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Harvesting System for Autonomous Robotic in Agriculture: A Review.

Reza Rahmadian[1], Mahendra Widyartono[2]

[1,2] Jurusan Teknik Elektro Fakultas Teknik Universitas Negeri Surabaya
UNESA Ketintang Surabaya
rezarahmadian@unesa.ac.id
mahendrawidyartono@unesa.ac.id

***Abstract* – Technology in the modern day has led to the development of agricultural robots that helps to increase the agriculture productivity. Numerous research has been conducted to help increasing the capability of the robot in assisting agricultural operation, which leads to development of autonomous robot. The development aim is to help reducing agriculture's dependency on operators, workers, also reducing the inaccuracy caused by human errors. There are two important development components for autonomous harvesting. The first component is Machine vision for detecting the crops and guiding the robot through the field and the second component actuator to grab or picking the crops or fruits.**

Keywords: *Machine Vision, Harvesting Robot, Autonomous Harvesting, Robot in Agriculture***.**

I. Introduction

One of the world's serious problem is Food security. Almost 842 million people are undernourished according to FAO[1] reports that in 2010. In addition, the limited land and the keep growing population only made this situation even more serious, because the demand of the food supply is growing as well. Food shortages happen when there is a gap between food supplies and energy and nutrients needed by people in the region. One of the cause of limited supply is the lack of food production, however problems like political and environmental problems in food production become an important reason for it too. The political issues can lead into a condition where some countries limit or ban exports and imports their food production in an attempt to counter domestic food price rises. As for the environmental problems, water shortage is the most immediate cause of food supply decrease. It is a serious matter that 70 percent of all water use is for irrigation [2]. The over extensive drilling of millions of irrigation wells in many countries, lead to the scarce of renewable ground water supply, because rainfall could not replenish it. Besides that, other changes in weather and climate such as global warming or the rise of sea level will definitely be another threat to food security.

In developing countries especially in Indonesia, the supply of rice as the main food actually fulfilled by the national product. However, the faming method used is still implements traditional techniques, this causes inefficiency to happen in some ways, such as in spraying pesticide, harvesting, processing, transporting and storing the crops. Because this inefficiency, the cost of production keep rising and it failed to achieve its maximum productivity, which lead the high price for the food source. To cope with this problem, recently even rice has to be imported in certain time of shortage showing the exceeding need for the food has become urgent and requires solution. Another significant problem in developed countries is the lack of workers to pick the crops in harvesting season, the reason for this shortage is partly because of the ageing population and/or the high wages cost of the workers. Some farmers must often leave the crops to rot says Wettels as in [1]. These developed countries are in dire need to have efficient agricultural technology that can increase their crop management to anticipate food insecurity.

Based on the need of efficient agriculture technology, The development of precision agriculture needs to be implemented to increase productivity and crop quality. Precision agriculture (PA) is an environmentally friendly procedure for farmers to implement different farming methods which consider critical factors that effect yields [3]. It is essentially a more precise form of farming management which makes use of modern technology. PA is the overall farm management used to optimize the crops produced while preserving resources. Agricultural technology is challenged to overcome the food shortage to supply food needs efficiently and in an evironmentally friendly manner.

Precision agriculture develops as it is supported by the progress of technology and management. Technology in agriculture benefits from advances such as those in agricultural production systems which have used the primarily developed technology for industries. They brought mechanization and synthesized fertilizers to agriculture and especially offered genetic engineering and automation which led to precision technology in agriculture[4].

The world's food requirements have become so high, and will continue to rise, so effective agricultural technology that is also environmentally friendly is certainly needed. With various characteristics of the fields used for farming; soil contour and type, weather, water, air, and plants, the variety of agricultural technology should thus fit these characteristics.

Agricultural robots with sophisticated methods that produce the right tool for the farming need to be designed, tested, and produced. With the varied farming conditions of different agricultural countries, and disparities in their expertise, equipment, availability of electricity, funds and other resources, it is highly likely that manufacture of agricultural robots could increase effectiveness in a variety of different conditions. This thesis aims to provide guidance on the principles of the manufacture of agricultural robots using data and information gathered and analyzed from various sources and research results.

II. Harvesting System

As was previously discussed, food shortage as it was stated by the FAO report [5] is the world's most serious problem. The fast growing population of the world causes the demand for food supply to increase every year. This is not only due to the population growth, but also another important cause of the food shortage, which is food production. The problems that relate to the food production include some cases such as the politics-economics (import and export limitation), environment (temperature rise, water shortage or pest contamination), workers availability and also inefficient farming techniques which directly affect the food supply.

In developed countries the lack of production could be because of a lack of availability of workers for harvesting. In the peak harvesting period, farmers need extra workers for harvesting; they usually find wages-based immigrant workers, because hiring local workers would cost them more than what they can gain from the harvest. However, there are not as many immigrants as needed to do the work. This may mean that not all the crops are harvested at the same time and leads to late harvesting and damaging crops. On the contrary, in developing countries the numbers of these wages-based workers are abundant; they even work at a lower rate compared to developed countries' basic salaries. Also the availability of the land for farming fields is still high. These farmers' problems are more to do with the less effective farming method they implement. The use of traditional ways of seeding, weeding, and harvesting is time consuming and more costly for the farmers [6].

Food production problems like the environment, limited land availability, lack of workers and high cost because of inefficiency may be reduced by the farming intensification and sophisticated technology. Agricultural robots have begun to introduce ways to perform farmers' tasks more effectively and accurately. The wages also increase every year, which is why it is now becoming more and more difficult to hire sufficient workers while the farmers have to limit the cost of hiring the workers. An efficient robotic system may be the answer for this. Even if a robot system is merely able to do one specific task, for example harvesting, the need for many workers decreases, as does the cost of hiring them.

III. Machine Vision for Harvesting.

Researches and experiments about harvesting robot have been studied by many researchers around the world. For example, Kondo, Monta, and Fujiura [7] have been developing a harvesting robot for tomatoes, petty tomatoes, cucumbers, and grapes in Japan. In autonomous agricultural robots, especially harvesting fruits, devices for detecting the fruits are the most important. This sensing device detects which fruits are ready to harvest and it measures the distance between the fruit and the picking device. Machine vision is one of the commonly used sensing devices for fruit detection, recognition, and localization. Figure 10 is the hardware structure for an apple harvesting robot developed by De-An et.al [8] that used a Machine Vision system for detecting the position of the apples. Wang et.al [9] used the same system to separate apple images from the background; therefore the harvesting devices will be able to pick the apples accurately, as seen in figure 1.

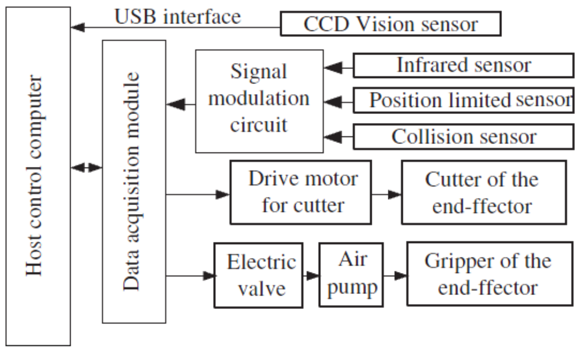

Figure 1. Hardware architecture for Apple harvesting robot [9].

Machine vision for robot navigation has been discussed in the previous chapter. Although there are similarities in the types of device, machine vision for harvesting has different processing from the one for navigation. For navigation, machine vision is used to detect crop rows to guide the robot through the field and detect obstacles in front of the robot or vehicle, while for harvesting, it detects the color and/or shape of the fruits and distinguishes them from leaves and branches so the end-effectors are able to pick up the fruits. To be able to recognize fruits from branches and leaves, machine vision has to capture the images and process them. Jimenez, Ceres, and Pons [10] states that image processing for fruit recognizing may be accomplished by several steps such as, image capturing, feature construction, noise removal, image enhancing, and segmenting to cluster the image into different classes. Regarding the nature of the image processing, segmentations such as color or intensity segmentations seems to be the central task for the processing.

Figure 2. The segmentation result between apple and background image [9].

Color or intensity of fruits can be the factor used to determine size or ripeness of individual fruits, De-An et.al [9] used a real-time automatic recognition vision system with a color CCD camera for capturing the apple images. The original unprocessed apple images always contain noise; therefore a vector median filter was applied to enhance the image. After the images had been filtered, to separate apple images from the background image, algorithms based on hue histogram statistic from the hue, intensity and saturation (HIS) model, and the double threshold and region growing method were employed. The result showed that the robot was able to recognize 39 apples in 10 minutes and the picking success rate was 77%. Another system that uses the Hue, Intensity, and saturation (HIS) for detecting fruit is Harrel et.al [11]. The system uses HIS components of each pixel, captured using a color camera and artificial lighting. Two thresholds were implemented based on maximum value for saturation and minimum value for hue. This robot was designed for picking citrus fruits, and the experiment was conducted for approximately 150 hours in a citrus grove, with the results showing that the robot successfully picked fruit on 75% of attempted picking cycles. Hayashi et.al[12] developed a strawberry harvesting robot and used three CCD cameras aided with five light sources consisting of 120 light-emitting diode (LED) chips. This machine vision unit captured the images and obtained what they called red regions (r'), obtained by comparing the red color with the value of the RGB color (r'=R / (R+G+B)). When the red region value was satisfied that was when the image was recognized as fruits. The other camera captured the RGB of the images and transformed these into HIS image for the fruits maturity assessment. The field test was conducted for about 3 weeks with 192 strawberry plants, and the results showed that the robot achieved approximately an 80% success rate.

Parrish and Goksel [13] used a thresholding method to obtain binary images to recognize. After the binary image was acquired, the image was filtered to smooth and eliminate both noise and irrelevant detail, enhancing the quality of the image. A roundness measurement was carried out to get the center and radius value of the fruits, and when the value was greater than a preset threshold then it could be accepted as an apple. Sites and Delwiche [14] developed a system for recognizing ripe apples and peaches using Black and White camera and color filters (630 – 670 nm) to increase the contrast, so it could distinguish between the fruits and the background. The experiment was conducted during night-time operations; therefore artificial light was added to aid the system capturing the images. The method could be divided into five steps. The first step was the thresholding method based on intensity on a constant 37% value. The second step was to filter, enhance, and smooth the images with a binary filter. The third step was to segment labeling, using 8-neighbor connected component labeling method. The fourth step includes the features extraction such as area, perimeter, compactness, and elongation. The final step was classification by a linear decision function or a nearest neighbor method. The results showed that the system successfully detected 90% of visible fruits for night-time experiments and 84% for daylight experiments.

A robot for asparagus harvesting developed by Baylou [15] was equipped with two CCD cameras (488 x 380 pixels) which were used to capture the asparagus tip. The captured images go through binarization operation that involves finding an optimal threshold to extract the images contour. This automatic thresholding will adapt itself to the lighting condition. A 3-element median filter was applied to avoid punctual noise present on a camera image; this filter seemed most suitable for treating contour images. However the study does not state the result of the experiment clearly.

Lu et.al [16] used a video camera with a CMOS photosensitive sensor to capture image of the apples in designing apple harvesting robot. Because the apple image under natural conditions contains large amount of noise, they implemented a vector median method to remove the noise. This method will reprocess the captured images to differentiate between the fruit, in this case apples, and the complex background. After the images were reprocessed, the combination method based on regional growth algorithms and color characteristics was implemented to segment them. When the experiment was conducted, some isolated dots, burrs and small hollows might appear in the segmented images. Therefore, to reduce this noise influence, they developed opening and shutting mathematical morphology. The opening operation was used to reduce the dots and burrs, while the shutting operation filled up small holes. These operation cycles continued until the ideal image was able to be obtained. The result showed that the robot was able to smoothly complete recognition and orientation of target fruit effectively.

Wang et.al [17] developed an apple harvesting robot with a new recognizing method called Support Vector Machine (SVM). This method improved the robot's machine vision accuracy and efficiency to detect apples, because it filtered the color noise from captured images and segmented the images based on regional growing methods and color properties. The detection experiment was conducted under several different lighting conditions, such as fruit, back lighting, fruits in shade, and cloudy weather conditions. The experiments showed that even with different lighting conditions the chromaticity of the images is hardly influenced, which is why they implemented the non-linear transformation to change images' RGB components to the HLS color. HLS model is a common color perception model; it describes color with three properties Hue, Lighting, and Saturation.

For the apple shape detection process, the SVM method was used to extract shape properties and classify them. These properties such as round variance ellipse variance, tightness, ratio of perimeter and square area can gather up outline properties of apple fruit. However, before acquiring the outline properties of the apples, Robert arithmetic operators were implemented to acquire the position of boundary pixels of the apple image, and after the edge pixels were acquired the calculation of the apple properties (round variance, ellipse variance, tightness, et cetera) can be done. The experiment result stated that this method has better recognition capability compared to the neural network method that is commonly used in fruit recognition. In addition, recognition rates for apple fruits color and shape properties with SVM method had higher rates of recognition compared to the method that only used the color or shape properties.

To recognize the shape of melons, Benady and Miles [18] used a laser line projector. The laser beam illuminated the scene and when it contacted the surface of the melon, the reflection of it was recorded as a curved line. The deformation of the initial straight line indicated the distance to the object by triangulation analysis. This analysis was used to get one profile at preset offsets, which later on this profile, it will analyze using Circular Hough Transform to obtain a matrix value that indicates the center of a melon. The expected size and shape helped to detect the melons, and the experiment stated that all fruits were successfully detected by the system. Cho et.al [19] developed a robot for harvesting lettuce with machine vision system for the sensing device. The system was composed of a color CCD camera (PULLiX), a frame grabber (Matrox corona-LC/8), and photoelectric sensors to detect the height of the geometrical shape of lettuce. The system captured the image of the lettuce and obtained information such as the leaf area and its geometrical shape. A chain code method was implemented to detect the lettuce outline and calculated the leaf area from the captured images. This information later was later used as an input variable of fuzzy controller to control the force of the gripper. The success rate of harvesting in this experiment was 94% and average harvesting time was about 5 seconds per lettuce.

Machine vision systems can be used for either autonomous navigation or for harvesting fruits; the difference between them was the processing of the image. For harvesting purposes, machine vision focuses on the process of recognizing the color and shape properties of the images. Machine vision is not the only method for recognizing fruit in harvesting robots, and several other sensing devices such as Laser system for cherry picking [20], Ultrasonic sensors [21], and Infra Red sensors [22] are already used in several researches; however these are not covered in this paper.

Machine vision may be the best solution for the sensing device in autonomous harvesting robot, however it is always a good thing to add another option for the sensing device, for example combining ultrasonic sensors and machine vision [21] or Machine vision with Laser Range Finder [22] to the advantage of the combination. On the other hand, Jimenez, Ceres, and Pons [22] studied digitalized images from its Intensity, Spectral, and range types, and stated that there are some weaknesses of the machine vision. For example the shadows that cover the fruits that disturb the image capture, there is no depth information acquired from the images, and there are confusing regions (such as patches of the sky, sun, or soil visible throughout the tree).

Automatic fruit harvesting systems are variously described in Li, Lee and Hsu's [23] paper. It describes several examples of mechanical harvesting methods, for example a mechanical harvesting method using a limb shaker, an air blast and a canopy shaker. It also gives examples of ongoing or already completed projects for automatic harvesters such as MAGALI Project, Eureka Projects and Agribot Procet. In addition, the paper also describes several examples of machine vision approaches and methods for image data analyzing in fruit harvesting.

Even though there are many studies about autonomous fruit harvesting robots, research for autonomous harvesting for other crops such as rice was hard to find. This may be because there are commercial machines for rice harvesting that have already been widely sold, or may be because rice usually grows in developing countries such as Indonesia where the cost of labor for harvesting rice is significantly cheaper than buying a rice harvesting machine, even more so for autonomous rice harvesting robots. This can be one of the future works and challenges; development of autonomous rice harvesting at affordable prices even for farmers in developing countries.

IV. ACTUATOR

Actuator is a device that controls and facilitates movement or mechanical operations of a system. The input source for this device can be from hydraulic fluid to electrical currents. Actuators in harvesting robots commonly facilitate the end-effector such as robotic arms, gripper, or even suction devices. The form of these actuators can be varied, from DC servomotor to vacuum cleaner.

Some robotic arms are used to grab fruits and vegetables during harvesting time. De-An et.al [8] used an ECMA (Delta Electronics, Inc) series servo motor and an IDC EC2 (Danaher Motion Co., LTD) series precise linear actuator to develop a robotic arm for picking the apples in their harvesting robot. The result showed that the robotic arm was able to pick 30 out of 39 apples. Six of the picking failures were because they were blocked by branches and three were because of their small size. Cho et.al [19] developed a robot for harvesting lettuce and used an AC servo motor (MC34C87) that was controlled by proportional-plus-integral controllers for moving the already cut lettuce to packing conveyor, with another servo motor also used to move the cutting blade to separate the lettuce from its roots. A pneumatic cylinder actuator was also used for moving the arm gripper back and forth to grip the lettuce. The movement of the arm gripper and the gripping itself were controlled by a fuzzy controller; the experiment result showed that the robot achieved 94% success rate.

Tanigaki et.al [20] manufactured a cherry-harvesting robot with a 3-D vision sensor, suction part and robotic arms to harvest the cherries. The arm for harvesting was based on up-down traverse axis manipulator, because the up-down movement requires large force (the movement being affected by gravity), an AC servomotor SGMAH-01BAA2C 100W from Yasakawa Electric powered this manipulator. Three axes for the robot arm did not require that much force, therefore all were driven by AC servomotor SGMAH-A5BAA21 50 W, and the remaining axis for moving the smaller parts of the robot arm was driven by small DC motors with reduction gears.

As seen in Figure 12 the robotic arms were also equipped with rubber plates to grip the cherry and a suction tube that was connected to a vacuum cleaner, with these fingers which were driven by small servo motors to open and close the fingers. Details of the cherry picking method can be found in the paper.

Liu, Li, and Li [24], developed an end-effector for spherical fruit harvesting robots that can be applied to any spherical shaped fruits such as tomatoes, apples, and citrus. As seen in Figure 13, the end-effector has vacuum suction and a gripper to hold the fruits while a laser cutter cuts the peduncle. The gripper has multi-fingers that ensure the tight grip on the fruits; these fingers are powered by servomotor actuators from Maxon DC Servomotor. After the fruit is gripped tightly, a high-power fiber-coupled laser diode cuts the peduncle of the fruits. The nLight's fiber-coupled laser diode was used for the actuator because it was able to deliver reliable high-powered light efficiently. This beam will go through standard focusing lens SMA-905 actuators to focus the laser beam to the peduncle. For the suction pad, a DC servomotor drives the suction pad back and forth to pull the fruits. The vacuum system itself contains a pressure sensor to detect negative pressure when vacuuming the fruits, so it will not damage the fruits.

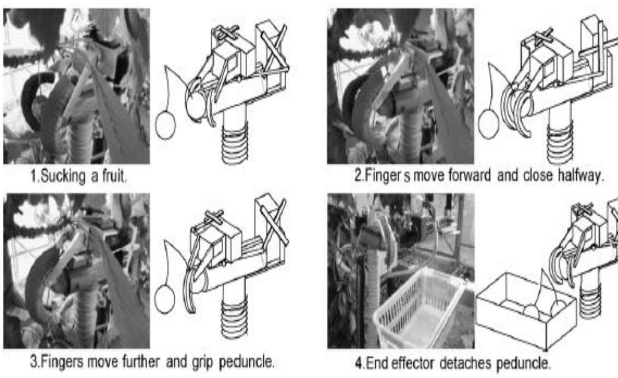

Figure 12. Picking method [20].

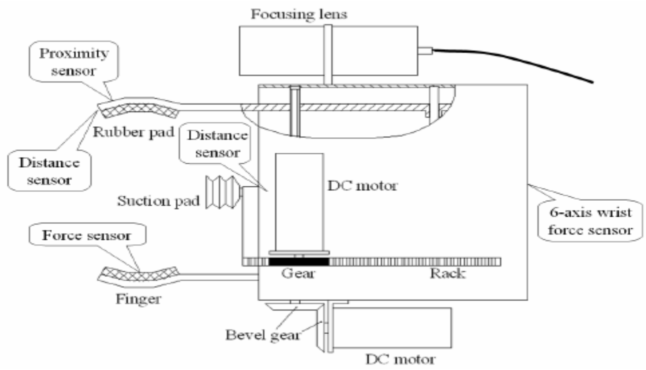

Figure 13. Harvesting Unit Kiu, Li, and Li [24].

The result showed that the Gripping and cutting unit able can be applied to harvesting robots, especially for harvesting spherical fruits, although the authors did not state any accuracy of the experiments.

Most of the researches used servomotors as actuators, to drive the robotic arms or the mechanical gripper; this may be because servomotor allows precise control of the end-effectors. Also the size of the servomotor that is used for robotic purposes is commonly small, therefore requiring less power. Overall, servomotors may be the best option for robotic needs because they provide accuracy, are cost effective, and come in small sizes for robotic end-effectors [25]. Other actuators such as suction devices, can be acquired from small vacuum cleaners, or may be from commonly used vacuum cleaners at home, as what Tanigaki et.al [20] did. They a used normal vacuum cleaner for their suction device for their cherry picking robots. In addition, adding several sensors such as a pressure sensor in the suction system will avoid damaging the fruits, because it controls the suction pressure. Therefore, using normal vacuum cleaners, which are commercially available, may be cost effective for suction devices for a harvesting robot.

V. CONCLUSION

To tackle the problems such as limited labour, limited funds and high wages, autonomous harvesting can be one of the solution offered. The autonomous harvesting system could be constructed from two important components, such as machine vision and the use of actuators.

The above discussion on the technology supporting precision agriculture is discussed further regarding its application on harvesting activity. Machine vision has an important role in harvesting, because the characteristics and nature of the crops is the signal whether they are properly harvested or not. Machine vision is thus widely improved and developed to detect the various crops to be harvested. For fruits and vegetables, the color and/or shape of the fruits distinguish them from other things like the leaves and branches so the end-effectors are able to pick up the right things that is the fruits or vegetables. Various characteristics of the crops may decide the modification of the machine vision technology. A real-time automatic recognition vision system with a color CCD camera is used for capturing the apple images. This kind of camera is also used in robots for asparagus harvesting to capture the asparagus tip. An apple harvesting robot detects the fruit with the support vector machine (SVM) and another apple harvesting robot does it with a video camera with CMOS photosensitive sensor. Beside machine vision Laser system, Ultrasonic sensors and Infra-Red sensors are also applied for fruit picking.

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