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Seedling-lump integrated non-destructive monitoring for automatic transplanting with Intel RealSense depth camera

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ABSTRACT

Non-destructive plant growth parameters measurement is an important concern in automatic-seedling transplanting. Recently, several image-based monitoring approaches have been proposed and potentially developed for several agricultural applications. The presented study proposed and developed a RealSense-based machine vision system for the close-shot seedling-lump integrated monitoring. The strategy was based on the close-shot depth information. Further, the point cloud clustering and suitable algorithms were applied to obtain the segmentation of 3D seedling models. In addition, the data processing pipeline was developed to assess the different morphological parameter of 4 different seedling varieties. The experiments were carried out with 4 different seedling varieties (pepper, tomato, cucumber, and lettuce) and trained under different light conditions (light and dark). Moreover, analysis results showed that there was not significantly different ($p < 0.05$) found towards light and dark environments due to close-shot near-infrared detection. However, the results revealed that the stem diameter relationship between RealSense and the manual method was found for $R^2 = 0.68$ cucumber, $R^2 = 0.54$ tomato, $R^2 = 0.35$ pepper, and $R^2 = 0.58$ lettuce seedlings. Whereas, the seedling height relationship between RealSense and the manual method was found higher than $R^2 = 0.99$, 0.99, 0.99, and 0.99 for pepper, tomato, cucumber, and lettuce, respectively. Based on the experiment results, it was concluded that the RGB-D integrated monitoring system with the purposed method could be practiced for nursery seedlings most promisingly without high labour requirements in terms of ease of use. The system revealed a good sturdiness and relevance for plant growth monitoring. Additionally, it has the perspective for future practical value to real-time vision servo operations for transplanting robots.

1. Introduction

Seedling transplanting is one of the most important functions during plant production. At a particular growth stage, the seedlings are transplanted into low density growing trays for further growth and development. During transplantation, seedlings are handled many times to replace rotten or missing plants with healthy ones. Generally, it is performed by the manual operations which require extra time and energy. In current practice, the seedling transplanting operation is considered a huge labour intensive (Kumar and Raheman, 2008). Besides high labour 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. Researchers suggested that it could be the most suitable choice to implement automatic robotic techniques for seedlings transplanting (Tsuga, 2000). Numerous research studies (Hwang and Sistler, 1986; Kutz et al., 1987; Ting et al., 1990a; Ting et al., 1990b; Humphries and Simonton, 1993; Tai et al., 1994; Xin et al., 2018) designed and patented the automatic seedling transplanter and concluded that the robotic transplanter can reduce the labour requirement of seedling transplantation by carrying out repetitive tasks accurately and reliably. The fully automatic transplanter for trays or pots can reach a high efficiency of 35,000 plants/h plants (Ryu et al., 2001; Tian et al., 2010; Ting et al., 1992; Han et al., 2018). Besides, researchers are trying to use the machine vision techniques (MVT) for determining the health status of the plant by placing the sensor cameras on the plug holder of the automatic transplanter. Because the MVT can detect and identify the status of the picked plant that whether the picked plant has good morphological structure or not. Furthermore, the system can easily identify plug out-hole.

Presently, MVT is gaining more popularity among researchers. At the same time, several studies had put forwarded and worked on the installation of the MVT with robotic transplanter. The studies concluded that the combination of both techniques could help to produce healthy and uniform seedlings with reduced time and labour requirements.

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Therefore, the use of sensor cameras for monitoring plant health status could be considered as a valuable, essential, and vital research topic and application issue in modern agriculture. Especially in the past few years, with the development of technological innovation, 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-destructive (Shimizu and Yamazaki, 1996; Lee, 2007; Müller-Linow and Pinto-Espinosa, 2015). Moreover, Tai et al. (1994) developed an MVT assisted in robotic transplanter. Their study concluded that the proposed algorithm was able to inspect uneven height growth medium blocks in randomly oriented seedling trays.

Studies reported that for monitoring seedling growth, the accurate measurements of seedling structure parameters and its functioning are very crucial (Alenyà et al., 2011; Papari and Petkov, 2011). The monitoring of the plant through machine vision system is somehow complicated because of some factors such as the existence of disturbance, complicated background, low-intensity contrast with the surface of the culture substrate, and strength inhomogeneity. However, plant segmentation is still a challenging problem in the practical application of the system. Similarly, the stereo vision is a technique for plant growth measurement (Andersen et al., 2005; Lati et al., 2013; Yeh et al., 2014; Aksoy et al., 2015). The method has fine resolution and good measuring speed, but its precision is not so efficient since it is delicate to the structure of a measured object. Furthermore, for 3D (three-dimensional) plant measurements, some scientists used ToF (Time-of-Flight) cameras (Alenyà et al., 2011; Klose et al., 2011; Chaivivatrakul et al., 2014; Song et al., 2014). Studied reported that organized light is another strategy to obtain 3D information. It has been used within high-accurate plant growth monitoring and other related research studies. However, the equipment is either complicated or expensive, which restrict its application (Li et al., 2013; Bellasio et al., 2012; Nguyen et al., 2015).

RGB-D sensors (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 (Yang et al., 2016; Hu et al., 2018). However, a few valuable efforts were carried out on Kinect and RealSense for open field crop monitoring, greenhouse plant measurement, apple plants modelling and used the depth-sphere transversal method to find three-dimensional geometric characteristics of the citrus fruit (Alenyà et al., 2011; Song et al., 2014; Li et al., 2013; Klose et al., 2011; Chaivivatrakul et al., 2014; Liu et al., 2017). A recent study by Liu et al. (2018) developed a recognition algorithm using the RealSense depth sensor for close-shot identification and location of the fruits for robot harvesting. 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. In the earlier works, the RGB-D sensor cameras are exposed top-rated in plant photo research. The RGB-D sensor 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.

Therefore, the object of this study was to perform the experiment and analysis of the seedling-lump integrated non-destructive monitoring with machine vision technique by using the RealSense SR300 depth sensor. Moreover, the present study offers an automatic seedling growth monitoring strategy which is based on the 3D depth point cloud technique.

2. Literature review as a related work

At present, artificial intelligent (AI) has achieved significant attention in traditional agriculture to plan several activities and missions properly by utilizing limited resources with minor human interference (Lakhiar et al., 2018a). Besides, humans also need decision making and automatic sophisticated computer monitoring and control techniques to reduce intentions and enhance the efficiency of the system. Up to now, several studies concluded that adoption of different computer intelligent techniques in agriculture (CITA) can increase the efficiency of the agriculture activities (Lakhiar et al., 2018b). However, the brief concept of the adoption of CITA can be found in the studies performed by different authors (Shamshiri et al., 2018a, 2018b, 2018c; Jiang et al., 2019; Xia et al., 2019; Liu et al., 2019).

In addition, computer-vision based (CVB) or MVT is one of the most popular research topics in the field of AI. It mainly refers to the use of computers to simulate human visual function, extract information from the images and understand it, and ultimately for actual detection, measurement and control (Shamshiri et al., 2018a). The basic principle of MVT is to convert light into electrical signals through photoelectric components, and then analyze and process the operation objects through various imaging technologies for extracting the useful information from the object. MVT is mainly used for performing the several agricultural activates precisely such as crop growth monitoring, monitoring environmental conditions, automation of agricultural production and identification of the quality of agricultural products (Shamshiri et al., 2018b). Generally, MVT is performed by using image processing techniques, which involves few basic processes such as image acquisition, pre-processing, segmentation, object detection and classification. Table 1 shows some previous studies conducted by using CVB applications with different algorithms, techniques and cameras in agriculture.

In recent years, researchers have paid much attention to using RGB-D cameras for agricultural automation and robotics, including plant monitoring. There are several types of RGB-D cameras such as RealSense, Kinect V2, Asus Xtion pro, structure sensor and many others. Furthermore, RealSense SR300 is one of the inexpensive devices, which reduces the cost of the application in various scenarios to a certain extent. It integrates the two-dimensional module and three-dimensional depth module, which enables the device to sense the depth information of objects. It's hardware structure mainly includes RGB camera, infrared camera and infrared laser transmitter are three core components. The combination of these three factors can obtain the depth information of the object perceived from the surrounding area (Liu et al., 2018).

3. Materials and methods

3.1. Materials

The machine vision system for monitoring seedlings growth was comprised of the sensor, data read software and computer. Moreover, the sensor was Intel RealSense SR300 depth sensor, the host computer was a laptop with the specification of Intel Core i5-6200U CPU 2.40GHZ 64-bit operating system, X64-based processor, and software's were Microsoft Visual Studio 2013, MATLAB R2016a and Image J. The 4 types of plant seedlings pepper, tomato, cucumber, and lettuce were selected. The seedlings were grown in two 50 cell trays and collected after 4 weeks of sowing. Moreover, after 4 weeks of seedlings growth, uniform size seedlings were randomly selected from each variety for monitoring and evaluating. However, Fig. 1 shows the chosen seedlings for the experiments, and Fig. 2 shows the sensor.

3.2. Methods

3.2.1. Monitoring strategy and overview of the proposed algorithm

According to the analysis, the seedling monitoring process was based on close-shot depth information. The purposed algorithm for monitoring of the seedling is illustrated in Fig. 3. Moreover, the proposed methodology can be further described in detail as: Firstly, we determined the distance between seedling and RealSense by depth thresholding. Afterwards, the seedling was

Table 1
Previous studies conducted by using computer-vision based applications with different algorithms, techniques and cameras in agriculture.

Author	Year	Application/model/system	Goals	Conclusion/remarks
Chikushi et al.	1990	SPIDER software	Measurement of cucumber root length	Analyzed plant root length with the accuracy of 98% correctness
Yang et al.	2000	Fuzzy logic decision-making system	Recognition and detection of weeds coverage for precision farming	Reduced herbicides usage for 15–64% and gave future perspective to utilize IT tools
Chen et al.	2002	Machine vision technology and applications	Poultry carcasses and apples disease detection	Focused on Hyperspectral imaging systems
Du and Sun	2004	Image processing chain based on five steps	Assessment of food quality	Cost-effective, and multipurpose image processing systems used for stress on the system
Erives and Fitzgerald	2005	Portable Hyperspectral Tunable Imaging System (PHyTIS)	hyperspectral images for Recover translation, scaling, and rotation	Increase precision farming applications and encourage image registration
Puchalski et al.	2008	Image processing techniques combination	Detection of apple defects	Acquired 96% accuracy in detecting bruises, scab, and frost damage
Tellaeche et al.	2008	Decision-making and image segmentation	Elimination of *Avena sterilis*, weeds growing in cereal crops	Strategy for selection of herbicide spray
Artizzu et al.	2009	Case-Based Reasoning (CBR) system	Discrimination of soil, crop and weeds from outdoor images	Obtained 80% correlation coefficient, for different fields and its conditions
Jin et al.	2009	Adaptive and fixed intensity interception and Otsu segmentation	Defects detection in yellow-skin potatoes	91.4% identification, 92.1% classification, and 100% observation
Terasawa et al.	2009	Graphical software for image correction and analysis	Detection of plant growth status	Enhanced color difference measurements based on remote sensing technology
Weis and Gerhards	2009	Image processing describing shape features	Detection of weed densities and species variations	Segmented plants background using Bi-spectral images
Beers et al.	2010	Image visualization techniques	Agricultural sustainable development through image processing	Focus on transition management and strategic niche management
Guijarro et al.	2011	Autonomous robot navigation imaging, controlled fuzzy clustering and thresholding	Recognition of weed textures, green plants, corn, cereal and barley	Identified viability for crops like rye or wheat, with reduced computation time
Mrunalini R. et al.	2011	K-means clustering algorithm with neural networks	Automatic detection of leaves through pattern recognition	Fuzzy logic and artificial neural network with computing techniques can be used to determine the crop diseases
Reis et al.	2012	Grape recognition system	Detection of white and red grapes bunches in color images	Classified 97% red and 91% white grapes, focused on low-cost alternatives
Silva et al.	2012	LabView software for image processing	Determination of weed coverage percentage	Determined weed coverage in tillage and no-tillage system after used of a color camera
Anand H. Kulkarni et al.	2012	Gabor filter and ANN classifier	Detection of plant disease	Features extracted and classified plant based on image processing technique
Sabah Bashir et al.	2012	Segmentation by co-occurrence matrix method and K-means clustering	Detection of plant disease using image processing	It can be used to classify various plant diseases
Piyush Chaudhary et al.	2012	Median filter by applying the Otsu method	Disease spot detection on plant leaf based on a color transformation	Disease classified based on calculating dimensions of the spot.
Prof. Sanjay B. et al.	2013	Image processing using vision-based detection algorithm	Detection of plant leaf diseases	NN's can be used to increase the recognition rate of classification process
Wu et al.	2013	Image processing and segmentation using Otsu's method	Automatic foreign fiber inspection in cotton products	Obtained accurate and speedy segmentation
Kelman and Linker	2014	Apple detection algorithm	Detection of mature apples through tree images	Resulted in 85% apple edges had 15% non-convex profiles and 40% non-convex apple profiles
Dionisio Andújar et al.	2016	Microsoft Kinect v2 camera	Estimation of weed-infested maize crops volume using Kinect Fusion algorithms	Results suggested that this method can be used for estimating volume, crop status determination and weed detection
Xiong et al.	2017	Stereo-imaging system	Reconstruction of the three-dimensional canopy structure of rape seedlings	Developed non-destructive and high-throughput stereo-imaging system for individual leaf shape
Manuel Vázquez-Arellano et al.	2018	Microsoft Kinect v2 camera	Estimation of leaf area by acquiring 3-D data of maize plants	Aligned and merged four-point clouds with MAPE of 8.8% and 7.8%

seen initially as close-shot monitoring to found any damages and then sent to further process. In the next step, RGB-D images were captured. Hence, all data sets were automatically gathered into the database of the Visual Studio C++. In order to remove the foreground and background from the depth images, thresholding was used. Furthermore, a depth point cloud of seedling was obtained based on the seedling segmentation into lump and stalk. Finally, we extracted the seedlings morphological features by using different algorithms.

3.2.2. Calibration of the RealSense depth sensor

First of all, an Intel RealSense SR300 depth sensor was fixed on a tripod stand and connected through the USB port with available data receiver source such as a laptop. Moreover, the Intel RealSense SR300 depth sensor was located 75–220 mm away from the seedlings in a straight path. Hence, the camera was set at 130 mm elevation with 30° down position for fastening the optimize vision of the selected monitoring object. However, Fig. 4 shows the calibration view of Intel RealSense depth sensor for obtaining the data from the selected object.

3.2.3. Close-shot monitoring of seedling with RealSense depth sensor

The primary purpose of the present research was to measure the seedling growth parameters with the close-shot monitoring system. Therefore, the whole monitoring strategy was based on the depth information. Besides, firstly, we determined the close-shot detection range of 75–220 mm by depth thresholding. Secondly, segmented the seedling into the seedling stalk and seedling lump based on the number of point clouds in the image. Thirdly, eliminated the interference of foreground and background and detected the top (stalk) of the seedling using top-down pixels in-depth data, and achieved to judge that whether the seedling stalk is healthy one or broken. In the same manner, the seedling lump was monitored whether it is healthy or has a

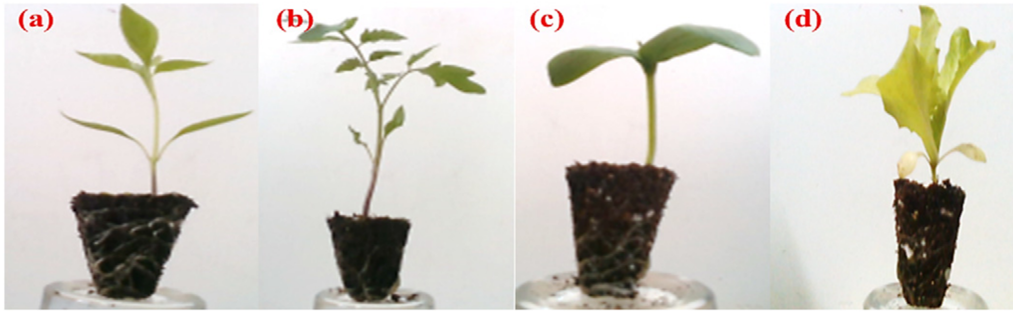

Fig. 1. Types of the selected seedlings (a) pepper, (b) tomato, (c) cucumber and (d) lettuce.

non-ideal condition. Fourthly, after the elimination process of redundant depth information, and fast segmentation of seedling into lump and stalk decided to send for further process. Finally, features were extracted from the depth images of the seedlings. Moreover, the measured parameters were included seedling height, leaf area, perimeter, and stem diameter. The whole procedure of seedling monitoring with Intel RealSense SR300 depth sensor is shown in Fig. 5.

3.2.4. Image acquisition with Intel RealSense SR300 depth sensor

3.2.4.1. RGB image acquisition. All kinds of plants look same at different growth stages, but the elements and properties of the different plants are unlike at every growth stage, within form, size, and color. Moreover, different growth stages of cucumber, pepper, tomato, and lettuce seedlings were analyzed in this research. The photos with the resolution of 640 × 480 were taken in RGB (24 bit) format. Every pixel in the image was composed by the mixture of three principles (corresponding to red, blue and green colors) between 0 and 255. After captured photos with RealSense depth sensor, the photos were moved to next step where different image-processing techniques were applied, which are described in Section 3.2.6. Fig. 6 displays the detailed process of RGB image acquisition.

3.2.4.2. Depth image acquisition. The first step was to capture the RGB images of the seedling. After that, we moved to the second step, which was to get the depth image of the seedling. Besides, the real program code of detailed information acquisition was accomplished on a computer through Microsoft Windows 8.1 and set up on Microsoft Visual Studio 2013 software system. Firstly, prepared an image obtained program, called the enable stream function to acquire the depth stream information. Subsequently, picked out the un-brief kind of pointer to obtain the depth of each pixel value as pointed to the first detail depth cache address. Afterwards, we used the integer pixel pointer of the depth image to regulate the widths of a frame data. Ultimately, access the intensity of each pixel (y × pixel pointer of the depth image + x) equivalent to the centre p (x, y) through a circular offset and output to the text document. There were 640 × 480 data points in each frame. The depth image acquisition algorithm is shown in Fig. 7.

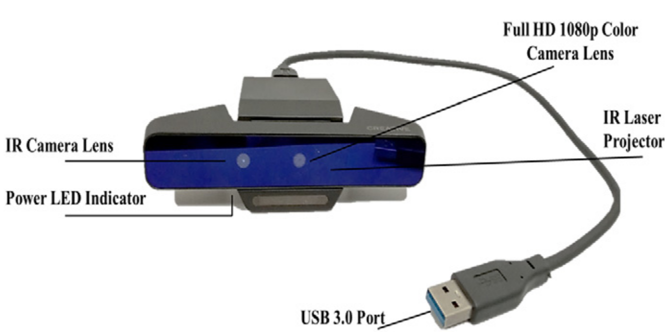

Fig. 2. Intel RealSense SR300 depth sensor.

3.2.5. Elimination of background and segmentation

The proposed scheme was mainly conducted in two steps: the first step was background removal, and the second was segmentation of the seedling image into lump and stalk. The goal of segmentation was

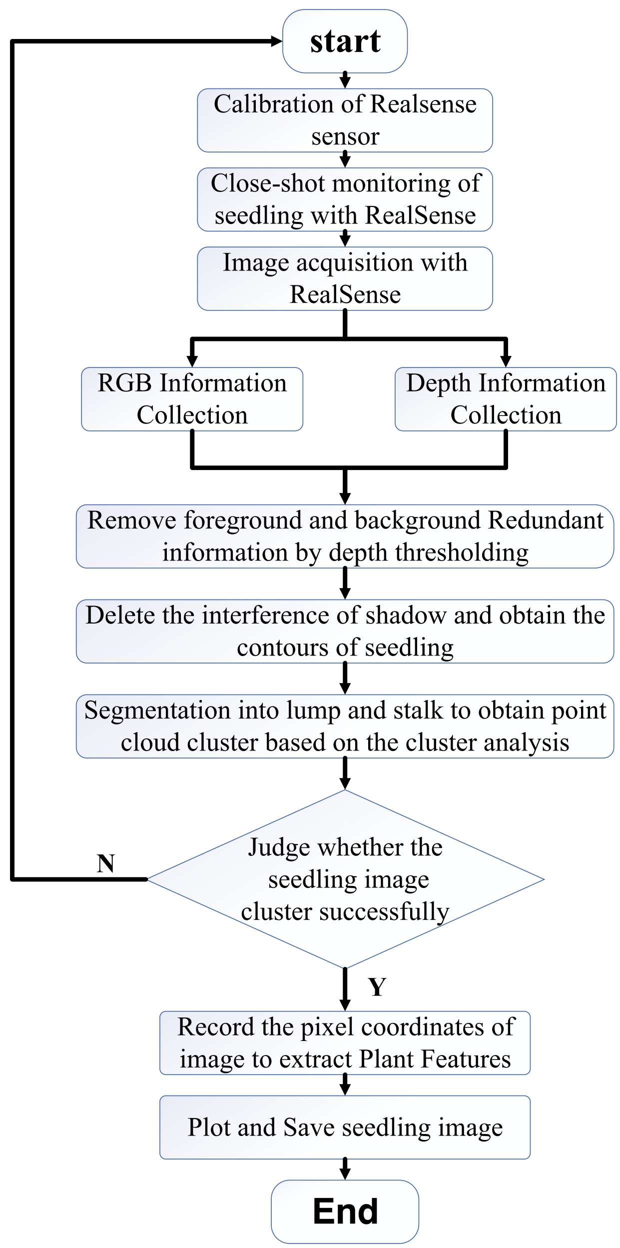

Fig. 3. Flowchart of the complete plant monitoring system.

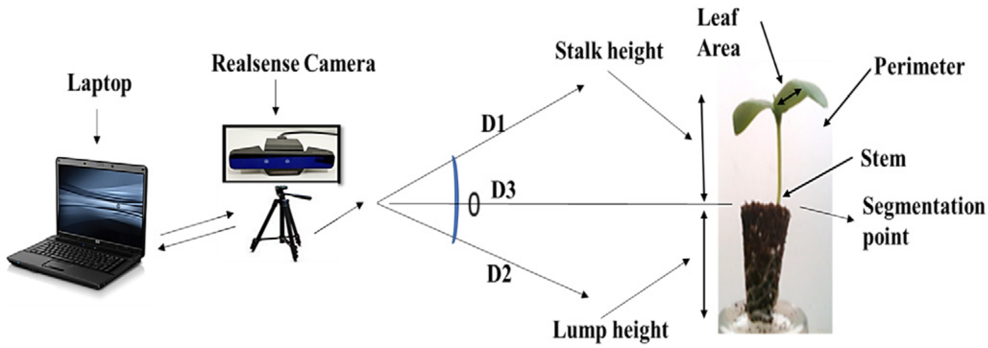

Fig. 4. Platform of our system for illustration of the obtain seedling data.

to segment the object by using a depth point cloud extraction algorithm for the acquisition of depth information. Further, the overall procedure of the proposed segmentation scheme is demonstrated below and presented in Figs. 8 and 9.

- Firstly, RGB-D images of seedlings were acquired with RealSense depth sensor and aligned for further process.
- Secondly, point cloud data of the seedling image contained some part of the environment (e.g., walls of the room) called background, which is usually diverse from the useful data of the depth information. Therefore, it was removed after setting the thresholding range.
- After that, we extracted the foreground pixels from the point cloud data by using integer pixel pointer. Consequently, the depth image was segmented into numbers of sub-areas accordingly after usage of integer pixel pointer on the depth image. Moreover, at this stage the only plant extracted and non-green background objects were removed.
- Simultaneously, the gradient vector field (GVF) was measured on the filtered depth image. Also, the middle of divergence was estimated with the gradient vector field.
- Lastly, according to the middle of the divergence of depth data, the automatic initialization of active contour models (ACM) was applied. As a result, the seedling was segmented into lump and stalk after used active contour model on the depth image.

3.2.6. Plant morphological features extraction with a machine vision system

3.2.6.1. Stem diameter. The stem diameter of the seedling was analyzed to assess the damages and week seedlings by using RGB-D data. Further, the seedling stem diameter was measured from the captured RGB-D images by using Image J Software.

Firstly, converted an image and into a binary image (Black and White). In the second step, a threshold range was set to tell the objects of interest apart from the background. Whereas all the pixels in the image whose values under the thresholds were converted to into black, and all pixels with values above the thresholds were converted to white. The third step selected the stem and made it duplicate. After that, by choosing the freehand tool highlighted the pointed area of stem and analyzed the stem diameter.

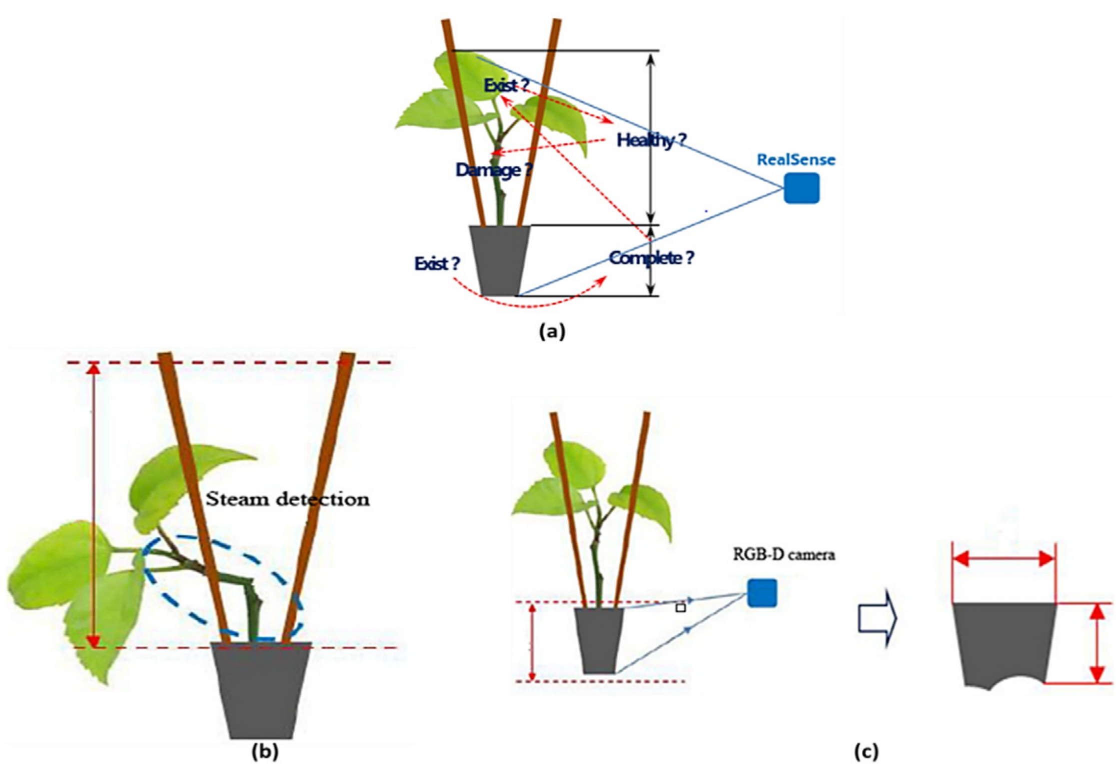

Fig. 5. Close-shot monitoring of seedling with RealSense depth sensor (a) main procedure for monitoring of seedling growth parameters measurement, (b) close-shot monitoring of seedling stalk after segmentation of lump, (c) close-shot monitoring of seedling lump after segmentation of stalk.

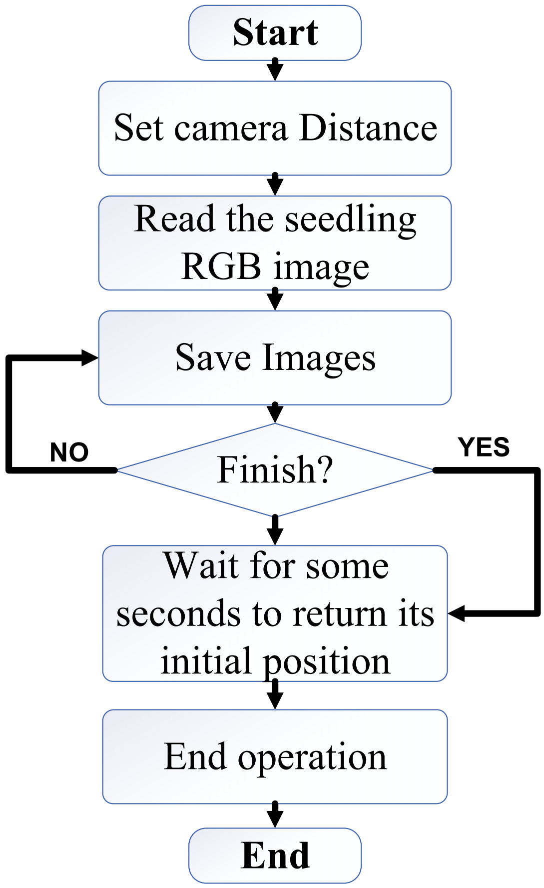

Fig. 6. Flowchart of RGB image acquisition.

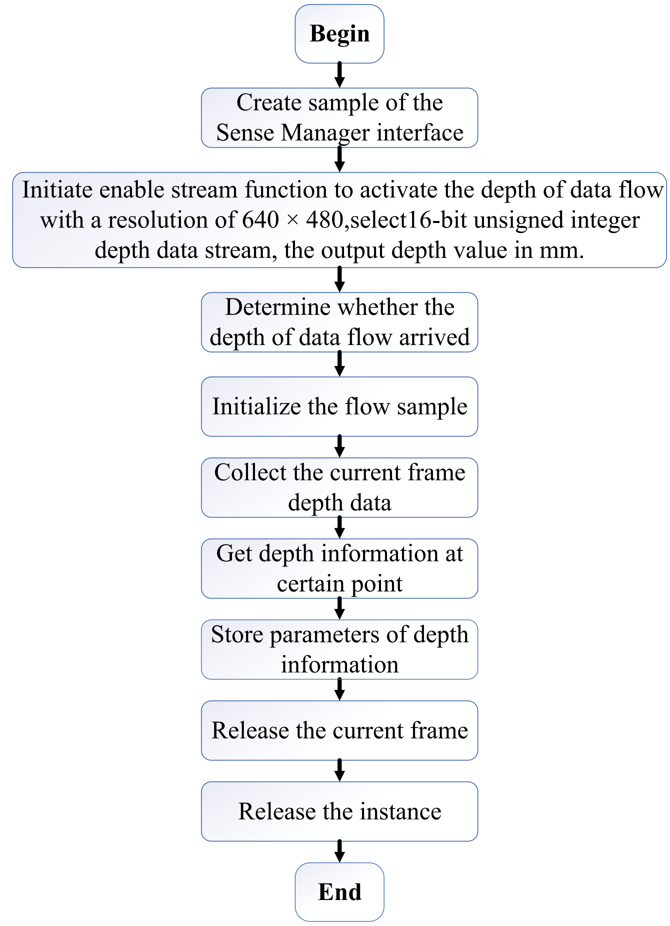

Fig. 7. Flowchart of the acquisition of depth point cloud data.

3.2.6.2. Plant height. Plant height was measured to assess the growth and development of the seedling. Moreover, regarding the experiment, plant height was measured based on point clouds of the segmented plant into lump and stalk (Fig. 10). The process of measuring plant height was done in MATLAB software. Relative height was calculated by the given expressions (1).

$$H_R = H_S + H_L \tag{1}$$

where H_R = relative height, H_S = height of the stalk and H_L = height of lump.

3.2.6.3. Leaf area. Leaf area measurement is used to track the growth and health status of the plant. Therefore, the objective of the measurement of leaf area was to know the status of seedling nutrition and development rate. It is the most essential photosynthesis organ of the plant which affects the bio-productivity in the leaf.

In a detailed procedure, firstly, acquired depth image from the RealSense depth sensor and then proceeded for further process. Hence, depth data received and stored into .text document format. Secondly, used the appropriate algorithm into MATLAB and extracted the number of pixels in the leaf area region with the help of the data cursor tool, however, Fig. 11 shows the graphic user interface (GUI) of the whole process. In which, the depth photo made up of pixels, where each connected region represents the pixels of the leaf area.

3.2.6.4. Perimeter. The boundary around the plant is called the perimeter of the seedling. To detect the perimeter of seedlings, first of all, opened depth image into MATLAB and scanned the image thoroughly by a suitable algorithm. After that, by running the program, the pixels on the

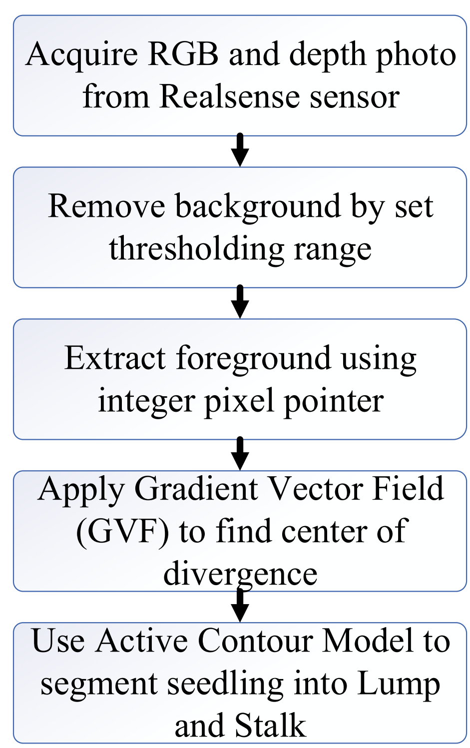

Fig. 8. Flowchart of the proposed segmentation arrangement.

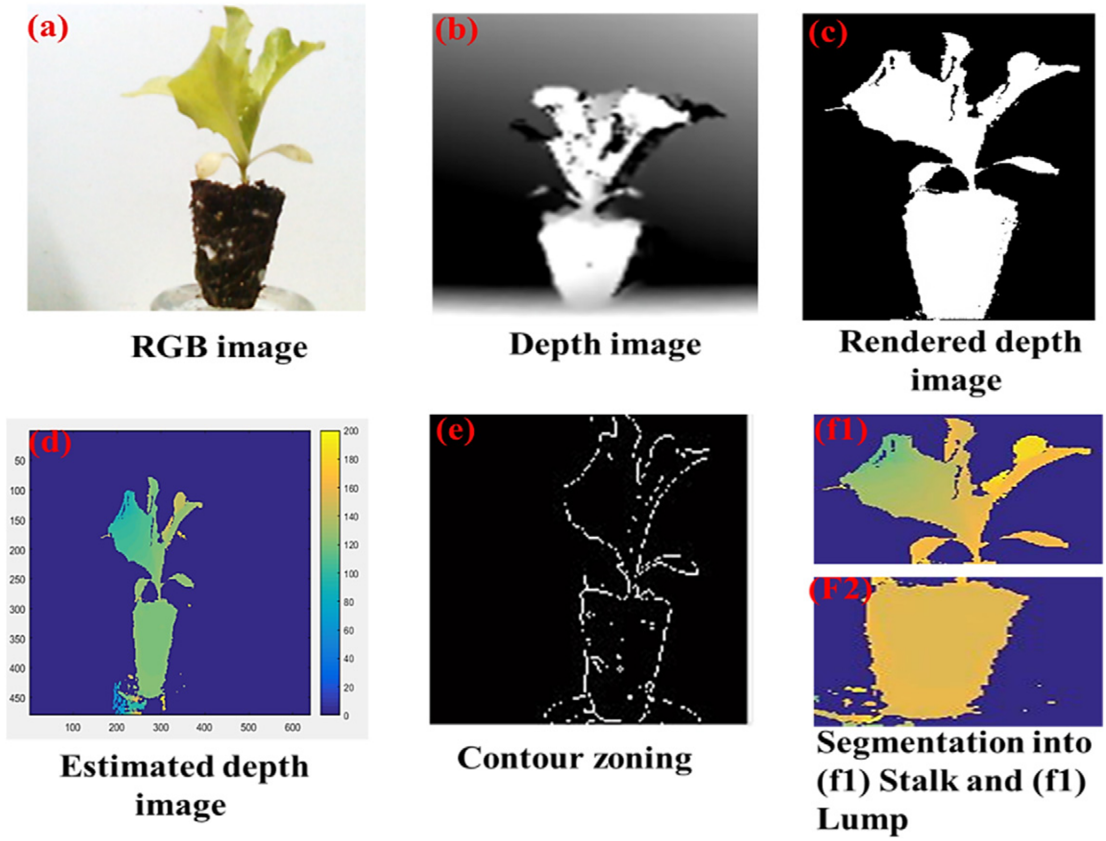

Fig. 9. Main procedure of point cloud processing based on RGB-D seedling segmentation.

edges of the seedling comes out, and a perimeter was measured accordingly, as shown in Fig. 12.

3.2.7. Monitoring of seedling in multi-views

To eliminate abrupt motions that cause seedlings to vibrate and low the quality of point-clouds, the continuous rotation was employed. Thus, to assess the realistic 3D mesh acquisition performance, 3D views of the seedling to be measured had been generated by positioning the sensor. The sensor emits an infrared light that scans vertically to cover the height of the seedling. The samples of 4 different seedling varieties were taken for the experiment. In which, 15 samples from each variety were collected to emulate the growth state and measured the height of seedling at different angles (0°, 45°, 90°, and 135°) with the close-shot range of 75–220 mm. The 4 views were set for each seedling to collect the depth information, and 60 total positions were collected. For each sample, the seedling was rotated every 45° continuously on the same place to receive entire depth-point cloud. Then, the depth information of the stalk and lump were distinguished with the feature extraction strategy of seedlings, using MATLAB. The multi-views of seedlings are shown in Fig. 13.

3.2.8. Monitoring of seedling in different light conditions

To analyze the RealSense depth sensor performance for monitoring the seedlings in the light and equate its effectiveness in the dark, the black and light environments were set for each experiment, as shown in Fig. 14. Since light conditions are a vital factor for seedling monitoring technology. The analysis in the dark was performed without light from 8

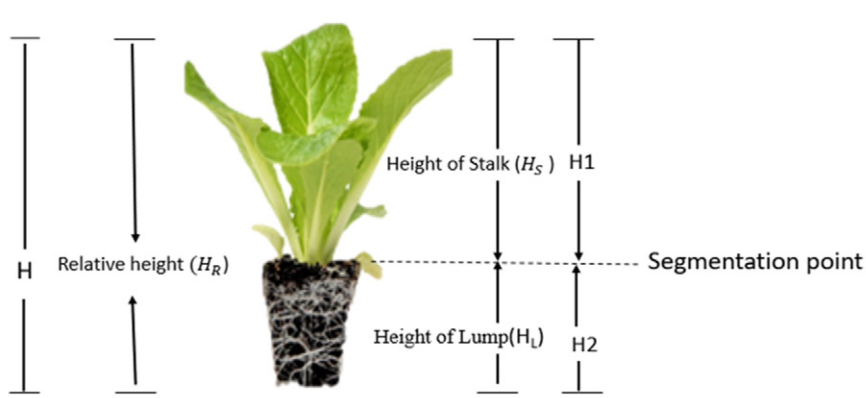

Fig. 10. Principles of the plant height extraction based on segmentation into lump and stalk.

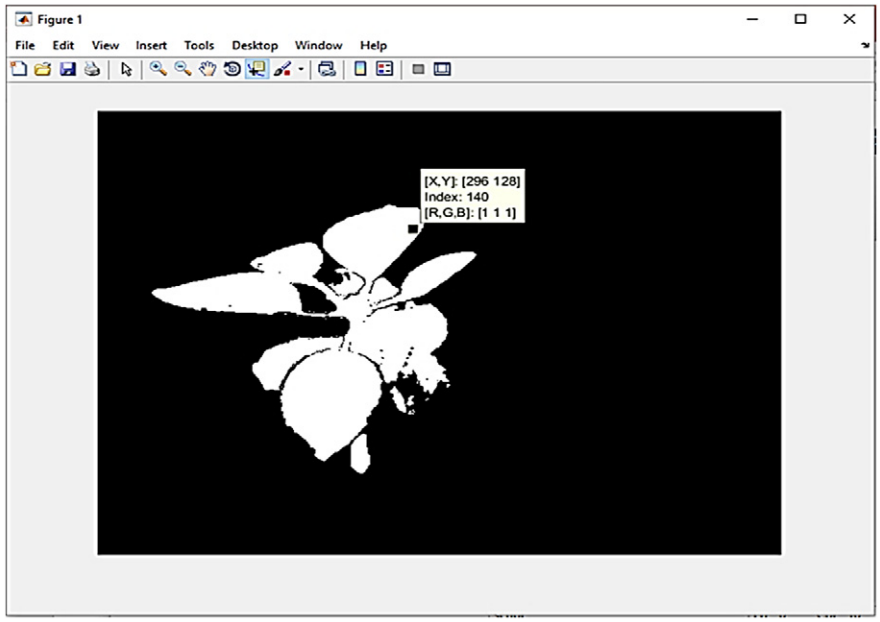

Fig. 11. The graphic user interfaces for measurement of leaf area and real-time visualization.

to 10 P.M. While, examined in the light was supported out with radiant light from 12 to 3 P.M.

3.3. Experiment to validate the RealSense depth sensor

To validate the RealSense depth sensor for seedling height and stem diameter measurements, 4 different seedling varieties were grown in the greenhouse at the Jiangsu University. In each, 15 samples for seedling height and 14 samples for stem diameter were randomly selected from each variety for validation of the experiment. This procedure permitted the RealSense depth sensor to be validated on seedlings for different sizes complexity. The data collection steps for manual and MV (Machine vision) were as follows:

- To validate the RealSense depth sensor firstly, the manual method was considered. Height of seedling (stalk and lump) was measured vertically from the bottom of the lump to the top of the stalk with measuring tape, and the stem diameter was measured with Vernier calliper.
- In the MV collection method, we used the RealSense depth sensor camera. Once the image captured from the RealSense depth sensor camera and received at the PC side, the processing functions were started on the image. The purpose of the RGB-D image was to obtain

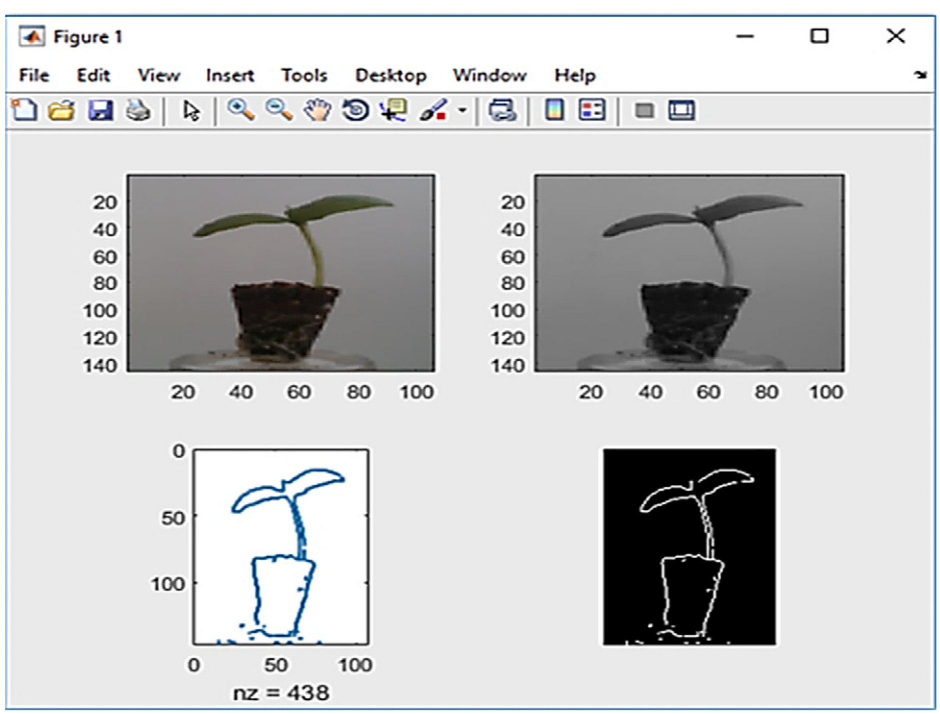

Fig. 12. Experiment scene of seedling perimeter measurement.

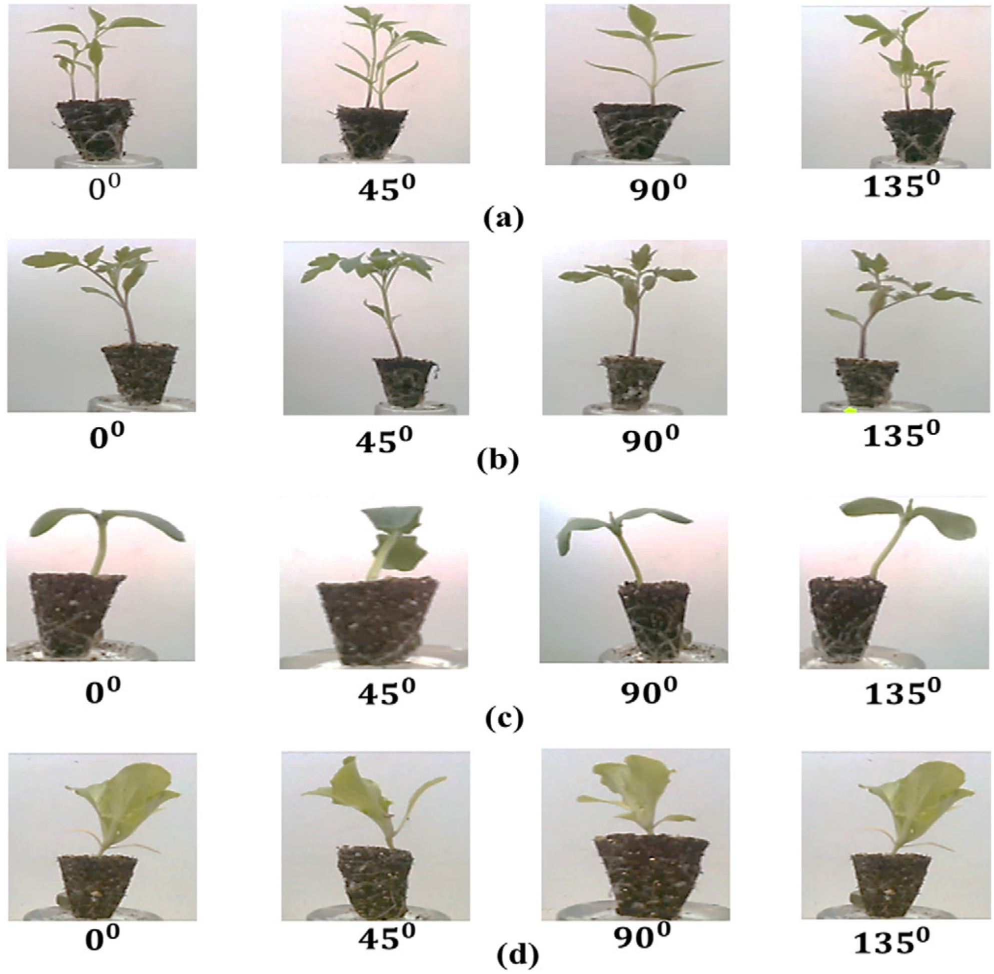

Fig. 13. Seedlings 3D view at different angles. Where row represents (a) pepper, (b) tomato, (c) cucumber and (d) lettuce.

its raw 3D point cloud, which allows measuring (a) the height of seedling and (b) the stem diameter of each seedling.

3.4. Data analysis

The variance of analysis (ANOVA) was used to determine the correlation between both methods and derived parameters. Regression analysis was done to see the effect of the purposed method. Whereas, its accuracy was evaluated using R^2 (coefficient of variation) also, the significance value was decided based on the p-value (0.05) at 95% confidence.

4. Results and discussions

4.1. Monitoring morphological parameters of the seedlings

The morphological qualities of 40 seedlings were examined by using the MV and grouped into 4 different varieties where each variety had 10 samples, respectively. However, the obtained results are shown in Fig. 15. As can be seen in Fig. 15, the measured average leaf area pepper (678.5 mm), tomato (850.5 mm), cucumber (420.6 mm) and lettuce (126.3 mm); average stem diameter of pepper (2.5 mm), tomato (2.7 mm), cucumber (2.8 mm) and lettuce (3.1 mm); average plant height of pepper (97.8 mm), tomato (40.7 mm), cucumber (39.7 mm) and lettuce (41.0 mm) and average perimeter of pepper (162.3 mm), tomato (162.3 mm), cucumber (138.0 mm) and lettuce (172.0 mm) was obtained. Thus, it could be said that the seedlings morphological parameters were significantly detected with the Intel RealSense SR300 depth sensor.

4.2. Multi-views performances of seedling height

The results of the multi-views performances had been surveyed over 4 different seedlings varieties in 60 total views. The monitored results are shown in Fig. 16. Furthermore, it can be seen in Fig. 17 that the different views had no significant effect on the accuracy of the Intel RealSense SR300 depth sensor. However, the success rate of lettuce was obtained highest than other means, while cucumber was found the lowest success rate. The highest height of seedling was observed of lettuce than cucumber, pepper, and tomato, respectively. Thus, it could be said that Intel RealSense SR300 depth sensor can be used for monitoring the seedlings in different positions.

4.3. Seedlings monitoring in different light conditions

In order to verify the RealSense depth sensor performance in different light conditions, the dark and light environment was set. The seedlings images were captured in a laboratory under two conditions: Light and Dark. Therefore, 4 types of seedling (tomato, pepper, cucumber, lettuce) were considered for the experiment in view of the height and shape characteristics. Total of 40 samples was analyzed in each condition with close-shot range. According to regression analysis, the effect of seedling height and shape detection effect remain the same within the light and dark environments at p-value (0.05). The results showed that there was no visible difference in the detection rate between light

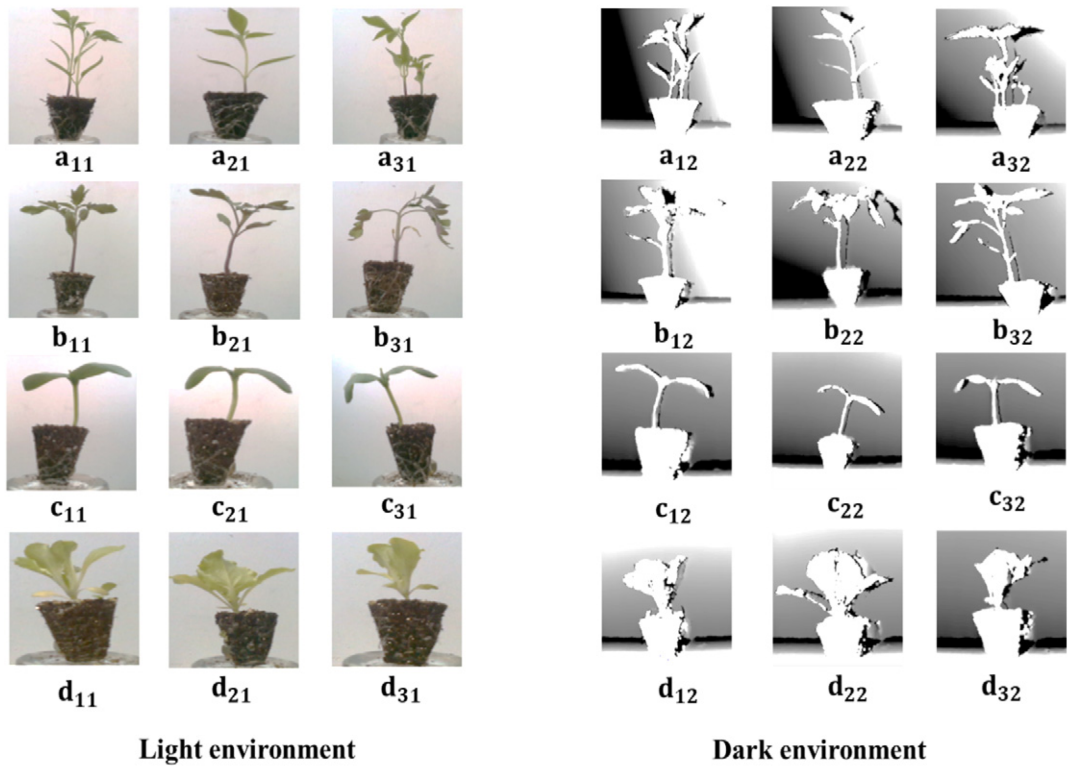

Fig. 14. Captured seedling images in different light conditions. Where row represents (a) pepper, (b) tomato, (c) cucumber and (d) lettuce.

and dark environment, which could efficiently conquer the light sensitivity. Thus, the proposed method has furnished the usefulness concept that different type of seedling plants can be monitor effectively in any light condition. Moreover, the recognition percentage of pepper was the highest, which ranged from 98 to 100%. Whereas the success rate of cucumber, tomato, and lettuce was ranged between 80 and 90%, 70–80%, and 85–95% respectively. However, the experimental results are illustrated in Fig. 18.

4.4. Validation of the sensor

The variance of analysis of the data indicates the strong and significant correlation in a proposed method for determining the stem diameter and height of the seedlings. Furthermore, the results of variance analysis (ANOVA) of seedling height (60 samples) and stem diameter (56 samples) of each variety is revealed in Fig. 19 (a and b). The analyzed result shows that there was a good linear relationship between

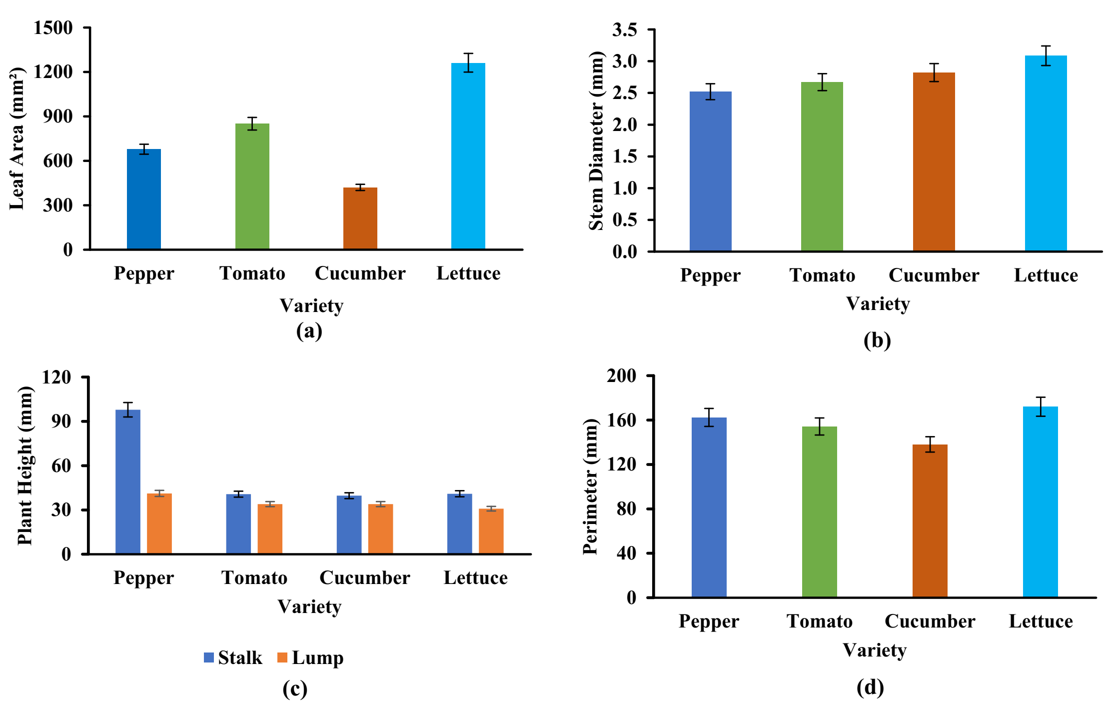

Fig. 15. Evaluation of seedling quality based on (a) leaf area, (b) stem diameter, (c) plant height, and (d) perimeter.

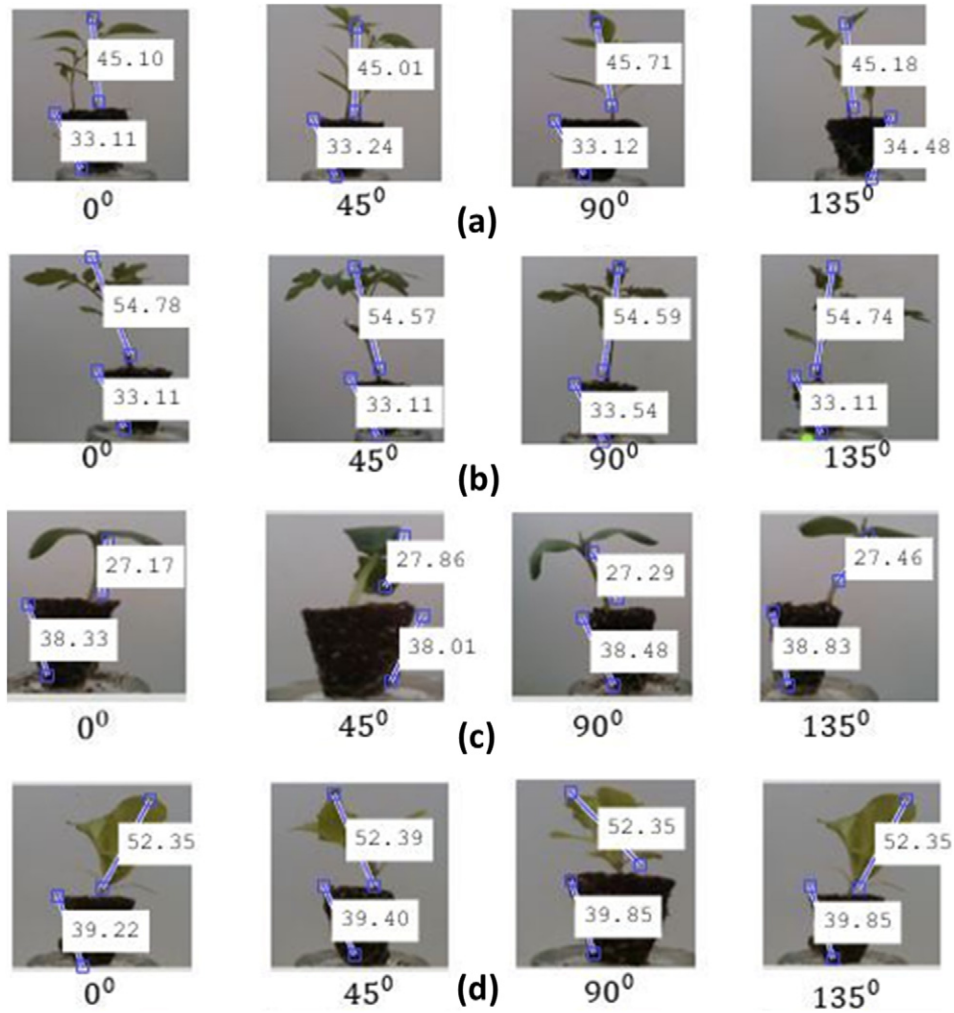

Fig. 16. 3D comparison between the seedlings ground truth (0°) and the SR300 acquired data at multi-views. Where row represents (a) pepper, (b) tomato, (c) cucumber, and (d) lettuce.

the obtained results with manual (reference) and MV methods. Fitting linear corresponding detail results are further shown in Fig. 20 (a and b). It can be seen in Fig. 20 (a) that the correlation between manual and MV for determining the seedlings height measurement, the value of the R^2 were found higher than ($R^2 = 0.99$) pepper, ($R^2 = 0.99$) tomato, ($R^2 = 0.99$) cucumber, and ($R^2 = 0.99$) lettuce. Furthermore, the highest average height of seedling varieties was obtained for pepper towards 160 mm. However, the correlation results of stem diameter for tomato, pepper, cucumber, and lettuce were ($R^2 = 0.54$), ($R^2 = 0.35$), ($R^2 = 0.68$) and ($R^2 = 0.58$) simultaneously, which is shown in Fig. 20 (b). Moreover, highest stem diameter (3.7 mm) was observed towards lettuce seedlings than cucumber, pepper, tomato.

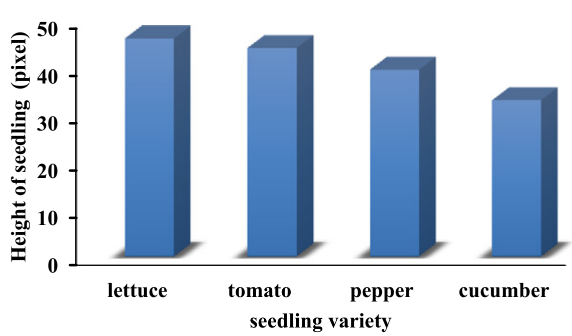

Fig. 17. Height of the seedling in multi-views.

Besides, a closer inspection indicated that 15 samples were clustered into one group in terms of total seedling height, and 14 samples were clustered into one group in terms of total stem diameter. Across, this indicated the R^2 of the seedling height was larger scatter around the regression line compared to stem diameter. In results, high R^2 value proved the accuracy of the RealSense depth sensor tool; therefore, it can be an excellent tool for monitoring seedling health status. Thus, it could be concluded that manual and MV methods were significantly different ($p < 0.53$) for stem diameter and ($p < 0.99$) for seedling height averagely, which was <0.05 at 95% (0.95) of confidence level.

4.5. Impact of multi-views-based comparison

The present study was aimed to propose seedling-lump integrated monitoring methods based on the close-shot range of 75–220 mm. Besides, the work was targeted to present an alternative technique for monitoring of the seedling growth parameters using image analysis and to introduce a new method that could provide the fastest results with useful techniques. Moreover, an image segmentation algorithm based on depth point-cloud was designed to evaluate the development of seedling growth through the MV. The algorithms were implemented in C++, Image J, and MATLAB software. The depth photos were captured in multi-views to accumulate the accuracy of the sensor. As shown in Fig. 17, by comparing mean lettuce had a more obvious success rate of monitoring than other means. Results proved that seedling monitoring with SR300 camera at any angle does not affect its actual height. Therefore, this method could be used for the operation of "eye-

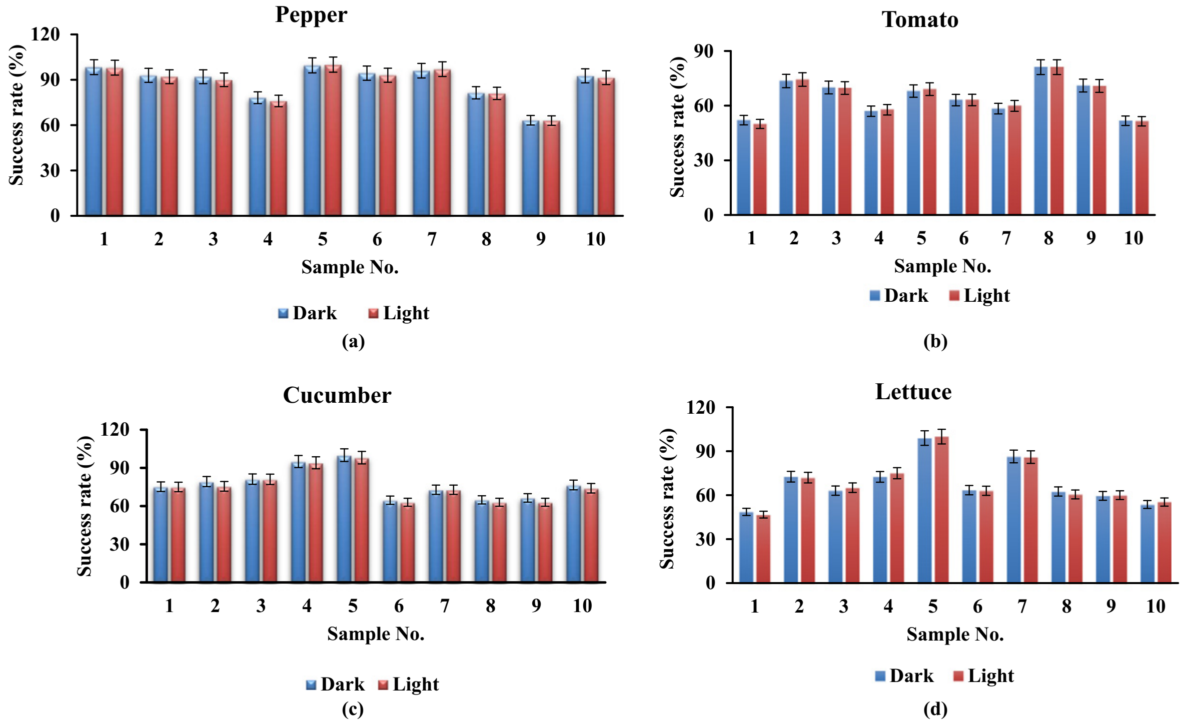

Fig. 18. Experimental results of RealSense depth sensor accuracy of (a) pepper, (b) tomato, (c) cucumber and (d) lettuce in different light conditions. Where *p*-value (0.05) in light and dark environment comparison.

in-hand" robot in the close-shot range (75–220 mm) can avoid any misclassification and ensure reliable monitoring.

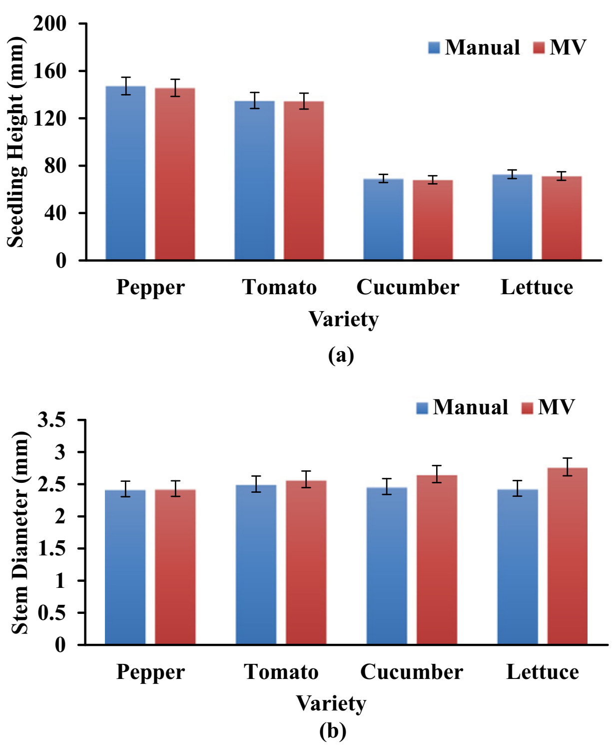

Fig. 19. Correlations of Manual and Machine vision (MV): RealSense (MV) measured seedling height (a), RealSense (MV) measured seedling stem diameter (b). Vertical bars represent standard errors. Means with the different letters above the bars are statistically significant at *p*-value (0.05) as determined by Duncan's multiple comparison test.

4.6. Influence of light condition

Light is an important factor in the monitoring of plants, and the purposed method was based on infra-red technology. RealSense depth sensor emerged infrared light on the sample and collects information. Thus, it could be fixed on transplanting robot and can be enabled to do day and night work under natural conditions smoothly. The RealSense depth sensor has an advantage of its minimum close-shot detection range (75 mm), which was confirmed in this study. The system was trained under light and dark environments and compared the results. Consequently, the obtained results showed significant *p*-value (0.05) performance in the dark as well as in the light environment.

4.7. Reliability of RealSense depth sensor for monitoring

RealSense sensor accuracy was checked by comparing the results of manual and MV methods based on seedling height and stem diameter. The results of the present study confirmed that the automated method is reliable as the standard manual method. The obtained results proved data collected from manually and RealSense SR300 depth sensor had a good linear relationship. However, manual measurement methods were time-consuming and labour-intensive. Therefore, they are not suitable for large-scale experiments. However, our proposed method is completely depended on visualization.

4.8. Close-shot monitoring of seedling

Seedling quality is the combination of its height, stem diameter, nutritious root size, and shape. These characteristics together determine how well the plant will flourish after transplanting in the field. Conventionally, plant growth parameters were measured manually by using measuring tapes or handheld instruments such as laser and ultrasonic distance meters. Therefore, we proposed an MV method for squeeze seedling quality based on morphological characteristics included seedling height, perimeter, stem diameter and leaf area, respectively. As a result, non-destructively and efficiently we found satisfactory results.

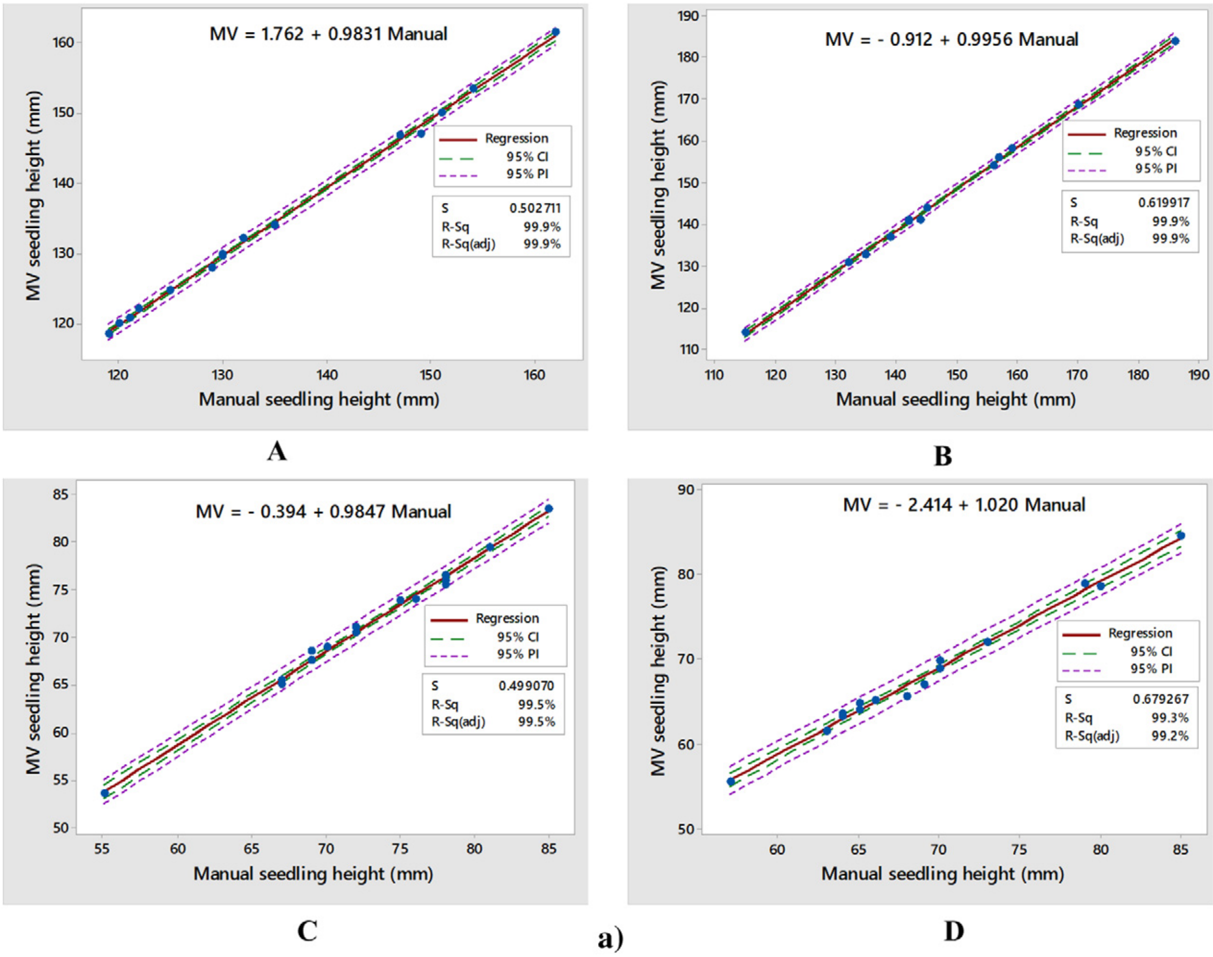

Fig. 20. Scatterplots of data distribution and fitting results measurement of seedling height (A), Stem diameter (B), obtained images from RealSense (MV) vs manual method. Where graphs show different varieties namely (a) pepper, (b) tomato, (c) cucumber and (d) lettuce.

4.9. Advantages of the proposed algorithm

The significant contribution and advantages of our study are lower equipment cost, including the automation, which enhances its performance and avoids obsolescence. By using an Intel RealSense SR300 depth sensor which works faster than other sensors and human efforts, saves time. The whole workflow of monitoring and data processing is automatic also the seedling key features can be measured accurately with a designed algorithm. However, the system has good robustness for different species of seedlings.

In currently available transplanting robots are only able to monitor the seedlings in trays within holes, but using our proposed method on the transplanting robot can monitor seedling out-hole. It monitors seedling with close-shot and works with higher speed, which allows it to see around, behind, and above the bulk of large machines. It can easily integrate into new or existing production systems. Digital images can monitor temporal changes in the plant structure. In addition, better quality inspection, analyzing, gauging, and assembly verification. As a comparison with present RealSense depth sensor and Kinect based methods (Yang et al., 2016; Hu et al., 2018), the proposed method has advantages in monitoring seedling with accurate growth parameters measurements.

4.10. Future works

We aimed to attempt a new method of seedling-lump integrated monitoring with the RealSense depth sensor. However, the analysis was based on depth information. The purposed method is suited for small plants such as seedlings. The calculated principles are in contrast to real policies. Through the application of this system, it can significantly reduce labour intensity and improve the level of scientific breeding and thus bring out high-quality seedlings to ensure and enhance the crop yields. This system is feasible and has practical value. It can be used on automatic transplanter. Moreover, the current study has a few limitations. In this work, the working distance of the RealSense depth sensor was set to 75–220 mm from the vegetation according to seedlings height. Therefore, RGB-D data of seedlings can be acquired accurately. However, the proposed method cannot be suitable to monitors large size plants. Besides, the related research and its practical application in robotic transplanting are ongoing.

5. Conclusions

At present monitoring plant, health status and phenology with RGB-D sensors are considered as a cost-effective method. However, the scope is to use the sensor camera for producing time-series information, results in a better understanding of the relationships between surrounding environmental conditions, plants health, and their performances. Furthermore, in this study, we used an Intel RealSense SR300 depth sensor and proposed an algorithm to determine the plant growth parameters. The SR300 is the second generation of front-facing camera developed by Intel company in 2016. It is a subassembly camera product that implements a short-range (SR), coded light, and 3D imaging system. The RealSense depth sensor can compute the distance between

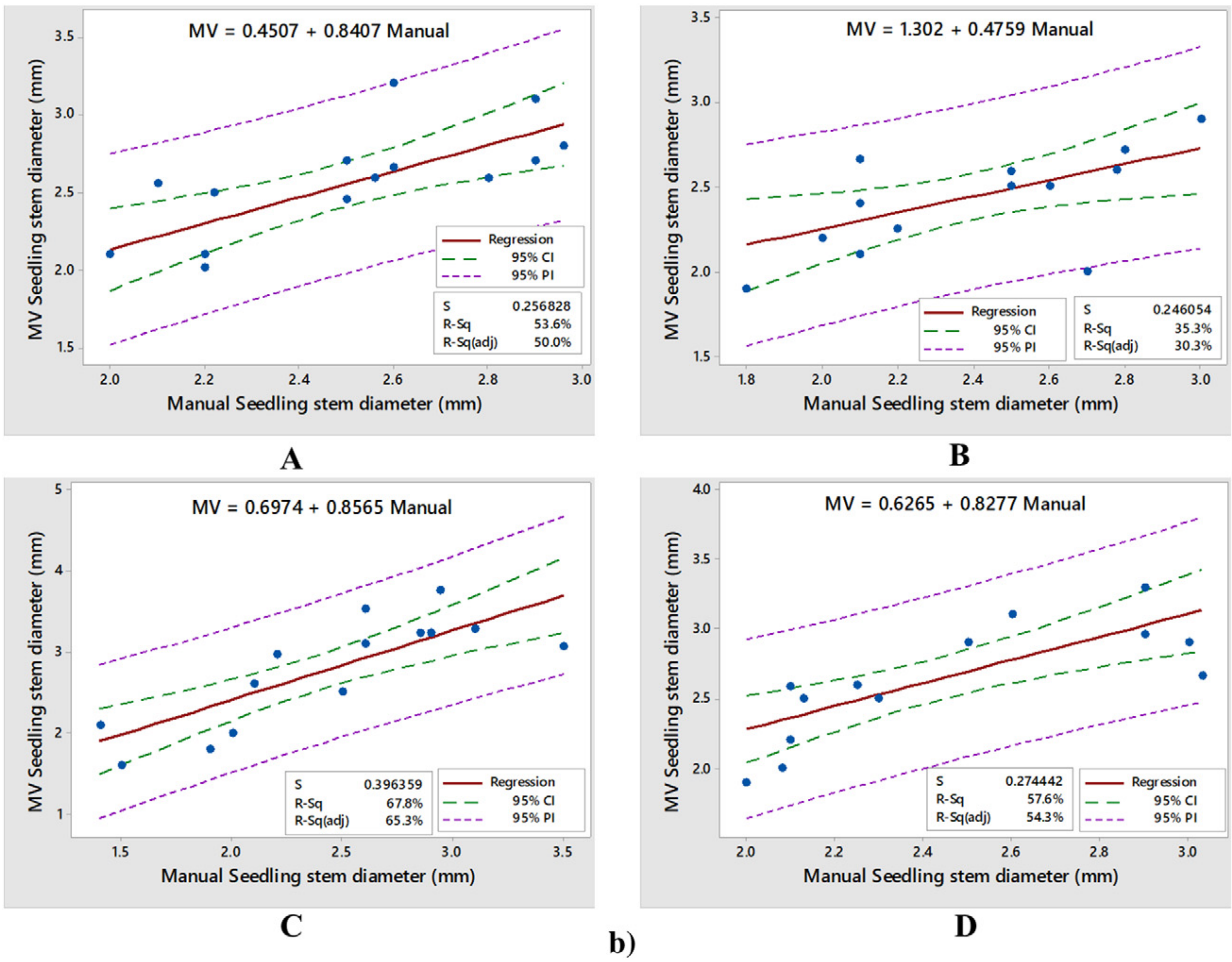

Fig. 20 (*continued*).

objects, detaching objects from the background layers and gives a much better object, facial, and gesture recognition than a traditional camera.

Acknowledgments

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