
	Orange	Two cameras	>90	Hannan et al. (2009)
Color + Texture	Apple	Camera	90%	Zhao et al. (2005)
	Citrus	Camera	75.3%	Kurtulmus et al. (2011a,b)
Color + Texture + Geometry	Peach	Camera	90%	Patel et al. (2011)
Color + 3D shape	Apple	Camera and Laser ranging sensor	>90%	Bulanon and Kataoka (2010)
Color + Texture + 3D shape	Apple	Camera	NR	Rakun et al. (2011)
CAM + LM	Citrus	Camera	86.81%	Lu et al. (2014)
I-component + a*-component	Tomato	Camera	93%	Zhao et al. (2016a,b)
Color + Amplitude image	Apple	Camera and ToF camera	>83.67%	Feng et al. (2014)
Color + Thermal image	Apple	Camera and thermal camera	74%	Wachs et al. (2009, 2010)
	Citrus	Camera and thermal camera	74.37%	Bulanon et al. (2009), Bulanon and Kataoka (2010)

CAM = Chromatic Aberration Map; LM = Luminance Map.

Table 4
The main kinds of multi-modal images recognition algorithms.

Pattern recognition types	Classification algorithms	Fruits	Correct/error rate	Reference
Statistical pattern recognition	Linear decision classifier	Peach	>89%/NR	Sites and Delwiche (1988)
		Apple	80%/3%	Bulanon et al. (2004)
	Bayesian classifier	Orange	>75%/6%	Slaughter and Harrell (1989)
	X-means clustering	Tomato	88%/NR	Yamamoto et al. (2014)
	PCA	Citrus	75.3%/NR	Kurtulmus et al. (2011a,b)
	Adaboost	Kiwifruit	>92.1%/7%	Zhan et al. (2013)
Fuzzy pattern recognition	FCM	Tomato	NR/16.55%	Wang et al. (2015)
Soft computing methods	Feed-forward neural network	Tomato	95.45%/NR	Arefi and Motlagh (2013)
	Fuzzy neural network	Apple	>92.31%/NR	Ma et al. (2013)
	SVM	Pepper	>74.2%/NR	Song et al. (2014)

applied color segmentation to multiple scene images to separate potential regions from background and verify them first with texture analysis and then by reconstructing in the 3D space.

The recognition methods based on multi-sensor fusion technology have been used to fruit recognition (Bulanon et al., 2009; Bulanon and Kataoka, 2010; Wachs et al., 2009, 2010; Feng et al., 2014). For overcoming the challenge of recognizing green fruit in the tree canopy, Bulanon et al. (2009) and Wachs et al. (2010) used infrared images and visible images fusion to improve fruit detection. The infrared image captured by thermal infrared camera and visible image captured by a color camera required image registration prior to image fusion. Maximization of the mutual information was employed by Wachs et al. (2009) to find the optimal registration parameters for image fusion. The authors argued that the recognition accuracy of fusion approach (74%) was increased compared to the conventional approach of detection using either color (66%) or IR (52%) alone. The amplitude image acquired by ToF camera and H component image extracted from HSI color space were selected as source images for fusion by Feng et al. (2014). The fusion algorithm which is aimed at enhancing the fruit object area distribution in the fused image could produce more accurate and robust fruit recognition. A summary of the major types of multi-modal based algorithms is given in Table 3.

4.3. Pattern recognition approaches

Pattern recognition approaches have long been investigated for application in fruit recognition (see Table 4). Early in the 1970s, Parrish and Goksel (1977) had suggested that pattern recognition approaches could be used for fruit recognition. Two linear classification techniques including a non-parametric linear classifier and linear decision function classifier were evaluated by Sites and Delwiche (1988). The outcome indicated that both classification algorithms produced similar results, and the non-parametric linear classifier was easier to implement. Bulanon et al. (2004) also developed an apple detection method using the linear decision classifier and the trichromatic coefficients as patterns. About 80% of fruit pixels were correctly classified under all lighting conditions with less than 3% error rate. Slaughter and Harrell (1989) used a Bayesian classifier to discriminate oranges from the natural background. The classification model using chrominance and intensity information could correctly classify over 75% of the fruit pixels. In order to solve the overlapping problem in plantlets recognition, Pastrana and Rath (2013) developed a novel pattern recognition approach using an active shape model (ASM). Yamamoto et al. (2014) applied the X-means clustering algorithm on the basis of K-means clustering to determine the optimal number of clusters and to detect individual fruit in a multi-fruit blob. Due to their similarities, fruit detection tasks can be conducted with the similar method for face recognition and detection. Kurtulmus et al. (2011a,b) used an 'eigenfruit' approach based on principle component analysis (PCA) to detect green citrus under natural illumination. Zhan et al. (2013) used an Adaboost algorithm to recognize the kiwifruit in field and achieved and ideal effect for the segmentation between kiwifruit and trunk, soil and branches. The Adaboost algorithm could combine the strengths of two weak classifiers and mitigate their shortcomings. Zhao et al. (2016a,b) also developed an algorithm combining AdaBoost classifier and color analysis for the automatic detection of ripe tomatoes in greenhouse. It argued that over 96% of ripe tomatoes were correctly detected.

These statistical pattern recognition approaches are developed according to the posterior probability of the samples. Thus, more and more attention are being paid on intelligent pattern recognition methods such as artificial neural networks (ANN), support vector machine (SVM), and fuzzy pattern recognition. ANN and SVM are supervised learning algorithms that have the ability to learn from the data through an iterative training process and improve its performance after each iteration. An olive recognition method using neural networks was presented by Gatica et al. (2013). The process of fruit recognition comprised of two stages: the first stage focused on deciding whether or not the candidate identified in the image corresponds to an olive fruit, the second stage focused on olives overlapping within the tree canopy. Arefi and Motlagh (2013) developed an experts system based on wavelet transform and ANN for ripe tomato detection. Totally 90 wavelet features were extracted from each tomato, and a feed-forward neural network was used to distinguish the ripe tomato from its background. An accuracy of 95.45% was obtained from the proposed recognition algorithm. In order to overcome the fuzziness and uncertain factor existing in the color image boundary pixels, a model combining quantum genetic algorithm and fuzzy neural networks was built by Ma et al. (2013). An improved fuzzy neural network could avoid redundant iteration and the tendency to fall into the local minimum of traditional BP neural networks. Ji et al. (2012) introduced a new classification algorithm based on support vector machine to improve the apple recognition accuracy and efficiency. The new classifier had balanced the recognition success rate and the time used in recognition. A statistical classifier, an ANN and a SVM classifier were built and used for detecting peach fruit by Kurtulmus et al. (2011a,b, 2014). Authors reported that 84.6%, 77.9% and 71.2% of the actual fruits were successfully detected, using the three classifiers for the same validation set. For improving the tomatoes identifying accurately, Song et al. (2014) also used a bag-of-words (BoW) model to locate peppers on the plant. The BoW model represented each image by a frequency distribution of its visual vocabularies, which was classified to a fruit class. Wang et al. (2015) presented a Fuzzy Clustering Means (FCM) algorithm to recognize the clustered tomatoes. The superiority of this algorithm was verified according to a comparison with K-means and Otsu threshold. In order to accelerate the computation of the traditional FCM, Xiong et al. (2013) presented

Table 5
The comparison of two types of eye-hand coordination control.

Eye-hand coordination	Principle	Advantages	Limitations
Open-loop visual control	Hierarchical controlling based on precision 3D measuring	Control law is simpler; controllability and region of stability are better	Performance depends on the accuracy of measurement, assembly and calibration
Visual servo control	Dynamic interacting between the robot and environment	Calibration is not required; real-time tracking is achieved and it is object friendly	Local minima of potential and unexpected camera trajectory

an improved FCM algorithm based on the fusion of the bicubic interpolation algorithm and the FCM algorithm. The improved recognition algorithm was available for litchi recognition which enabled the recognition system to operate in real-time.

5. Eye-hand coordination in harvesting robot

Vision-based robot control has been investigated for more than 30 years. This technology promises substantial advantages when working with the targets whose positions are unknown, or with manipulators which may be inaccurate. Visual information can be used for controlling the robotic manipulator or guiding its motion. The two types of vision-based control applications in robot control loop are called eye-hand coordination and visual navigation. Visual navigation has been widely applied (Khadraoui et al., 1998), while the eye-hand coordination is a bottleneck to improve the performance of harvesting robot. Thus, further developments in vision-based control for harvesting robot are necessary. In this section, an overview of the eye-hand coordination control in harvesting robot is given.

Traditionally, eye-hand coordination control systems were based on an open loop control framework which employs the "looking then moving" mode of operation. The control precision depends directly on the accuracy of the vision system, and the calibration of manipulator and assembly (Yau and Wang, 1996). An alternative to increase the accuracy of these subsystems is to use a visual feedback control loop (Corke and Hager, 1998). This particular vision-based robotic control mode is also called visual servo. The visual servo is a framework to implement "looking and moving" as a dynamical system. The task of visual servo for harvesting robot is to control the pose of the robot's end-effector using image features which are extracted from the image captured by the camera-in-hand or fixed camera (Hashimoto, 2003). The comparison of these two types of eye-hand coordination control is given in Table 5.

5.1. Open-loop visual control

The open-loop visual control mode is built for accurate positioning of the fruit object in 3D workspace. Therefore, vision systems of open loop control may consist of stereo vision or laser range sensor that can measure the spatial distance between the target fruit and the end-effector. Following a precision distance measurement, the trajectory of the manipulator can be planned through calculating the kinematics of the robot. Hence, the manipulator kinematic model and calibration of vision system have to be very precise.

In the study of vision-based control for robotic harvesting of cherry tomatoes (Kondo et al., 1996), a open-loop visual control scheme was implemented based on the 3D position detection acquired by a stereo camera. The end-effector was first sent to a location based on the X, Z position of the fruit and the Y (depth information) of the cluster center. If the fruit could not be reached, the end-effector advanced forward 50 mm (in Y direction) in the next movement. Thus, the author argued that the harvesting success rate was affected by the accuracy of the calculated depth. Inoue et al. (1996) also developed an open-loop visual control scheme based on precise position detection for robotic harvesting. The minimum distance gathering path to effectively touching the target fruit could be calculated from this control model. In order to improve the precision of position measurement, multiple visual sensors are employed in the vision system. Hayashi et al. (2010) developed a machine vision unit equipped with three aligned cameras to enhance the recognition rate. The center camera was used to calculate the inclination of the peduncle, whereas the two cameras mounted on both sides of the center camera form a stereovision system to determine the 3D position of the fruit. Han et al. (2012) also developed the strawberry harvesting robot based on open-loop visual control. The 3D position of target strawberry was acquired by a color stereoscope camera and a laser device. The performance of the vision-based control scheme in field tests showed that the execution time for successful harvest of a single strawberry was less than 7 s.

In some cases, the fruit position in the tree canopy would be influenced by wind or manipulator movement. When this situation occurs, the efficiency of open-loop visual control for robotic harvesting is very low. Shen et al. (2011) have researched on the increasing harvest efficiency of the fruit harvest robot in oscillatory conditions. The oscillation frequency was obtained by curve fitting and applying fast Fourier transform to video samples. With the calculated movement duration of the end-effector, it can eliminate the time waiting for the oscillation to decay. Font et al. (2014) also investigated a vision control strategy by combining open-loop visual control and visual closed-loop control. A stereovision camera mounted on a robot arm could acquire the initial fruit location. With the open-loop visual control, the grasper could move quickly to the front of the target fruit. The final picking operation was conducted by iteratively adjusting the vertical and horizontal positions of the gripper through closed-loop visual control. Aiming at solving the positioning problem, Zou et al. (2012) developed a binocular stereo vision system and position principle of the picking manipulator in virtual environment (VE). The stereo vision data was mapped to the manipulator and was guided by accurate positioning in VE. The simulation results in VE could be applied to control harvesting robot operation and to correct the positioning errors in real-time.

5.2. Visual servo control

Compared to open-loop visual control, the input of visual servo is continuous and contains dynamic image information. Therefore, frame rates of the video must match the closed-loop bandwidths of

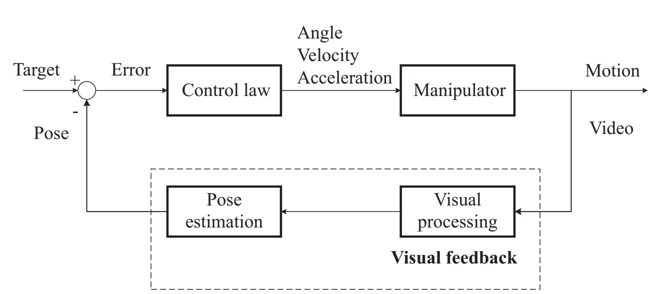

Fig. 6. The structure of visual servo (Pan et al., 2000).

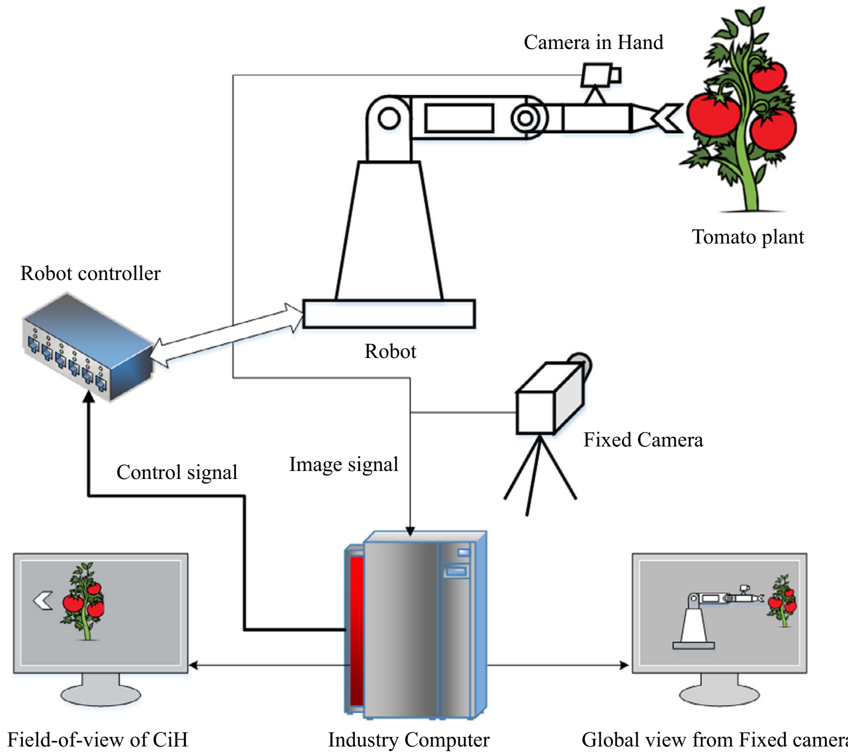

Fig. 7. Schematic diagram of a cooperative vision system for harvesting robot.

vision controllers. As shown in Fig. 6, pose estimation is the core issue of visual feedback control. Input of the visual servo control are the time-varying position errors between the target fruit and end-effector. The advantages of visual servo are that its performance does not relay on the precise kinematic model of the robot and the calibration of the vision system.

Mehta and Burks (2014) developed a visual servo system for robotic citrus harvesting. As shown in Fig. 7, a cooperative vision system consisting of a fixed camera and a camera-in-hand (CiH) was incorporated such that the fixed camera and provided a global view of a tree canopy. The CiH, due to its proximity, provided high resolution fruit image. In contrast to the open-loop visual control model the visual servo control strategy used perspective camera geometry to obtain absolute range estimates. The estimated range information can be used to generate a global map of fruit locations, and a rotation controller was developed to orient the robot end-effector towards the target fruit such that the fruit could enter the field of view of the CiH. The performance of the proposed visual servo controller was demonstrated using a 7 DOF robotic manipulator in an artificial environment. Van Henten et al. (2003a,b, 2010) introduced a novel eye-hand coordination approach based on the A*-search algorithm which could assured collision–free motions when the robot harvested cucumbers in a greenhouse. Eye-hand coordination based on the A*-search algorithm had assured an optimal motion path was obtained such that the cucumber picking time can be reduced. Zhao et al. (2011) developed an apple harvesting robot consisting of a manipulator, end-effector and image-based vision servo control system. In the visual control system, the image-based vision servo (IBVS) control method was employed for localization and picking motion for the target fruit. The IBVS was often used to control the manipulator according to image features. The key issue of this method is how to calculate the Jacobian matrix which describes the relationship between camera coordinate and robot coordinate (Harrell et al., 1985). Robot joint motion could be controlled based on feedback from the position of a target fruit in an image. Vision servo was accomplished by controlling the velocities of each joint according to the vertical and horizontal offsets of a fruit's image position from the image center (Harrell et al., 1990). Moreover, the closed-loop bandwidths of vision controllers could be varied from 1.0 to 1.1 Hz.

6. Examples of fruit harvesting robots

Robotics harvesting is not a new phenomenon but with the history of over 30 years. Currently, harvesting robots have not been advanced to the commercialization stage because of their low efficiencies, low intelligence, and high costs. On the other hand, different designs of fruit harvesting robots have emerged in recent years. Examples of major fruit harvesting robots are shown in Table 6. For convenience, the examples of harvesting robot are categorized according the types of target fruit or vegetable. The vision schemes and eye-hand coordination models of the harvesting robots are described in the table. The performances of different vision-based control approaches applied in various harvesting robot are also shown in the table.

7. Challenges and future trends

7.1. Enhancing the vision-based control of harvesting robot

With the development of robotic technology and sensor technology, enhancing the performance of fruit harvesting robot can be a positive trend in meeting the challenges. Several suggestions are given to improve the ability of the harvesting robot to deal with the complex working environment (Bac et al., 2014).

Firstly, improvements in sensing are required. The sensors currently used have certain shortcomings in the application to fruit recognizing (Gongal et al., 2015). Additionally, the combination of multi-sensor may satisfy the performance required for fruit

Table 6
A comparison of the development of harvesting robots in the main countries.

Products	Robots	Vision scheme	Eye-hand coordination	Success rate	Speed	Reference
Fruits	Apple harvesting robot	A camera-in-hand and positioning sensor	Open-loop visual control	77%	15s	Zhao et al. (2011)
		A camera-in-hand and a laser range sensor	Open-loop visual control	>90%	7.1s	Bulanon and Kataoka (2010)
	Citrus harvesting robot	A fixed camera and a camera-in-hand	Visual servo control	NR	<8s	Mehta et al. (2014)
		A fixed camera	Visual servo control	50%	36s	Harrell et al. (1990)
	Melon harvesting robot	A far-vision CCD and a near-vision CCD	Visual servo control	>85%	<22s	Edan et al. (2000)
	Strawberry harvesting robot	A stereovision system and a central camera	Visual servo control	<41.3%	11.5s	Hayashi et al. (2010)
		A stereo camera, a camera and a laser sensor	Visual servo control	NR	7s	Han et al. (2012)
	Watermelon harvesting robot	A stereo vision sensor and a camera in hand	Visual servo control	100%	12s	Sakai et al. (2007)
		A stereo vision sensor	Open-loop visual control	66.7%	NR	Umeda et al. (1999)
	Kiwifruit harvesting robot	Eight cameras (four stereo vision systems)	Open-loop visual control	NR	NR	Scarfe et al. (2009)
	Grape harvesting robot	A camera-in-hand	Visual servo control	NR	NR	Kondo (1991)
	Cherry harvesting robot	A red and infrared laser active sensor	Open-loop visual control	66.7%	14s	Tankgaki et al. (2008)
Vegetables	Tomato harvesting robot	A binocular stereo vision sensor	Open-loop visual control	70%	3s-5s	Kondo et al. (1996)
		A stereo vision sensor	Visual servo control	88.6%	37.2s	Ji et al. (2014)
	Cucumber harvesting robot	A fixed camera and a camera-in-hand	Visual servo control	80%	45s	Van Henten et al. (2002)
		A near-infrared camera and a camera	Open-loop visual control	74.4%	65.2s	Van Henten et al. (2003a, b)
	Radicchio harvesting robot	A camera-in-hand	Visual servo control	NR	<7s	Foglia and Reina (2006)
	Mushroom Harvesting robot	A monochrome camera in hand	Visual servo control	>80%	6.7s	Reed et al. (2001)
	Eggplant harvesting robot	A camera-in-hand	Visual servo control	62.5%	64.1s	Hayashi et al. (2001, 2002)
	Sweet-pepper harvesting robot	Two ToF cameras, a stereo camera and a camera	Open-loop visual control	79%	NR	Hemming et al. (2014)
	Asparagus harvesting robot	Two infrared laser sensors	Open-loop visual control	NR	NR	Sakai et al. (2013)
	Rosa harvesting robot	A stereo vision camera	Open-loop visual control	82.22%	NR	Kohan et al. (2011)

detection and localization (Fernandez et al., 2013). Though given the large number of articles that described a number of fruit recognition algorithms, the development of advanced image processing algorithms is also a challenge for precision fruit recognition. Recently, more and more attentions have been attracted by new visual sensors such as ToF camera, light-field camera, and chlorophyll fluorescence camera. The core of the application considerations of these sensors is how to take advantage of the data acquired.

On the other hand, vision control precision and efficiency for fruit harvesting robot need to improve. There are many recent works regarding eye-hand coordination for outdoor operation robot (Mariottini et al., 2006). The control law of calibration-free eye-hand coordination was described byHager et al. (1994). Base on the auto disturbance rejection control (ADRC) strategy, Su proposed an advanced calibration-free eye-hand coordination which has a strong adaptability and robustness (Su et al., 2004). Another new visual servo control approach based on adaptive neural network has been applied for dynamic positioning of underwater vehicles (Gao et al., 2015).

7.2. Human–machine collaboration

To date, the commercial application of fruit harvesting robot is still unavailable because of lack of high efficiency and economic justification (Edan, 1999). One of the new approaches to improve the applicability of robotic harvesting is to combine human workers and robots synergistically. This approach for robotic harvesting is to separate the fruit recognition stage from the harvest stage by marking the target fruit a priori. In the Agribot project, a robot was designed and built for a new aided-harvesting strategy, involving a harmonic human–machine task distribution (Ceres et al., 1998). Ji et al. (2014) introduced an assistant-mark approach to recognize and locate the picking-point of the harvesting robot. Bechar and Oren has defined and implemented the collaboration of a human operator and robot applied to target fruit detection (Bechar and Edan, 2003; Oren et al., 2012). Experimental results indicated that the target recognition system based on human-robot collaboration could increase the target fruit detection rate to 94% and reduce the time needed by 20%.

7.3. Multi-arms cooperating for robotic harvesting

Another approach towards the goal of efficient robotic harvesting is the multi-arm robotic harvester. The idea is that a number of manipulators are mounted on the mobile robot platform, and each of the robotic arms is assigned a specific fruit to harvest. Zion from Israel has designed a multi-arm melons harvesting robot which enabled the maximum number of melons to be harvested (Zion et al., 2014). According to the idea of multi-robot cooperation for fruit harvesting, Noguchi et al. (2004) also proposed a master–slave robot system for field operations. In this multiple robot system, a high level of autonomy on the robots was achieved to allow them to cope with unexpected events and obstacles.

7.4. Making the environment more suitable for robotic harvesting

There are major technical challenges in automation due to the uncontrolled environment in combination with the fact that the harvest objects and materials are highly inconsistent in shape and size. The harvesting robot working in the complex natural environment requires a higher degree of skill and a wider range of operating. In order to improve the efficiency of robotic harvesting in the future, collaboration among engineers and agronomists is needed. Many engineers, working with agronomists, in the world now have developed advanced robots (Burks et al., 2005; He et al., 2013). Their solution for the problem of low harvest efficiency is making environment robot more user friendly. Trees or plants can be pruned to obtain suitable plant geometry for robotic harvesting and, hence, the picking cycle time can be reduced (Edan et al., 1990).

8. Conclusions

In this paper, a broad overview of the development of vision control technology applied in fruit harvesting robot is given. Vision control for fruit harvesting robot includes two key elements, fruit recognition and eye-hand coordination. For recognizing the target fruit in the canopy, different types of visual sensors and image analysis algorithms are equipped in the fruit harvesting robots. Two-dimensional imaging data of the target fruit have been successfully acquired from monocular camera, hyperspectral imaging, and thermal imaging. Three-dimensional surface reconstruction of the target fruit requires data acquisition from binocular stereoscope or structured light sensor. There is a large difference in the image processing algorithm between 2D imaging schemes and 3D imaging schemes. The scheme of fruit recognition for robotic harvest may depend on the species of harvesting fruit. Moreover, the performance of the fruit recognition system is also influenced by many factors such as variable light, occlusions and many others. Therefore, the reliability of recognition methods must consider the environment in which the robot is working, and the proper selection of sensors.

In addition to the techniques reviewed, the development of eye-hand coordination control for fruit harvesting robot is also described in this paper. We have classified eye-hand coordination into two main categories according to whether the visual control is open-loop or close-loop. There is a large difference in the control principle between open-loop visual control mode and visual servo. The input image of open-loop visual control is a static image. However, the input of visual servo is the video image where frame rates of the video must match the closed-loop bandwidths of vision controllers. The performance of the open-loop visual control relies on the precision calibration of the camera and manipulators. The fruit harvesting robot adopting visual servo can arrive at certain control precision without calibration. With the advancement of current imaging technologies and the development of new control algorithms, more information will be available to aid recognizing the target fruit and speeding up fruit picking.

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