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Robotics and Automation in Agriculture: Present and Future Applications

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Abstract: Agriculture is the backbone of society as it mainly functions to provide food, feed and fiber on which all human depends to live. Precision agriculture is implemented with a goal to apply sufficient treatments at the right place in the right time with the purpose to provide low-input, high efficiency and sustainable agricultural production. In precision agriculture, automation and robotics have become one of the main frameworks which focusing on minimizing environmental impact and simultaneously maximizing agricultural produce. The application of automation and robotics in precision agriculture is essentially implemented for precise farm management by using modern technologies. In the past decades, a significant amount of research has focused on the applications of mobile robot for agricultural operations such as planting, inspection, spraying and harvesting. This paper reviews the recent applications of automation and robotics in agriculture in the past five years. In this paper, the recent implementations are divided into four categories which indicates different operations executed for planting management starting from a seed until the product is ready to be harvested. Towards the end of this paper, several challenges and suggestions are described to indicate the opportunities and improvements that can be made in designing an efficient autonomous and robotics system for agricultural applications. Based on the conducted review, different operations have different challenges thus require diverse solutions to solve the specific operational problem. Therefore, the development process of an efficient autonomous agricultural robotic system must consider all possibilities and challenges in different types of agricultural operation to minimize system errors during future implementation. In addition, the development cost needs to be fully considered to ensure that the farmers will be able to invest their capital as a consumer. Therefore, it will become highly possible for the autonomous agricultural robotic system to be widely implemented throughout the world in the future.

Keywords: Agriculture; Applications; Automation; Food security; Robotics.

1. INTRODUCTION

In the recent era, precision agriculture plays an important role to maintain the future food security with less labor and energy and at the same time improving the environmental management to ensure a productive agricultural output. The work of precision agriculture focuses on controlling the way the seeds, fertilizers and agrochemicals are applied to the soil and how the harvesting process is executed. The execution of agricultural operation differs based on the type of agricultural land. For agricultural lands, the categorization is divided into four types which are confined feeding operations, cropland and pasture, orchards and vineyards and other agricultural land [1]. The confined feeding operation land consists of the ecosystems which has been modified by human to provide a large and specialized livestock production. On the other hand, cropland and pasture land is usually used for agricultural crop production such as soybean, corn and wheat and it is also being used for pasture. Orchards and vineyards land is used to grow plants which produce fruits and nut crops which include grapes, apples and pears. Lastly, the other agricultural land type is the ecosystems which is being used to produce food and fiber which does not fall into the previous aforementioned land type. The example of other agricultural lands are farmsteads, small farm ponds and corrals.

As of today, the implementation of precision agriculture is not being limited to only a specific land type. The development of precision agriculture has been focusing into several areas such as technology, digitalization, impact on society, skills, environment and productivity [2]. In technology, the application in wide range of technologies such as geo-referencing, Global Navigation Satellite System (GNSS), data storage and analysis, advisory system and autonomous navigation has been widely used in the development of Precision Farming (PF). The digitalization of agriculture has been widely implemented in parallel with the development of Information and Communications Technology (ICT)-revolution. Digitalization technologies such as cloud computing and Internet of Things (IoT) have enabled an efficient and precise farming management in the scope of numerous data collection which can be easily to be shared and interpreted. Similar to the way which computers have changed

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the human life, precision agriculture is also designed to trigger societal changes in rural community and initiate new social models and business in addition to make life easier by reducing workloads for the farmers.

Recently, automation in agriculture has becoming a trend where agricultural operations such as cultivation, inspection, spraying, pruning and harvesting are executed autonomously to overcome the labor shortcomings in agriculture. The term automated agriculture is used to relate any parts of the equipment or machine that is designed to remove the manual intervention in agriculture [3]. The work of agricultural automation is mainly focusing on autonomous vehicle applications such as robot or tractor where it is being used to minimize the tough, deadly, risky and long working conditions experienced by farmers and at the same time offers a precise and efficient operation and control system. In addition, the output quality and quantity need to be maintained to be in good quality and consumable for human. Therefore, the development of an efficient automation system in agriculture has becoming an interest in current research in agricultural field nowadays to ensure the sustainability of the food security in the near future.

This paper reviews the recent applications of automation and robotics in agriculture in the past five years. The categorization of present application has been conducted based on four important agricultural operations which are planting, inspection, spraying and harvesting. The implementation of automation and robotics in agriculture will be varied in its structure, planning and also execution as different agricultural operation has its specific objectives that need to be fulfilled. Then, the review will be continued by stating some of the challenges and possible future development of automation and robotics in agriculture which may be possible for future automation and robotics development.

2. AGRICULTURAL AUTOMATION AND ROBOTICS: PRESENT APPLICATIONS

In agriculture, the automation of specific operations has enabled the farmers to manage the crop production efficiently with less energy and cost. Factors such as lack of agricultural workers in addition to the aging farmer's population and increasing agricultural wage has made the farmers and researchers to play an interest in the development of automation system in agriculture. The implementation and development of agricultural automation has been executed by autonomous robots and agricultural machineries such as tractor which usually attached with cultivator, planter, cultipacker and chisel plow. Figure 1 shows several agricultural robots and machineries which requires automation to enhance the efficiency of the agricultural operation.

Based on Figure 1, the application of automation and robotics in agriculture can be varied significantly. The execution of agricultural operation needs to be executed by different robotics and vehicle structure based on the type of land and operation requirement. Different robot and vehicle structure had its own limitation that need to be solved by using other machineries. The robotic structure has limitation to execute extreme operations in agriculture due to its sensitive characteristic towards water and mud. Therefore, the tractor is being used to execute such task due to its great ability to traverse inside the muddy structure and less protection towards electronic circuit. On the other hand, tractor application only limits to a wide area due to its large structure. Thus, the application of the small area needs to be executed by mobile robot. For drone application, it is only applicable to open area and its application would be insignificant to a closed area such as the greenhouse as the probability of collision will be increased. To explore more on present application of automation and robotics in agriculture, the categorization was made based on different agricultural operation

(a) (b) (c) (d) (e)

Figure 1. Agriculture robot and machineries (a) BoniRob [4] (b) Shrimp robot [5] (c) Chisel cultivator [6] (d) DJI AGRAS MG-1S Drone sprayer [7] (e) Combined harvester [8]

(a) (b) (c)

Figure 2. Planters (a) Single-seed corn planter [11], (b) Minimum-tillage planter [16], (c) Billet planter [18]

2.1 Planting

Planting is a process where the seeds or young plant will be planted into the soil for plant growth phase. This process requires a higher level of precision as different plants require specific distance between each plant to optimize the growth and at the same time maximize the yield. The classical way of planting method requires a farmer to manually insert each seed into the soil. This approach requires a lot of time and energy as this process needs a lot of consistency and precision where it usually covers a wide agricultural area. Therefore, a planter machine has been introduced where the farmer will operate the machine by controlling the machine motion and at the same time the seed will be planted into the soil. Figure 2 shows the planters which have been designed for planting process for different plants. From Figure 2, the designed planter usually will be towed behind a tractor where the planter will exert a repeated motion to plant the seed. As the tractor and planter is manually operated by human, the consistency of the row will be affected as the row will not be in a straight line and there are some areas where the planter is unable or miss to plant the seed. Therefore, an efficient autonomous system is needed where it will ensure to produce a straight-line plant row and will not miss any seed planting.

To solve the problem faced by manual planting method, autonomous system has been introduced for several crops such as corn [9, 10, 11, 12, 13, 14, 15], wheat [16,17], sugarcane [18] and vegetable [19]. To design an efficient autonomous system for planting process, several considerations have become the main objectives in the design process [9]. First, the robot or vehicle must be able to move accurately in a straight path despite on the bumpy road in the farm field. This requirement is very important as the consistency of straight seeding process is needed to ensure the efficiency of the automation process in the next planting process such as inspection or harvesting. The next requirement is related to the level of soil moisture which must be considered as it may affect the soil digging process. In the soil digging process, specific seed requires specific digging depth. Therefore, the digging depth must be kept constant by adapting the soil moisture level and soil compaction in calculating the digging force for cultivation process. Finally, the seeding detection is needed where this system will detect the presence of seed when the vehicle is ready to plant the seed. This system is very important to ensure the planter will plant the seed without missing any unintended planting area.

Most of the conducted research in planting process focuses on the development of the autonomous seeding system with the main objective to ensure that the seed will be planted in a consistent distance and depth. In [9], an autonomous seeding robot has been designed using Agribot platform. In this development, an Infrared (IR) sensor has been used to check the condition of seed tank and also for row detection and it showed a satisfactory result in terms of the distance accuracy between the seeds. In [10-11,18], a seed metering unit control system has been designed to enable the planting consistency. In planting process, seed metering device is usually used for metered seeds discharging into the soil. It is usually used to classify the seed into a single or a group of seed before it is being deposited at the predetermined time with accurate intervals. To access the performance of the seed metering device, different speeds and different seed spacing is needed and the planting quality is measured by using plant spacing uniformity, variation among rows, fuel consumption and negative slippage. From the result, it has been shown that the efficient design of seed metering unit is able to provide a better planting quality and approximately 22% improvement in fuel saving.

Other methods to ensure the consistency of the seed spacing in planting operation is by using a global positioning system. In [12], a control system for seed and fertilizer has been developed using Global Navigation Satellite System (GNSS)/ Inertial Measurement Unit (IMU) combined sensing technology. In the designed system, the vehicle will execute the operation based on the target application rate of seed and fertilizer by comparing the target parameter to the time and space data obtained from GNSS/IMU. This application has been proven to be efficient with the maximum error of 4.91% at 5.8 km/h. In addition, literature [13-14] introduces a Global Positioning System (GPS) based variable-rate seeding control system for maize planter. In this application, the GPS receiver is used to locate the real-time seeding position, travel speed and course angle in a fixed frequency. Then, the data receives from GPS is further processed to obtain latitude, longitude, travel speed and course angle. This implementation is found to be a low-cost system for an efficient variable-seed control system with an average seeding accuracy of 97.64%.

In addition to the global positioning system approach for an efficient seed planting operation, a seed spacing uniformity using a high-speed camera has been developed by [15]. In this implementation, a Fuji F660EXR camera with a sustained speed of 320 frames per second is used to monitor the seed falling trajectories which is attached at the Unissem pneumatic planter outlet. From the implementation, the result shows that the seed spacing uniformity is found to be very efficient at 95% confidence level at speed range of 3 to 4.5 km/h. In [20], an infrared sensing system was developed that consists of Infrared Light Emitting Diodes (IR LEDs) and photo diodes to measure the sowing rate of chickpea, wheat and alfalfa seeds in planters. In this approach, the output voltage of the light-receiving sensor will be converted into analog value which then transformed into a model to calculate the sowing rate. This approach has been found to be significant to measure the sowing rate with the coefficient of 0.94 for model determination.

The consistency of the automation system for planting process is really important as it is the first part of agricultural operation. If the operation is executed inconsistently, it will negatively affect the next operations which are solely depending on the plant distribution which has been developed in the planting process. The development of an efficient planter with seed detection will be able to ensure the optimized planting process with low operational cost and at the same time maintaining the consistency of seed distribution throughout the field. Therefore, the automation of planting process would be much efficient and convenient for the farmers in the future with a good planting quality.

2.2 Inspection

Inspection in agriculture is a process where the plants are being inspected or observed for any diseases or quality defects. In agriculture, plant diseases are primarily responsible for the reduction in production which causes economic losses. As agricultural environment is very dynamic, numerous unexpected and abnormal stress situations such as abnormalities in temperature, humidity, water levels, disease emergence, and pests has affected the plants and its products. If those abnormalities are not managed in a timely manner, severe and irreparable damages may be occurred [21]. To execute the inspection, traditionally farmers will manually observe the abnormalities in plant by using their human vision system. As the age of farmers are increasing in the past few years, the efficiency of inspection operation has been reduced as the quality of the human vision system is depleted with age. In addition, the implementation of automation in agricultural inspection requires a system to replace the ability of human vision to execute the inspection process. Therefore, computer vision has been widely used to replace human vision in performing plant inspection in agriculture.

Computer vision is an advanced technology for image processing that has a propitious outcome and has becoming a great potential to replace human vision in doing some detailed work in inspection process [22]. A computer vision system has been widely adopted in some heterogeneous domains which includes agriculture. In agriculture, it is noteworthy that image processing and computer vision applications have grown due to the reduced equipment costs, increased computational power and increasing interest in non-destructive food assessment methods [23]. Most of the implementations of vision system in agriculture are used for disease detection and some of the implementations is used for product quality checking. Figure 3 shows some of the implementations of vision system in agricultural inspection process.

Based on Figure 3, several examples of plant inspection are shown where Figure 3(a) shows a disease detection of rose leaf, Figure 3(b) for sugar beet leaf and Figure 3(c) for sunflower leaf while Figure 3(d) shows the quality assessment of the corn kernel. Those implementations are being implemented with specific objectives either to detect diseases or to evaluate the quality of agricultural products. In terms of image processing efficiency, several methods such as Neural Network based algorithms [26-30], K-Nearest Neighbors [31], Support Vector Machine (SVM) [32], Particle Swarm Optimization (PSO) [26], Genetic Algorithm (GA) [24] and Machine Learning [33]. Most of the implementations of image processing algorithms for agricultural inspection in the past five years are using Neural Network based algorithm such as Deep Convolutional Neural Network [26], Convolutional Neural Network [27], Deep Neural Network [28], Regions with Convolutional Neural Network (R-CNN) [29] and Back Propagation Neural Network [30]. From the results, the Neural Network based algorithm shows a good performance in agricultural inspection with a maximum accuracy of 98% [28].

In addition of the implementation of image processing method in agricultural inspection, some researchers also make use of the hyperspectral imaging for plant disease detection. In [34], a new Normalized Different Spectral Indices (NDSI) is used in detecting peanut leaf spots. This method is being implemented by measuring the deviation of hyperspectral vegetation index which is specific to leaf spot detection. Furthermore, other method such as immunochromatography has been used to detect the fumonisin chemical compound which may contaminate the agricultural product [35]. This method implements an ultrasensitive gray-imaging-based quantitative immunochromatography detection method to trace the chemical compound in agricultural products.

With the advancement of Industrial Revolution 4.0 (IR 4.0), cyber physical system become the main focus area where all devices and sensors are interconnected in a cloud. Therefore, the technology of agricultural inspection is also evolving towards IR 4.0. Recently, IoT are becoming a trend in agricultural inspection process where farmers can monitor and control their agricultural control systems using computer and mobile apps [36-39]. Most implementation of IoT in agricultural inspection are used to monitor plant diseases in real time by capturing images and collecting sensory data such as moisture, temperature, humidity and soil pH level from the farm and displayed inside a website or mobile apps. Therefore, diseases such as early blight, light blight and powdery mildew can be detected in a timely manner by the farmer before the epidemic starts to break. In addition to monitor the farm condition, the IoT technology also enable the farmer to control other agricultural system such as irrigation and spraying and it also able to provide a warning message to the farmers for any abnormalities in plant condition with the help of artificial intelligence [37].

Inspection process is one of the important agricultural process with the main aim to detect the disease and maintain the quality of agricultural products. The automation of inspection process is really important as it will reduce the inefficiency of manual inspection techniques executed by farmers. The action of autonomous inspection is usually conducted by placing a camera in fixed position, attached on the mobile robot platform or on a drone. From the autonomous design and its implementation in inspection process, the disease prevention and quality checking of agricultural products will become more accurate and efficient to maintain the food security in the future.

(a) (b) (c) (d)

Figure 3. Agricultural inspections (a) Rose leaf [24] (b) Sunflower leaf [25] (c) Sugar beet leaf [26] (d) Corn kernel [27]

Table 1. Parameters used in designing variable rate spraying method

References	Disease/Detection	Parameter(s) used
Elizabeth et al., 2019 [45]	Greenhouse crop diseases	Volume rate, target location and airflow rate
Trygve et al., 2018 [46]	Weed removal in carrot farm	Weed species and size
Danielle et al., 2017 [47]	Vineyard spraying operation	Sprayer travel speed and position (latitude, longitude)
Marco et al., 2017 [48]	Poplar diseases	Sprayer setting, nozzle types combination, airflow rates and air direction
Keyvan and Jafar, 2017 [49]	Nitrogen fertilization in greenhouse crops	Plant needs and requirements based on image features (entropy, energy and local homogeneity)
Ales et al., 2016 [50]	Grape leaf diseases	Average leaf velocity, leaf RMS velocity, turbulence level, spray coverage front/back side and droplet density
Mariano et al., 2016 [51]	Weed removal in wheat farm	Weed spatial distribution
Jasmine et al., 2016 [52]	Flower pollination	Gravity, wind and drag
Roberto et al., 2016 [40]	Grape powdery mildew	Level of diseases

2.3 Spraying

Spraying operation in agriculture is a standard method of applying pest-control chemicals, fertilizers or growing medium which are applied as a fine mist to plants for disease treatment and plant growth management. In most of the farming practices, pest-control chemicals are usually applied uniformly throughout the fields to control the spreading of diseases. This technique is applied despite several pests and diseases exhibit at an uneven spatial distribution, especially during early stages of development [40]. Therefore, to minimize the cost of pest-control chemicals usage in agricultural operation, selective spraying was introduced and investigated in the past two decades [41-42]. The automated selective spraying system, usually executed by a highly automated equipment or mobile robots, enables the selective targeting of pesticide application only where and when it is needed. The main objective of this selective operation is to reduce the amount of pesticide usage and preventing the establishment of infection and its epidemic spread throughout the greenhouse [43].

In the development of autonomous selective spraying method, previous researches are focusing more towards designing an efficient spraying system with minimum operational costs. To achieve the aforementioned objective, variable rate spraying method is designed that allows farmers to automatically adjust the pesticide or herbicide volume rate to the target based on the canopy size and treatment requirement [44]. Table 1 shows the measured parameters used in designing an efficient variable rate spraying system which is used as a part of autonomous agricultural spraying system in disease control. Based on Table 1, the parameters chosen in designing a variable rate spraying method differs based on plant species and spraying requirements. Based on those parameters, the volume and the flow rate of spraying agent will be calculated which will be used in spraying operation. The variable rate spraying method is proven to reduce the pesticide use up to 85% compared to homogeneous spray or canopy method [40]. Therefore, this method is highly recommended to be used and implemented by farmers. With the vast automation and robotics technology, this method will be able to reduce the pesticide use with a great precision without exposing hazardous chemical effects directly on farmers.

In addition of reducing the pesticide use, some researches also focusing on navigation management with the objectives to reduce the operational cost of the robot such as time and energy with a great position tracking. This research field is very important to ensure that the robot would be able to navigate towards the target precisely with a minimum travel cost in executing spraying operation. To reduce operational cost, literature [53] propose a multi-objective algorithm called Non-dominated Sorting Genetic Algorithm using Reference Point Based to optimize objectives such as travel time, distance and routing angle. In [54-55], the investigation of robot travel speed effect on mass discharge flowrate of pineapple leaf fibre is conducted where several robot speeds are tested to find the most optimized speed for composite spray operation. Finally, literature [56] propose a route planning algorithm using Simulated Annealing which considered objectives such as distance, fuel, herbicide volume, input cost and time.

Despite reducing the operational costs in designing navigation system for spraying operation, researchers also focusing on maintaining great position accuracy for agricultural robot. In [57], the development of a wheel-type robot tractor is designed for weeding and spraying. To improve its auto steering system with stable navigation accuracy of less than 0.05 m, Real-Time Kinematic GPS (RTK-GPS) and IMU are used for position and attitude sensor for navigation system. As the cost of RTK-GPS is expensive for robot development, literature [58] propose a data fusion algorithm using MSPI to filter noisy raw data from low cost sensors such as Differential GPS, IMU and vision sensors for vineyard pesticide spraying robot.

However, this implementation shows a lower accuracy level with a minimum deviation of 0.11 m which is higher compared to RTK-GPS based implementation.

As most of the implementation of autonomous spraying operation in agriculture implement a land-based vehicle, some implementations also consider the use of Unmanned Aerial Vehicle (UAV) for this operation. In [59], UAV swarm is used for non-uniform crop spraying where a multi-agent area coverage method Heat Equation Driven Area Coverage (HEDAC) used to reduce over-spraying. In addition, literature [60] implemented Genetic Algorithm to adapt its behavior to dynamic weather conditions for pesticide spraying application. From this implementation, the spraying accuracy can be maintained by controlling the behavior of UAV adaptively based on several parameters such as wind speed and direction and pesticide deposition.

The replacement of human force in executing spraying operation is very important to reduce the risk of hazardous chemical substances to the farmers. With the vast development of automation technology, the transition phase of human replacement in spraying operation will become much easier with the main objective to treat the plant disease with minimum operational cost. However, much researches are still being conducted to ensure that the implementation of automation in spraying operation will provide infinite benefits to the farmers in controlling plant diseases to maintain the food security in the future. Therefore, researchers are still able to improve the current methods and techniques in developing an efficient spraying operation in agricultural application.

2.4 Harvesting

In agriculture, harvesting is a work of collecting the agricultural products to be processed or sold. To operate this process, the fruits or vegetables need to be collected and stored for further processing or it may be directly sold to the buyers. As this process need a detailed observation with repetitive procedure, it is known as a very time-consuming and labor-intensive process. Therefore, the development of autonomous harvesting system has been actively conducted over the last decades. Several implementations have been done in the past few years for various types of crop such as strawberry [61-64], apple [65-70], tomato [71-73], kiwi [74-75], capsicum [76-77], grape [78], litchi [79], citrus [80], pumpkin [81] and heavyweight crop [82]. Most of the implementations are focusing to enhance the accuracy of harvesting system by proposing several approach and methods with different software and hardware structure architecture.

To execute an autonomous harvesting process, several steps are required. First, the mobile robot must be able to locate the target location to identify the object or location that needs to be harvested. Then, the robotic arm will be carefully navigated towards the target location without colliding with any obstacles. Finally, the cutting mechanism will take place where the operation usually starts by fruit grasping, stem cutting and the harvested product will be stored into storage compartment embedded inside the mobile robot structure. Therefore, each step in autonomous robotic harvesting process represents different challenges that need to be optimized and solved by agricultural researchers in developing an efficient harvesting robot.

Numerous works have been conducted in the past few years to determine the target location for agricultural harvesting. Most of the implemented works taking the advantage of the vision system to determine the location of the fruits. The designed vision system is developed to solve two complex problems which related to the wide varieties of the detected object due to its natural characteristics and the complex and loosely structured workspace with large variation in illumination and degree of object occlusion. Therefore, various vision schemes need to be used to solve a specific problem for target detection in harvesting process [83]. Table 2 shows the summary of four different vision schemes used for target detection in agricultural harvesting.

In addition to an accurate target detection, the success rate of harvesting process using agricultural robots in dense crops also relies on robust motion control and end-effector placement at the target fruit or vegetable [84-85]. Therefore, several researches have been conducted in the past years in robot arm motion planning for agricultural harvesting operation. In [74], a motion scheduling system has been successfully implemented to coordinate four robot arms for autonomous kiwifruit picking system with 51% success rate. In addition, literature [86] implement a “U-move” movement where the torque exerted by each motor was monitored to avoid excessive torque that may damage the arm and plant canopy. Despite the robot arm motion planning algorithm design, the identification of obstacles also important for success harvesting process. In [65], the apple tree branches were identified using contrast limited adaptive histogram equalization (CLAHE) method with 94% accuracy. Therefore, the obstacle-free path for robot arm can be generated for an efficient apple harvesting operation.

Table 2. Vision schemes for agricultural harvesting target detection

Vision Scheme	Functions	Advantages	Disadvantages
Monocular [87-88]	Determine target location by color, shape and texture	Simplest and lowest cost	Illumination changes will affect detection accuracy
Binocular [79,89]	Determine target location by color, shape and texture and localize the target fruit	Able to obtain 3D feature of the detected object	Require sensor calibration, computationally expensive and inevitable 3D measurement error
Spectral Imaging [90-91]	Determine target location by using spectroscopic and image information extraction	Able to detect target object in complex and loosely structured workspace	Expensive sensor and computationally expensive to process the image
Laser [92-93]	Determine target location by extracting 3D object feature	Able to obtain 3D feature in various illumination conditions	Require big image data for accurate 3D visualization

Table 3. Factors considered for harvesting robot gripper design and mechanism

References	Plant type	Factors Considered in Agricultural Gripper Design and Mechanism
Ya et al., 2019 [61]	Strawberry	Target positional and localization error
Zhiguo et al., 2019 [71]	Tomato	Human factors (Body height, shoulder tip, waist and knee height)
Baohua et al., 2018 [72]	Tomato	Grasping velocity, input force, contact time and gripper stiffness
Longtao et al., 2020 [75]	Kiwifruit	Target position accuracy and grasping pressure
Ruud et al., 2019 [76]	Capsicum	Position and angle between plant parts
Yi et al., 2019 [80]	Citrus	Stalk orientation and harvesting posture
Ali and Noboru, 2018 [81]	Pumpkin	Target orientation and compression yield force

Before the fruits or vegetables were cut to be harvested, the grasping mechanism took place where the end-effector will be carefully positioned towards the target. To maintain the quality of the harvested product, grasping without damaging the harvested product has become the key barrier to the replacement of manual labor by robotic system [72]. Therefore, several works have been conducted to investigate the factors that affected the product quality by using different grasping mechanism and design. Table 3 shows the summary of the factors considered in designing the end effector for efficient grasping mechanism in maintaining the quality of harvested product. Based on Table 3, a diversity of factors can be observed where the factors were chosen based on the physical characteristics and structure of the harvested product. Therefore, the gripper design and mechanism for different applications need to be custom designed to maintain the product quality in harvesting process.

The work of harvesting in agriculture is very important as the quality of the harvested product will be also affected by the way the harvesting process is being conducted due to its fragile characteristic. If the plants are treated well throughout the growing period, the quality of the product is still not guaranteed to be good as the product may be damaged while it is being harvested by the application of robotic and automation. Therefore, numerous ongoing researches are still being conducted to ensure that the efficiency of the robotic and automation application in harvesting process will be similar or better compared to the way human works to harvest the agricultural product in a timely manner without affecting its quality.

3. AGRICULTURAL AUTOMATION AND ROBOTICS: CHALLENGES AND NEXT PHASE

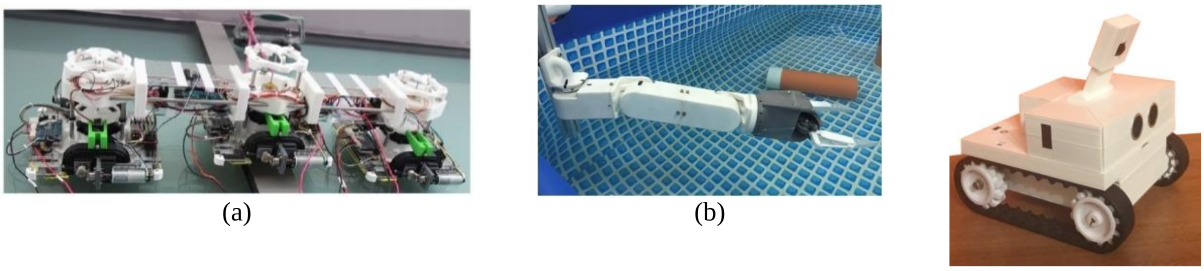
The statistics of automation and robotics system market in agricultural application is expected to be projected from USD 7.4 billion in 2020 to USD 20.6 billion by 2025 throughout the world [94]. Factors such as labor reduction, growing population and requirement of high productivity has enabled the growth of agricultural automation and robotics. The opportunities of the development require vast technology maturity to ensure that the manufactured automation and robotics product to be reliable and robust to be implemented in various agricultural operation. Therefore, numerous researches are still being actively conducted to overcome many challenges to operate different agricultural tasks in several working environment and conditions. Therefore, this section will discuss about several main challenges faced by agricultural researchers in developing a reliable system for agricultural operation and also the expectation of farmers from the developed system.

In planting process, numerous works have been developed to design an autonomous planting process with great accuracy. Based on the conducted review, most of the researches are focusing on the seed uniformity and detection which is one of the main objectives of planting process. However, more focuses should be also concentrated on the path correction to maintain the straight-line row. Challenges such as non-uniform soil surface and soil stiffness for a diverse type of soil such as sand, loam and clay with dry or muddy soil condition has made the research to become more challenging to track and maintain the robot structure in executing planting task thus sometimes it may lead to inconsistent row arrangement.

For inspection process, most of the designed algorithms were able to identify the disease or defect in simulation and real experiment with a great degree of accuracy. However, most of the implementations in real experiment are executed by taking a real plant disease or quality defect and it was then placed into a clean background for detection purpose. This procedure must be further improved by taking the real plant image inside a real environment with dynamic background. Therefore, the plant disease and quality defect detection will become more realistic to be implemented for future robot design thus the robot would be able to clearly imitate the way human conduct the plant inspection process.

Based on the conducted review for implementation of robotics and automation for spraying task, most of the implemented researches are focusing towards designing an efficient spraying system with minimum operational costs. To ensure the optimum execution of spraying process, a diverse set of parameters has been identified as shown in Table 1. In addition to the conducted researches for spraying, extensive focus also needed for spraying management where the developed autonomous system must be able to identify an optimized route to execute the selective spraying operation by considering several spraying characteristics such as spraying capacity and refill mechanism to ensure that a fully autonomous system to be realistically implemented in real spraying application. In harvesting, most of the conducted researches are focusing on the target detection to identify the location of the harvested product. It is undeniable that the target detection is one of the most important research areas in harvesting operation however, more researches can also be conducted in harvesting management where the autonomous system is able to plan a specific strategy to harvest a maximum amount of agricultural product with shortest time and at the same time considering the constraints of storage capacity and the distance to the depot. Therefore, the harvesting process can be executed efficiently with a minimum operational cost.

Despite several challenges in different agricultural operation, farmers are also concerned about the cost requires to invest into agricultural robotics and automation. Some of the farmers are afraid to invest their money into technologies that may not benefit them in the future. Therefore, agricultural researchers need to come out with ideas in designing a multifunctional agricultural robot with affordable cost. One of the suggestions that may be used in designing agricultural robot is the modular robotic design with great robustness. Figure 4 shows the implementation of modular robot design in different applications. As



(a) (b) (c)

Figure 4. Modular robotic applications (a) Window cleaning robot [95], (b) Underwater robot arm [96], (c) Mobile robotic platform [97]

different operations in agriculture have different working mechanism and method, it is recommended that the structure of the robot to be easily detachable and can be replaced by other structures based on the specific function and requirement of operation. Therefore, farmers only need to invest to one main robotic system with different types of detachable structure to complete the agricultural operations from planting to harvesting. From that, the investment cost will be much lower as the farmers are not required to buy different types of robot for different agricultural operation.

4. CONCLUSION

Robotics and automation in agriculture plays a major role in maintaining the food security in the future. The implementation of robotics equipment has enabled farmers to execute agricultural operations in a timely manner with the vast technology offered by the developed system. Operations such as planting, inspection, spraying and harvesting will be conducted efficiently with minimum operational costs and human labor as the development of robotic system in agriculture is generally focusing to imitate the behavior of human labor in the completion of agricultural operations. As different agricultural operation requires specific characteristics and specifications based on the specific environment and plant species, numerous researches are still being conducted to ensure that the developed autonomous system will become more efficient with minimum errors. Several challenges are still available to be resolved by agricultural researchers and several intensive researches are conducted to investigate the cause and solutions to the challenges. By combining all the technologies developed for each operation, a systematic autonomous agricultural robotic system may be designed in the future for creating a robust and efficient agricultural robotic system to be implemented widely to the farmers throughout the world with the main objective to produce high amount of agricultural output in maintaining food security in the future.

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