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Machine vision technology in agriculture: A review on the automatic seedling transplanters

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Abstract
In the field of plug seedling production, it is necessary to monitor the morphological characteristics, eliminate the inferior seedlings and transplant the seedlings from high-density trays to low-density trays. Mostly, the above process is performed by following the manual operations, which is vast labor-intensive due to high labor costs, availability and manageability, low production efficiency, and inconsistent subjective judgment criteria of manual monitoring are difficult to guarantee the transplanting of the quality seedlings. The above factors significantly restrict seedlings production and create difficulty for increasing the seedlings production on a large scale. Therefore, this review article discusses the automatic seedling transplanters and provides important information about the use of machine vision technology for automatic seedling transplanters. Moreover, the rising labor costs and increasing agricultural products are turning farmers towards the latest automation technologies. Several research studies suggested that it could be the most suitable choice to implement automatic robotic techniques with machine vision technology for seedlings transplanting. In addition, automatic-seedling transplanting with machine vision techniques are fast, timesaving, and provide a guarantee for the quality, and it has significance for improving efficiency, reducing labor intensity, assuring the transplanting speed, and promoting rapid seedlings production development on a large scale.

Keywords: plug seedling, transplanting machine, sensor, machine vision, agriculture

1. Introduction

At present, one of the major tasks is to end hunger and poverty by using food production systems in a sustainable way. Also, it is our main concern to make plans for providing clean and fresh food for the coming generations [1, 3]. The concerns, challenges, and problems are predicted due to the rapid variations in global climate, increasing drylands, population growth, urbanization, rising costs of agribusiness, soil degradation, and water scarcities. Studies reported that these issues have significant effects on world food production (WFP). In addition, the increasing population is one of the main issues because studies predicted that the world population could expect to surpass ten billion people in 2050, which will 34% higher than the current population of the world. This population increasing trend would result in a rise in global food requirements triple compared to the present [4, 6]. Authors [7, 8] revealed that WFP is increasing faster than the population, and per capita consumption is continuously increasing with time. Studies [9, 10] informed that WFP must be increased by 70% to deliver sufficient food production for the fast-growing population. Because of the increasing population, urbanization, and infrastructure development scenario are rapidly changing throughout the world. Besides, if we will take China as an example, China's rise in population, urbanization, and infrastructure development is increased very fast compared to other countries of the world [11]. Cook [12] stated that it's well known that China is the largest food producer and consumer country in the world. The changes in food production and consumption in China and their environment have significant effects, not just China, but also the global environment, which is essential concern us all. The Chinese agriculture sector is currently facing significant environmental challenges. The country has much to gain by shifting towards more sustainable production methods. In particular, improvements in China agriculture are associated with the food system that would have global environmental benefits. Thus, it is essential for major food-producing countries like china- which offers around 50.6 million tons of the world's production to implement the modern, automated, and user-friendly technologies into the traditional agriculture sector for producing the maximum food stocks [4].

Seedling transplanting is one of the essential functions of plant production. Many growers prefer to start their gardens from nursery-grown seedlings rather than from seed [13]. However, at a particular growth stage, the seedlings are transplanted into low-density growing trays form high density growing trays for further growth and development. In addition, during transplantation, seedlings are handled many times to replace rotten or missing plants with healthy ones, which is performed by manual operations [14]. Studies suggested that the manual seedling transplanting operations are expensive and time-consuming due to high labor costs, availability, and manageability, therefore, it could not be expanded for large-scale seedling transplanting operations. Tsgusa [15] reported that the use of automatic robotic techniques for seedlings transplanting could a suitable option to deal with the above issue. The growers can produce more seedlings with higher quality at lower expenses in a sustainable way that is less dependent on the labor force. However, the implementation of the automatic transplanters can significantly decrease the labor requirement by transplanting the seedlings in less time and can work for a longer time without any difficulties even for large-scale seedling transplanting operations. Currently, numerous research studies [16, 21] had been designed and patented the automatic robotic seedling transplanters. These studies concluded that robotic transplanter could reduce the labor requirement of seedling transplantation by carrying out repetitive tasks accurately and reliably. However, the fully automatic transplanters for trays or pots can reach a high efficiency of 35,000 seedlings/hour. Moreover, machine vision technology (MVT) has gained increasing attention in agriculture for performing several activities and tasks with minor human interferences such as land-based and aerial-based remote sensing, fields plowing, seeds planting, weeds handling, growth monitoring, fruits, and vegetables picking, sorting, grading and even packaging. This is because MVT not only recognizes the size, shape, color, and texture parameters of the selected objects but also provides numerical attributes of the selected objects [22]. As mentioned above that the automatic transplanters could be widely used in agriculture to transplant the seedlings by using minimum energy. However, it would be advantageous to combine the MVT with the automatic seedling transplanter. Previously, some studies put forwarded and worked on the installation of the MVT system with automatic transplanter. The research and development of MVT for an automatic transplanting system are of considerable significance to reduce the burden of the laborer and improve production efficiency. The advantages of using MVT for seedling transplanting are accurate, nondestructive, and yields consistent results. It will significantly improve the seedling industry's productivity, thereby reducing high costs and labor requirements [13, 23].

Thus, the purpose of this review article is to provide an idea and significant knowledge about the use of automatic seedling transplanting and monitoring of vegetables, and fruits seedlings using different sensor cameras. The rest of the paper is organized is as follows: section 2 describes MVT in agriculture. Section 3 provides information about the current research situation of the automatic seedling transplanter. Sections 4 and 5 discuss the MVT used for automatic seedling transplanters and existing problems and Development. Finally, section 6 represents the conclusions of the study.

2. Machine vision technology in agriculture

Currently, the traditional agriculture sector is experiencing an automation revolution. The modern techniques are creating greater efficiencies and profitability in traditional agriculture through improved yields and lower operating costs. With rising labor costs, increasing aesthetic standards for agricultural products, and greater global competition, farmers have been turning to the latest available automation technologies into agriculture. While there are many types of automation technologies used in agriculture, MVT is at the core of many of the latest technological developments in precision agriculture [24]. Moreover, MVT is a branch of computer science that has really grown over the last 20 years to become an important feature of manufacturing. It is the science that deals with object recognition and classification by extracting the useful information of the object from its captured image. MVT combines image-processing and pattern-recognition techniques. However, the major tasks performed by MVT can be grouped into three different processes: image acquisition, processing or analysis, and recognition [25]. Currently, MVT in agriculture is used to detect plant positions, calculate plant emergence, row spacing, row length, and compare data to the planting date. Throughout the season, farmers can receive data on canopy cover, plant height, and stand count. Farmers even know average tree diameter, flower count, and more, without having to even step into the field themselves [26, 27]. Bhargava and Bansal [28] reported that MVT has various applications in the field of agricultural like identification of land, recognition of pest infected areas, automatic classification, and detection of plant disease from shape, texture, and color and evaluation of nitrogen recognition plant. A basic MVT mainly consists of a camera, a computer equipped with an image acquisition board, and a lighting system. Also, computer software is required for transmitting electronic signals to computers, acquiring images, and performing storage and processing of the images [29-32]. Fig. 1 shows the seedling monitoring with Intel Real Sense depth sensor.

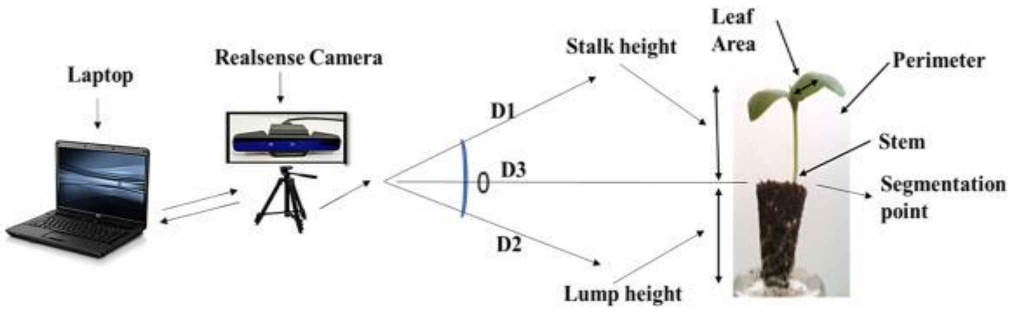

Fig 1: Seedling monitoring [13]

2.1 Time-of-flight (ToF) camera

The depth measurement of the ToF camera is based on the time-of-flight principle. The phase (cross-correlation), offset, and amplitude of ToF camera are measured by transmitting radio frequency-modulated light and reflecting it back to the sensor. Aleny`a *et al*. [33] used the ToF camera to purposed a method of segmenting plant images into their surface patches by combining hierarchical color segmentation with quadratic surface fitting using depth data. The results showed that the obtained surfaces fit well with target leaves, and candidate leaf approached by robot-mounted camera closer to the target. In 2015, Gongal *et al*. [34] used the ToF camera to obtain 3D coordinates of fruits in apple trees. The obtained 3D coordinate information was used to identify the duplicate apples, which is visible in images captured from the opposite sides of the crown. The accuracy of this method in identifying duplicate apples was 87%. However, this study did not evaluate the position accuracy of the camera system, but some errors in the system were observed due to errors in recording 3D position information in apples recognized in color camera images. Furthermore, Vázquez-Arellano *et al*. [35] used a three-dimensional image obtained by the ToF camera to reconstruct the maize growing area. The three-dimensional point cloud data of maize were acquired by the ToF camera to realize three-dimensional reconstruction and simulate the growth environment of maize crops.

2.2 Laser Range Finder

The working principle of the laser range finder is the time-of-flight (ToF) of light. The laser range sensing unit includes a laser source for transmitting a pulsed laser beam and a sensor for receiving a beam reflected back from an object. Laser rangefinder scans the scene horizontally and vertically to create its three-dimensional coordinate map, thus, providing the range information of the whole scene. In recent years, researchers have widely used laser rangefinder in agricultural automation and robotics, including fruit positioning in canopy [36]. Moreover, in 2015, Feng and coworkers [37] proposed an MVT system for identifying and locating cherry tomato fruit strings. The system combines laser ranging and visual servo technology to achieve precise positioning of fruit strings in the field of view. The R-G color feature was used to segment the image to extract the ripe fruit from the background. As a result, the fruit strings were ranged. This study concluded that the average recognition accuracy of the vision system was 83.5%. In the same year, Mirwaes *et al*. [38] proposed a method for obtaining automated fast and accurate data from the segmentation of plant organs. They successfully grouped 3D point clouds and demonstrated clustering results with monocotyledonous and dicotyledonous plant species with high accuracy.

2.3 RGB-D camera

RGB-D cameras (Intel RealSense and Microsoft Kinect) have changed the field of monitoring and growth measurement as they obtained the 3D detail and colored data of the object within an actual time altogether. Several researchers presented Kinect (v1) for plant growth assessments [39, 40]. However, a few valuable efforts were carried out on Kinect and RealSense for open field crop monitoring, greenhouse plant measurement, apple plant modeling and used the depth-sphere transversal method to find three-dimensional geometric characteristics of the citrus fruit [41-45]. In the earlier works, the RGB-D cameras are exposed top-rated in plant photo research. The RGB-D camera could generate real-time intensity data, which is a less computational cost for 3D mapping. The RGB-D indicator is exceptionally economical in contrast with other sensors. However, plant foliage research using an RGB-D sensor in an all live scene, and it has not been substantially analyzed. Rakun *et al*. [46] proposed a detection model for estimating the leaf numbers, diameter, and yield of apple fruits. The model integrates the color, texture and three-dimensional shape of the target object to achieve solid reconstruction, thus realizing fruit recognition. In 2013, Yang *et al*. [47] used color and depth images to detect cell tray contour from the color image and segmentation of soil from cell tray in the depth image. After segmentation of depth image, they generated a 3-D point cloud of each cell and calculated the normal vector with the help of a neighbor algorithm and principal component analysis algorithm. As a result, they obtained the depth of the ground substance based on the normal vector after segmentation of the soil cell tray wall and bottom of the cell tray. Alhwarin *et al*. [48] built an IR stereo acquisition system with two Xtion cameras to eliminate the defect that a single Kinect or Xtion could not detect transparent, glossy or dull depth images, and, thus, obtained a relatively complete depth image. IR projection was used to improve dense stereo matching to eliminate the interference of transparent or reflective objects. In 2014, Dong *et al*. [49] used Kinect to obtain tomato color and depth image and fused the segmentation results of a color image in HSI and Lab color space to recognize the tomatoes. They obtained the spatial coordinates of tomato centroid through the three-dimensional reconstruction of depth image to achieve positioning. Although the method utilizes both depth and color information, and the depth information was mainly used as an auxiliary location that cannot avoid the defect of illumination sensitivity of color images. In the same year, another research team of Li *et al*. [50] proposed a four-step method for automatic detection and segmentation of tomato plant stems based on Kinect. In which image data acquisition, preprocessing, stem detection, automatic stem segmentation was included and then stored the correct segmented texture samples including stems and leaves in the texture database for further use. The results showed that in the simulated greenhouse environment, the accuracy of stem detection of cherry tomato varieties was 98.4%, the true positive rate was 78.0%, while that of common tomato varieties was 94.5%, and the true positive rate was 72.5%. Finally, combining L-system theory with digital tomato organ texture data, a real 3D virtual tomato plant model was constructed, which can display various structures and postures in real-time. In addition, in 2015, Xia *et al*. [51] successively used the mean shift clustering and active contour model to remove background and extract leaf boundary from the depth image acquired by Kinect to realize the segmentation of individual leaves of red pepper in the greenhouse. However, when the continuous depth information was transferred to the discrete gray value, the errors resulted in the sharp reduction of the depth difference between adjacent objects, which affected the target segmentation and the reliability of identification. Furthermore, Liu *et al*. [52] developed a recognition algorithm using the RealSense sensor for close-shot identification and location of the fruits for robot harvesting (Fig. 2). Their study reported that the proposed recognition algorithm has several benefits such as fast foreground, background removal, and may contribute to high real-time vision-servo operations of harvesting robots.

Fig 2: Experimental setup of close-shot identification On-Branch Citrus Fruit with RealSense [52]

3. Automatic seedling transplanter

At present, automation technology is significantly and successfully implemented in traditional agriculture equipment for performing the many tasks. It is becoming an indispensable tool to reduce the workload and increase the productivity of several agricultural applications. Automation technology has the advantage of performing repetitive tasks, trying to reduce the farmers' workload, and optimize process times [53-55]. In addition, the automatic seedling transplanting is an essential prospect for monitoring of crop health and beneficial to increase crop production. Furthermore, plug seedling cultivation is the critical link in vegetable production. It is not only one of the key technical measures to improve the comprehensive benefits of vegetable production, but also can promote the vegetable industry to develop well and rapidly. Generally, the plug seedling transplanting technology was originated from European and American countries in the 1970s. In the middle of the 1980s, Chinese technical workers explored a moderate system of plug seedling transplanting and got an effective result. Moreover, compared with conventional seedlings cultivation methods, plug seedling cultivation relies on the emergence of high seedling rate, neat seedling, fewer diseases and pests, and mechanized process. The advantages of fewer pests and diseases and a high degree of mechanization are hindered. Besides, it has become the primary way of vegetables and flower seedlings production in many countries in the world. The survival rate and quality of seedlings are the key factors that must be considered in the process of transplanting seedlings in pots and trays. They are also essential factors for the technical and economic evaluation and social comprehensive benefit evaluation of factory vegetable seedling cultivation. However, Fig.3 displays one type of automatic seedling transplanting machine.

Fig 3: PC-21 transplanter developed by VISSER Company [60].

3.1 Research status of the automatic seedling transplanter

In practical seedling production, the seed germination rate is limited due to individual variation of seeds and differences in the seedling management environment. In addition, there are unhealthy and non-germinating seeds, resulting in the phenomenon of empty and missing seedlings in subsequent mechanized batch transplantation. In order to make the growth of the seedling uniformly, they are transplanted from high-density trays to low-density trays. Thus, it is necessary to monitor the growth (morphological characteristics parameters), quality, and eliminate the inferior seedlings. However, the practical problems such as high labor cost, low production efficiency and inconsistent subjective judgment criteria of manual monitoring are difficult to guarantee the transplanting quality of the seedlings and insufficient conditions for intensive seedling production. It restricts the development of seedling cultivation technology.

In current practice, the seedling transplanting operation is considered a vast labor-intensive [14]. Besides high labor costs, availability and manageability are becoming a significant concern for the development of the plug production industry. Therefore, it is difficult to enlarge the manual seedling transplanting production on a large scale. In addition, due to labor shortages, there is an urgent need to replace high manual labor through intelligent equipment. Researchers suggested that it could be the most suitable choice to implement automatic robotic techniques for seedlings transplanting [15]. The research on the seedlings transplanting technology was started earlier in developed countries, and currently, it is growing faster in the up-gradation of transplanting technology and equipment.

Moreover, the first robotic seedling transplanter was designed in 1987 by Kutz *et al*. [17]. They designed bedding plants transplanting robots by using computer graphics and simulation and tested with a puma 560 robot. Besides, a seedling gripper was designed on the computer-aided design (CAD) system based on the control program. The robot was able to transplant 90% of seedlings with no damage to the plants. Ting *et al*. [56,57] developed a seedling robot with the function of identifying seedlings based on the four-degree-of-freedom industrial robot arm called ADEPT-SCARA. In addition, the CCD camera was installed on the top of the transplanter in order to capture the images of seedlings. The average time taken to transplant a single seedling was measured experimentally about 2.60 to 3.25 seconds, which satisfy the transplanting operation in real-time. In 2001, Korean researchers Ryu *et al*. [58] developed a transplanting robot with an image recognition function. The working principle of the robot was followed as: firstly, the seedling images captured through the CCD color camera and transferred to the computer system. Secondly, the computer control system was able to recognize the color and growth characteristics of seedlings leaves for automatically judging the quality of the seedlings and the information of the position of the plugs. Moreover, in 2004, Albertus [59] designed a set of an automatic machine that can transmit multiple trays at the same time, and based on the visual recognition system, replanting and transfer functions can be achieved. The above-mentioned greenhouse seedling transplanting machines are all were carried out in the laboratory.

In recent years, Japan, the Netherland, and other countries of the world have successfully developed many types of greenhouse based automatic transplanter by relying on advanced technology and generous financial strength, which have been used for practical production practices. In addition, the Dutch VISSER company [60] has developed a series of automatic transplanter with MVT for seedlings transplanting and replanting functions. The developed machine aimed for small flower seedling transplanting operations. The MVT system can be used to classify and transplant seedlings according to the number of grades required by the user. Another greenhouse automation equipment developed by the Dutch VISSER company was Pic-O-Mat PC 11/4 seedling transplanter (http://www.visserite.com). The seedling unit was equipped with a needle plug-in structure with 4 gripper's seedling claws on each robot arm. However, transplanting speed was up to 6000 plants/hour, and the rate of the artificial transplant was more significant than 7 to 8 times. The XT616 transplanter designed by transplant systems of Australia is one of the special transplanter series for tea seedlings. The transplanter was relatively small in size, high in reliability and flexibility and suitable for large-scale seedling production lines and small and medium-sized seedling households. The machine controls the end-effector separately by using the communication mode of CON bus control technology. The system was able to display the self-diagnosis information of the seedling of the cell tray through the color touch screen, and the manipulator was able to adjust directly according to the needs of the seedling transplantation through the control terminal [61]. In 2008, Jiang *et al*. [62] developed a transplanting prototype based on the MV technology system. By using the MV technology to obtain healthy seedlings recognition and comprehensively judging, either the seedlings are suitable for transplanting and position the roots of the seedlings to achieve healthy seedling transplanting operation. In 2009, Zhou *et al*. [63] designed a transplanting machine suitable for transplanting seedlings with multiple specifications. In the same year, Subo *et al*. [64] designed and invented an automatic transplanter in Shenyang Agricultural University. The developed transplanter can automatically transplant the vegetable and flower seedlings of different specifications from high density to low density with reliable transplanting performance. In 2011, Zhang *et al*. [65] from Agricultural Machinery Research Institute and Jingpeng Global Technology jointly designed the JXPYZ-1 type plug seedling automatic transplanting machine. The transplanter had an MV judgment system for bad seedlings, which can complete the functions of identifying and eliminating bad seedlings in cell tray during seedling transplantation. The results reported that the transplanting efficiency of the transplanter could reach 1560 plants/h with the damage rate of seedlings less than 3%. In 2012, Qi *et al*. [66] developed inverse kinematics of the parallel mechanism kind of knowledge for the transplanting of greenhouse seedlings. To achieve a two-dimensional translational five-bar parallel mechanism, the driving motor was fixed on the frame to moving with the high speed and short-medium plug seedling transplanting. In the same year, Feng [67] developed an automatic transplanter suitable for flower seedlings. Moreover, the transplanting machine control system identifies the seedling growth of the cell tray and identify the high-quality seedlings, suitable for transplantation and position of the empty cell. Also, it was able to drive the gripping claws to grab the seedlings from the cell tray and transplant it to the top of the cell tray for planting.

4. Machine vision technology used for automatic seedling transplanters

MVT for recognition of seedlings has the characteristics of fast processing, the fusion of a large amount of information, and many other functions. It has been widely used in intelligent agricultural production. Image recognition of healthy seedlings is an organic combination of image processing technology, feature extraction theory, and detection of crop growth quality theory. This technology is of great practical significance to improve the efficiency of intelligent transplantation, improve the survival rate and vegetable yield after transplantation, reduce production costs, reduce energy consumption, and further promote the healthy and sustainable development of the vegetable industry [13]. Fig. 4 shows the full-automatic transplanting machine with a machine vision system developed by our research team.

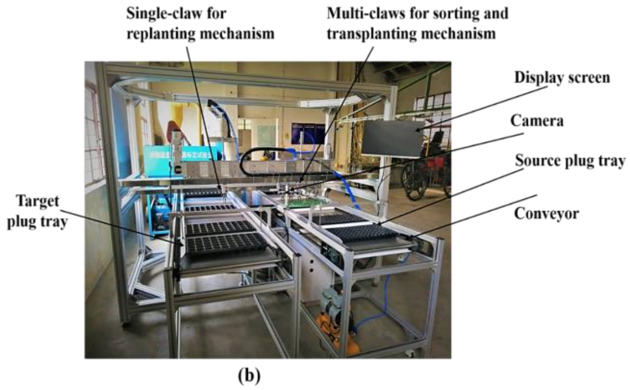

Fig 4: Full-automatic transplanting machine with machine vision system developed by our research team

Presently, several studies had put forwarded and worked on the installation of the MVT with automatic transplanter. However, to produce uniform seedlings with less time and labor requirements in greenhouses, several growers are using automatic seeder and seedling growth intelligent equipment [23]. Therefore, the research and development of MVT on an automatic transplanting system are of great significance for reducing the burdens and can effectively solve the problems of long detection cycle, reduced effectiveness, low efficiency, poor accuracy, and high labor intensity, which are greatly influenced by subjective and objective factors. At the same time, it is of considerable significance to the automation and intellectualization of agricultural product detection. It helps to accurately evaluate the grade quality of plug seedlings and is an effective way to promote sustainable high-quality, high-yield and stable yield of agricultural production. Also, it is a great significance for protecting the interests of farmers and ensuring national food security [68]. In addition, the application of image recognition technology in the transplanting machinery of plug seedlings has been widely carried out in several countries of the world. Especially in the past few years, with the development of technological innovations, several types of sensor cameras have been used for monitoring plant health status with high definition. Among them, hyperspectral are continually emerging. The sensor cameras provide a broad, purpose, and precise necessary data through non-destructively [69-71]. In addition, Tai *et al*. [21] used MVT into the intelligent transplanter for the grow-out tray that contains transplanted plugs. The transplanter uses a cell plug tray, and the position of plug seedlings was positioned by a single camera. However, the designed algorithm can calculate the depth data of the plug tray to control precisely and transplanted seedling trays with a 95% success rate. In 2001, the research team of Ryu *et al*. [14] used MVT on automatic transplanter to monitor seedlings, which was based on the information of the seedling leaves. They identified empty cells when the leaves of the neighboring cells were overlapped, which leads to the identification failure. In 2007, Ren [72] designed a transplanting system based on MV for eliminating inferior potted seedlings and replanting healthy seedling. An appropriate threshold was selected to enhance the gray level of the image by setting the color difference yield (3 *G-R-B). The noise of the binary image was removed by the blob analysis method. The edge of the leaves was segmented using a morphological watershed algorithm, and each cell plug was extracted.

Furthermore, Yu [73, 74] introduced the MVT into three translation parallel transplanting robot. An MVT with the function of green plant seedlings identification was constructed. The obtained image was compared in HSI and analyzed segmentation effect in color space and RGB color space, and location of seedlings in plug tray based on the image. The program was simple; the running time was small, and the center position obtained by image processing was close to the actual root position of seedlings. Besides, the research team of GAO *et al*. [75] used an intelligent recognition judge system for the detection of the diseased seedling. They acquired the four samples from the tray and compiled them into one picture. Through image processing, the characteristics of each sample were used to be compared with the disease seedling sample. They concluded that with intelligent recognition arithmetic, the vision system has more automatic and higher efficiency. Tong *et al*. [76] used the watershed algorithm to distinguished bad and good plugs through a different linear transformation of three components, R, G, B, and determined the color characteristics of the image through segmentation transformation. They found the leaf area of each cell in the plug tray and classified the seedlings according to the characteristic of the seedlings for transplanting. The results reported that the obtained identification accuracy was 98.6%, 96.4%, 98.6% and 95.2% for tomato, cucumber, aubergine, and pepper plants, respectively.

4.1 Seedlings recognition based on RGB images

Research of the seedling identification based on CCD camera, coordinates and contour line, characteristics, and leaf area measurements were performed by several researchers around the world [77-88], some are mentioned below. In 1993, the research team of Humphries and Simonton [20] used the image tracking algorithm to divide the plant into parts with similar geometric characteristics and then used the Bayesian classifier to classify the plant with color information. The recognition of leaf, stem, and other characteristics was completed. This study concluded that plant growth characteristics could be measured accurately with the color images. Another study in 1995 by Chen *et al*. [81] applied MV technology to identify vegetable cultivation. After collecting the images of radish seedlings and spinach seedlings with CCD color camera, the contour lines of vegetable seedlings and leaves were obtained by the direct searching method and mathematical method according to the generating conditions of impeller profile. The characteristic parameters such as position coordinates of vegetable seedlings were accurately identified, along with growth quality, growth environment and growth order of seedlings was also determined. Results suggested that segment discrimination can provide useful information for automatic transplanting of the vegetable seedlings. In 1996, the research team of Ling and Ruzhitsky [82] proposed the image reorganization system. The reported that the proposed system quickly and accurately measures the canopy leaf area of a single tomato seedling based on a multi-mode segmentation algorithm. In 2003, the research team of Mizuochi and Dohi. [80] purposed the method for identifying a lack of seedlings, ill seedlings, and weak seedling growth. They fixed threshold value and analyzed the G component of a color image of tray seedlings, in order to achieve separation of cotyledon and vermiculite. According to perimeter and circularity characteristics, this study identified the healthy seedlings which could judge the abolition of ill or abnormal seedlings. In 2007, Ren [72] used the conversion of color characteristics to identify the tomato seedling from the background off and under the uses of a connected domain analysis algorithm. According to the seedling characteristics, this study extracted soil hole of each seedling and leaf area and recorded the center position of the soil hole appropriate for transplanting. Moreover, in 2009, Sun [83] proposed a method for the identification of devoid or ill seedlings in a cell tray frame. By using gray value theory, he segments background using the 2g- R- B color feature parameters and obtains leaf area based on the segmentation threshold blade pixel ratio. In the same year, the research team of Jiang *et al*. [84] used the MV system to reduce transplanting time and image processing algorithm based on the morphological watershed to segment the border of leaves. This study concluded that the leaf area and perimeter of the tomato seedlings were extracted with a reasonable identification rate of 98%. In 2010, Sun *et al*. [85] conducted the study and achieved the segmentation, cutting of the background, and the extraction of the basic structure of the seedling tray frame by using contrast enhancement method, image subtraction method, and second fixed threshold method, respectively. The binary images of the cell tray seedlings were obtained, and the characteristics of the color and leaf area of the cell tray seedlings were extracted. The coordinates and position of the seedlings were marked by chain code method, and the color parameters of seedlings such as scorpion, stone, and hundreds were used as the reference basis for judging the bad seedlings. Furthermore, Liu *et al*. [86] implemented the image processing technique for the identification of the seedling growth parameters. According to the characteristics of seedlings, the super green method (2G-R-B) and normalized super were used for the image of the seedlings. The green method (g-r-b) and the color difference method (Cr) was used for segmentation, while super green method and the color difference method was used to obtain the gray seedling images. The threshold value segmentation process was performed and then segmented through the white adaptive threshold. It was verified by experiments that the threshold image segmentation affected the optimal obtaining gray image of the plug seedling image by super green method, but the research base was studied that healthy seedling identification method for color features is not suitable for severe overlap of the leaf surface of the tray. Hu *et al*. [87] used different gray-scale factors to process seedlings images. The gray-scale image of seedlings under the gray-scale factor of 1.8G.1.5R-1.8B recommended for an optimal image process, which is obtained by the Otsu automatic threshold segmentation method. Next to, method of denoising effect of mathematical morphology and a single connected region statistical method was compared. The relative error of the leaf area of seedlings in connected areas was found small, and the centroid coordinates were suitable for transplanting the seedlings, which were calculated by the centroid method. Syed *et al*. (13) proposed and developed a RealSense-based MVT for the close-shot seedling-lump integrated monitoring. They concluded that the RGB-D integrated monitoring system with the purposed method could be used for monitoring the nursery seedlings most promisingly without high labor requirements.

5. Existing problems and development

Scholars have carried out many years of research by considering the automatic transplanting with mechanized visualization and got the number of useful results. However, due to the independence of the existing transplanting schemes, the detection-sorting-transplanting-replanting system is complex, detection of non-healthy seedlings, abundant of non-healthy seedling, and substantial operating time are the fundamental problems. Through reading the above research background, the following problems are urgently needed to be solved:

1. Lack of research on key technology of recognition algorithms. At present, many types of research have been done on how to accurately obtain the image feature information of the seedlings from the algorithms of image graying, threshold segmentation, morphological processing, etc. In addition, the existing recognition techniques based on depth information are mainly realized seedlings identification by 3D reconstruction of the point cloud, image feature extraction, or fusion with RBG information, they are much more complex and minimal for the recognition of healthy seedlings. Therefore, it is necessary to further study the multi-feature extraction methods, which can represent the health of the seedlings.
2. Bad versatility of sensors. Low resolution is a significant flaw of recognition based on TOF technology, so it cannot meet the real-time requirement. Although the recognition accuracy based on laser rangefinder is high, it can only achieve two-dimensional scanning of the target. At present, plants, fruits, and vegetable recognition based on RGB-D camera are mostly based on its data characteristics for 3D reconstruction, and the color information is mostly used. Also, illumination has a specific impact on it, and the algorithm of 3D reconstruction is complicated and time-consuming, which makes the real-time performance of recognition affected. Therefore, the use of a suitable camera for sorting of healthy seedlings during transplanting could enhance the efficiency of the relevant industry, to further promote the MV technology in automatic transplanter.
3. Restrict of transplanting agronomic conditions. Because in the automatic transplanting system, there is a requirement that the agricultural environment should be favorable, but unfortunately, it is not standardized which can easily lead to an increase in manufacturing cost. In addition, the existing seedling planting environment of plug seedlings is not reliable that's cannot meet the agronomic conditions of the plant health, which need to be changed to improve the operation performance of transplanting seedling cultivation system.
4. Lack of research on key technology to identify healthy seedlings. The existing recognition methods of healthy seedling mostly use the leaf color, leaf area, and other characteristics as the criteria of healthy seedlings. Moreover, there is not a proper comprehensive criterion for the identification of healthy seedlings. Therefore, by setting the threshold range of the morphological characteristic's parameters such as leaf area, stem diameter, and plant height, we can judge the growth quality of the seedlings. So, it is necessary to further study and establish a more scientific theoretical method to distinguish the healthy and nonhealthy seedlings, so as to make the algorithm more applicable and accurate.

6. Conclusions

The objective of the study was to present the information about the current research status of seedlings automatic transplanting machines, MVT and the use of different sensors for recognition of fruits, vegetables, and plants. This study concluded that the combination of MVT with robotic transplanter could help to produce healthy and uniform seedlings with reduced time and labor requirements. Thus, the use of sensor cameras for monitoring plant health status could be considered as a valuable, essential, and vital research topic and application issues in modern agriculture. In addition, automatic-seedling transplanting with MVT are fast, timesaving, and provide a guarantee for the quality, and it has significance for improving efficiency, reducing labor intensity, assuring the transplanting speed, and promoting rapid seedlings production development on a large scale.

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