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Article

Three-Dimensional Imaging in Agriculture: Challenges and Advancements in the Phenotyping of Japanese Quinces in Latvia

Edīte Kaufmane [1,*], Edgars Edelmers [2,3,*], Kaspars Sudars [3], Ivars Namatēvs [3], Arturs Nikulins [3], Sarmīte Strautiņa [1], Ieva Kalniņa [1] and Astile Peter [4]

1 Institute of Horticulture, Graudu Iela 1, Ceriņi, Krimunu p., Dobeles reg., LV-3701 Dobele, Latvia; sarmite.strautina@lbtu.lv (S.S.); ieva.kalnina@lbtu.lv (I.K.)
2 Medical Education Technology Centre, Rīga Stradiņš University, Anniņmuižas Bulvāris 26A, LV-1067 Riga, Latvia
3 Institute of Electronics and Computer Science, Dzērbenes Iela 14, LV-1006 Riga, Latvia; sudars@edi.lv (K.S.); ivars.namatevs@edi.lv (I.N.); arturs.nikulins@edi.lv (A.N.)
4 Division of Electronics and Embedded Systems, KTH Royal Institute of Technology, Brinellvägen 8, SE-11428 Stockholm, Sweden; astile@kth.se
* Correspondence: edite.kaufmane@lbtu.lv (E.K.); edgars.edelmers@edi.lv or edgars.edelmers@rsu.lv (E.E.)

Abstract: This study presents an innovative approach to fruit measurement using 3D imaging, focusing on Japanese quince (*Chaenomeles japonica*) cultivated in Latvia. The research consisted of two phases: manual measurements of fruit parameters (length and width) using a calliper and 3D imaging using an algorithm based on k-nearest neighbors (k-NN), the ingeniously designed "Imaginary Square" method, and object projection analysis. Our results revealed discrepancies between manual measurements and 3D imaging data, highlighting challenges in the precision and accuracy of 3D imaging techniques. The study identified two primary constraints: variability in fruit positioning on the scanning platform and difficulties in distinguishing individual fruits in close proximity. These limitations underscore the need for improved algorithmic capabilities to handle diverse spatial orientations and proximities. Our findings emphasize the importance of refining 3D scanning techniques for better reliability and accuracy in agricultural applications. Enhancements in image processing, depth perception algorithms, and machine learning models are crucial for effective implementation in diverse agricultural scenarios. This research not only contributes to the scientific understanding of 3D imaging in horticulture but also underscores its potential and limitations in advancing sustainable and productive farming practices.

Keywords: *Chaenomeles japonica*; germplasm; genotypes; fruit size; characterization; volumetric data; point cloud

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1. Introduction

1.1. Japanese Quinces

Globally, the ornamental cultivation of the Chaenomeles species is widespread, with over 300 varieties being cultivated for aesthetic purposes in various regions, including Europe, Canada, and the United States. In contrast, the use of *Chaenomeles japonica* as an agricultural fruit crop is predominantly recognized in the Baltic nations and, to a lesser extent, in Scandinavia, Germany, and Poland. The fruits of this species, referred to here as CHAE, are noted for their significant biochemical composition, which encompasses a range of organic acids; sugars; phenolic compounds; vitamins, such as vitamin C; and amino acids, as well as essential minerals and trace elements. These components contribute to the fruit's pronounced antioxidant properties [1–4].

In Latvia, systematic breeding of CHAE for fruit production began in the 1950s, with expansive plantations being established in the subsequent two decades. By the 1990s, the plantation area in Latvia had grown to about 300 hectares [5]. Initially, these commercial plantations were derived from seed-propagated plants, which exhibited considerable genetic variability. This heterogeneity resulted in less uniform and economically advantageous yields, compared to plantations established with selected vegetative cultivars. Despite large-scale fruit production, the lack of diversified processed products led to a decline in the industry [6,7]. However, in 2002, the Latvian Institute of Horticulture (LatHort) innovated and patented a method for producing candied CHAE fruit [8]. This new product has been adopted by over 20 companies, spurring the resurgence of CHAE commercial cultivation through exports. Notably, CHAE candied fruits have gained international market traction, with exports from companies like "Rāmkalni" SIA (Latvia, Krustiņi) extending to China and Australia, constituting 3–5% of their total production, which is about 10–15 tons monthly. Additionally, baby purees containing organically grown CHAE are now being exported to various countries, including Kuwait, Saudi Arabia, India, and Korea. These developments suggest a considerable, yet-to-be fully tapped global market potential for Japanese quince products. Presently, Japanese quince is a substantial commercial crop in Latvia, with cultivation areas expanding fourfold over the past six years to 706 hectares in 2022, indicative of its increasing popularity annually in Latvia and other Baltic Sea nations like Poland.

A new breeding initiative was launched in the 1990s at LatHort with the goal of developing CHAE cultivars suited to the Latvian climate, utilizing Ch. japonica due to its superior winter hardiness in the colder northern European climates [5]. Between 1998 and 2002, LatHort collaborated with Swedish and Lithuanian researchers to assess a diverse range of CHAE germplasms as part of the EU Project "Japanese quince (*Chaenomeles japonica*)—a New European Fruit Crop for Produce of Juice, Flavour and Fibre" (EUCHA)" [9]. CHAE plants have demonstrated considerable adaptability under various growing conditions, though the inheritance of desirable characteristics is not always guaranteed. The preferred attributes for prospective cultivars include robust winter hardiness of both the plants and their flower buds, absence of thorns, high and consistent yields, disease resistance, and superior fruit quality with rich biochemical content, coupled with early ripening and upright growth with minimal branching [10]. The fruit morphology of Japanese quince is notably varied [11], with some genotypes producing large, ribbed fruits and others displaying fruit shape polymorphisms, including both ribbed and smooth oval or round fruits on a single plant. This morphological diversity can fluctuate annually or may be due to genetic instability. Distinct differences in productivity, fruit quality, size, and biochemical composition have also been observed among different genotypes [12]. Following an assessment at LatHort, three cultivars—'Rasa', 'Darius', and 'Rondo'—were selected and officially registered in Latvia. These varieties are distinguished by their high yield, fruit uniformity, and early to mid-September ripening times, with individual fruits typically weighing between 40–60 g [13].

In order to improve the quality of quince fruits and other parameters, the breeding work at LatHort continues. Plant phenotyping (description and evaluation) has always been a major field of research in plant breeding. To distinguish candidates for cultivars in fruit breeding, it is necessary to describe and evaluate the characteristics of several thousand seedlings. Traditional phenotyping methods (measuring the length and width of the fruit with a calliper and weighing) are used to characterize the size and shape of the fruit, which are very labor- and time-consuming [14]. Since several parameters are evaluated in points, the results can be relatively subjective, and results may differ among different evaluators.

1.2. Three-Dimensional Technologies in Plant Phenotyping

Over the past thirty years, advancements in capturing three-dimensional (3D) surface information from plants have revolutionized our understanding of plant architecture and growth [15–17]. The utilization of 3D measurement technologies provides invaluable insights into the structural development of plants, encompassing entire canopies, individual plants, and specific plant organs. This non-destructive method allows for ongoing monitoring over time, making it an integral part of plant phenotyping [18]. A key aspect of 3D measurement is its ability to distinguish actual growth from mere plant movement at both the plant and organ levels [19].

Plant phenotyping is an essential process that bridges the gap between genomic research and the practical agricultural traits of plants [20]. In this context, 3D measuring devices play a crucial role, offering precise measurements of plant geometry and growth. These devices employ a variety of techniques, including laser scanning, structure from motion (SfM), terrestrial laser scanning, structured light approaches, time-of-flight sensors, and light-field cameras. Each technology caters to different scales, from individual plants in laboratories to thousands of plants in experimental fields or open fields. The chosen technique depends on specific requirements, such as robustness, accuracy, resolution, and speed, essential for generating functional structural plant models, differentiating growth from movement, visualizing diurnal patterns, and assessing the impact of environmental stress on plant development [21–23].

All these technologies yield point clouds, where each point is defined by X, Y, and Z coordinates in a 3D space, and may include additional data like color or intensity, representing reflected light. Unlike 2.5D methods that measure from a single perspective, true 3D models incorporate point clouds from multiple viewpoints, offering less occlusion, higher spatial resolution, and greater accuracy. The resolution in these scans is defined as the minimal distance between points, while accuracy refers to the proximity between the real and measured points.

Active techniques include triangulation-based systems like laser triangulation (LT) and structured light (SL), as well as time-of-flight measurements, such as terrestrial laser scanning (TLS) and time-of-flight (ToF) cameras. Passive methods encompass light-field cameras (LF) and structure-from-motion (SfM) approaches.

The use of 3D technologies in plant phenotyping offers several advantages. These technologies enable the acquisition of multi-source phenotypic data throughout the entire crop-growing period, allowing for the extraction of various plant parameters, such as height, width, leaf length, leaf area, and inclination angle [24]. Additionally, 3D model-based methods permit the simultaneous extraction of multiple morphologic traits, including canopy height, plant volume, and leaf area index (LAI), while mitigating plant occlusion [25]. Low-cost 3D imaging devices have been shown to be highly reliable for plant phenotyping, with the potential to be implemented in automated application procedures, thus saving acquisition costs [18]. Furthermore, 3D reconstruction technology has been widely used to analyze crop phenotypes, offering a valuable tool for the development of digital agriculture [26].

However, there are also challenges and limitations associated with the use of 3D technologies in plant phenotyping. For instance, there are issues related to low accuracy, expensive equipment, and complicated operation in crop 3D reconstruction research, with recognition efficiency being determined, to a large extent, by the shading between crops [27]. The complexity of the analysis of 3D representations has been identified as a bottleneck hindering the wider deployment of 3D plant phenotyping [23]. Additionally, while 3D mesh analysis shows potential for accurately estimating specific morphological features and monitoring them over time, there is a need for further development and testing in the context of high-throughput plant phenomics [23]. Moreover, the complexity of the plant geometry being scanned significantly influences the computational power and resources needed for the scanning process, particularly when scanning intricate objects like leaves [28]. In this context, the employment of multispectral scanning, which integrates various sensors, such as thermal, LIDAR, NIR, RGB, and THz, has demonstrated superior efficiency, compared to monospectral scanning techniques [29].

In conclusion, the use of 3D technologies in plant phenotyping offers numerous advantages, including the acquisition of multi-source phenotypic data, simultaneous extraction of multiple morphologic traits, and cost-effectiveness. However, challenges such as low accuracy, complexity of analysis, and limitations in mesh analysis need to be addressed to fully leverage the potential of 3D technologies in plant phenotyping.

In this research, we employ structured light (SL) technology, which is widely used for imaging 3D data. SL employs specific patterns, such as grids or horizontal bars, in a defined temporal sequence. Each pattern change is captured by the camera. By using a predetermined camera–projector setup, the deformation of these patterns is measured to link 2D points with their corresponding 3D information [30,31]. SL setups, typically large and time-consuming in image acquisition, necessitate the movement of either the object or the measurement system for comprehensive coverage. Commonly implemented in industrial applications for reverse engineering or quality control, SL provides high resolution and accuracy within a substantial measurement volume [32].

2. Materials and Methods

When conducting this study, a diverse array of software programs, programming languages, and libraries were employed to address various computational and analytical needs:

- Jamovi (ver. 2.4) software: This was utilized for statistical computations [33].
- R language: In addition to Jamovi, it was also employed for statistical analyses [34].
- Python programming language: This was used for the development and implementation of algorithms.
- Libraries: Open3D (ver. 0.17) was pivotal in processing point cloud data, offering advanced functionalities for 3D modeling and object detection. NumPy (ver. 1.26) was used for data manipulation and computational tasks. PyQt5 (ver. 5.15.10) enabled the creation of intuitive graphical user interfaces.

2.1. Acquisition of Fruit Measurements Using the Manual Method

The study meticulously focused on Japanese quince fruits (*Chaenomeles japonica*) cultivated and harvested for analytical evaluation at LatHort, an orchard situated in Dobele within the southern region of Latvia. These fruits were strategically planted in the spring of 2019, with its precise geographical coordinates being WGS84 56°37′335″ N, 23°33′233″ E, ensuring a consistent and controlled environmental setting for growth.

In 2022, a comprehensive evaluation was conducted on eleven distinct genotypes of *Chaenomeles japonica* at LatHort. This assessment primarily revolved around two phenotypical parameters of the fruits: their length and width, both measured in millimeters. Notably, the width of each fruit was meticulously measured at its thickest point to ensure accuracy and consistency. This measurement process was conducted using a calliper.

2.2. Three-Dimensional Data Acquisition and Postprocess

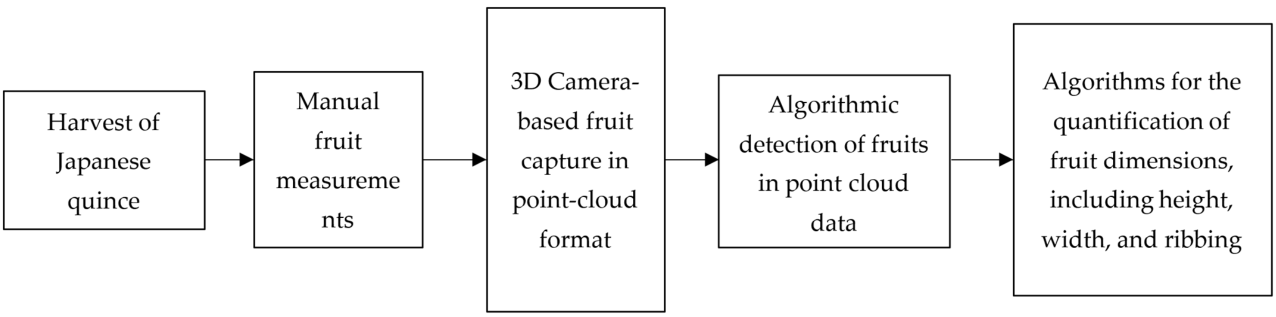
In this study, Japanese quince samples were systematically arranged on a flat surface in a fixed position to ensure consistency in data capture. A key aspect for achieving optimal results was maintaining a fixed distance between the camera and the objects. The experiment involved placing 30 fruit samples on a plate arranged in a 4×8 grid, with each point cloud encompassing 30 samples of a particular species. In total, 22 point clouds were captured using the Zivid One+ Medium camera (Zivid, Oslo, Norway) positioned at a fixed location and operated via the Zivid Studio program [35]. Notably, every alternate point cloud represented a repeated capture of a specific fruit variety, leading to the analysis of 11 unique point clouds.

The Zivid One+ Medium camera is adept at capturing both RGB and depth information and is particularly suitable for small-to-medium objects within a range of 0.6 m to 2.0 m. The precision of this camera ranges from 0.06 mm to 1.0 mm, depending on the distance. This camera employs structured light 3D technology, an effective method for accurate 3D imaging. All captured point clouds were saved locally and, without any preliminary data processing, were directly loaded into the Python environment using the Open3D library for subsequent analysis.

This methodology harnesses the potential of three-dimensional point cloud data to facilitate precise measurements. The core of this system is anchored in the utilization of three sophisticated algorithms: the k-nearest neighbors algorithm (k-NN), the "Imaginary Square" algorithm, and a unique method involving object projection analysis on a reference plate.

1. The k-NN algorithm, renowned for its efficacy in pattern recognition [36], is specifically employed for color differentiation within the dataset. A fundamental prerequisite for the application of the k-NN algorithm is the initial training phase, wherein the algorithm is exposed to multiple color samples representative of the target object. This process is crucial for enabling the algorithm to discern and subsequently exclude background and irrelevant data points based on the defined color parameters of the object, in this case, Japanese quinces. For objects exhibiting a spectrum of colors, each distinctive hue is incorporated into the classification scheme to ensure comprehensive identification.
2. In scenarios involving multiple fruits within a single point cloud, the need for discrete object detection becomes paramount. The "Imaginary Square" algorithm is ingeniously designed to address this challenge. Initiated at the point of maximum 'y' value within the point cloud, this algorithm progressively expands a conceptual square, encompassing an increasing number of data points. The expansion of the square continues as long as a sequential increase in data points is observed. The termination of square growth occurs upon reaching a plateau in point increment, suggesting the potential identification of an object. However, if objects are in close proximity, the algorithm may erroneously perceive them as a singular entity. To circumvent this, defining an upper limit on the object size becomes essential, beyond which further expansion of the square is deemed unnecessary.
3. The third algorithm pivots on the concept of projecting the object onto a base plane. This is achieved by a reverse application of the k-NN algorithm, where the focus shifts from the object to the background. This reversal aids in the identification of outlier points delineating the base projection of the object. The inherent limitation of 3D imaging in capturing the area obscured by the fruit results in voids within the point cloud, which, in this context, represent the base projection of the fruit. The analysis commences in the region defined by the "Imaginary Square" algorithm, with each projection being scrutinized individually. This involves identifying the point with the maximum 'y' value on the projection perimeter and generating an 'analysis point' from which four vectors extend to the nearest perimeter points. This procedure, potentially iterated with slight adjustments to the analysis point, furnishes a detailed understanding of the projection's perimeter, thereby inferring the spatial dimensions of the object situated above.

Such an integrated approach, combining color differentiation, spatial segregation, and projection analysis, presents a robust framework for accurately determining the dimensions of fruits, an advancement that holds significant promise in the field of precision agriculture. Scheme 1 illustrates the comprehensive pipeline for the phenotyping process.



Scheme 1. Phenotyping pipeline utilizing 3D camera technology for Japanese quinces.

2.3. Experiment Conditions and Specifications

Ambient light under perfect conditions for the 3D Zivid One+ camera (Table 1) was 0 lux. The brightness of the camera was high enough to ensure the capturing of a quality scene in any ambient light. Point clouds were not calibrated to physical units. We had to convert point cloud units to physical units (cm). Our task was to perform radiometric and geometric calibrations on the imagery to convert digital number (DN) values to reflectance values. This involved correcting for sensor-specific characteristics and atmospheric conditions. Plant size was computed based on the number of pixels after image classification.

Table 1. Zivid One+ camera specifications.

Projector brightness	0.25x to 1.8x; 1x = 400 lumens
The field of view angle	0 (Directly above)
Resolution	1920 × 1200 (2.3 Mpixel), Native 3D Color
Point cloud output	3D (XYZ) + Color (RGB) + SNR
Exposure time (minimum per pattern projection)	6.5 ms
Focus distance	1000 mm
Optimal working distance	700 to 1500 mm
Camera distance from objects	1000 mm
Field of view	702 × 432
Spatial resolution	0.37 mm and 3.71×10^{-4} mm per distance (z)
Capture time	200 ms
Point precision in Euclidian distance	110 µm
Local Planarity Precision in Euclidian distance	190 µm

3. Results

3.1. Characterization of Japanese Quince Fruit Parameters Using Manual Measurement Techniques

The evaluation of Japanese quince fruit parameters was conducted with the specific objective of acquiring comparative data to align with parameters derived from 3D imaging techniques. This exercise involved the meticulous manual measurement of key phenotypical parameters, which are closely related to the methodology employed in 3D analysis. These parameters were measured using traditional manual methods, specifically utilizing a calliper for precision. The detailed results of these manual measurements are systematically presented in Table 2. This comparative approach is instrumental in validating the accuracy and reliability of 3D imaging techniques by juxtaposing their results with those obtained through conventional manual measurement methods.

Furthermore, a diverse range of genetic phenotypes of fruits, encompassing varieties such as Ada, Alfa, Darius, Rasa, Rondo, and the SR1 series (SR1-1 through SR1-6), is vividly illustrated in Figures 1 and 2 and extensively described in Table 3. Each of these phenotypes represents a unique genetic profile, offering a rich tapestry of variation within the species. To ensure consistency and optimal visual representation, all fruits were carefully photographed at the peak of their ripeness. This timing was meticulously chosen to capture the fruits in their fully matured state, thus providing a clear and accurate visual comparison of the different phenotypes.

Table 2. Measurements of Japanese quince fruits using the manual method.

	Genotype	Fruit Length (mm)	Fruit Width (mm)
N	Ada	30	30
	Alfa	30	30
	Darius	30	30
	Rasa	30	30
	Rondo	30	30
	SR1-1	30	30
	SR1-2	30	30
	SR1-3	30	30
	SR1-4	30	30
	SR1-5	30	30
	SR1-6	30	30
Median	Ada	49	47
	Alfa	40	44
	Darius	37	42
	Rasa	44	52
	Rondo	46	47
	SR1-1	45	47
	SR1-2	40	47
	SR1-3	43	50
	SR1-4	37	40
	SR1-5	43	45
	SR1-6	46	47
Standard deviation	Ada	4	3
	Alfa	3	2
	Darius	4	4
	Rasa	4	4
	Rondo	6	4
	SR1-1	6	3
	SR1-2	3	3
	SR1-3	4	4
	SR1-4	4	3
	SR1-5	4	3
	SR1-6	4	3

Figure 1. Genotypes of Japanese quince species: Ada (**A**), Darius (**B**), Rasa (**C**), Rondo (**D**), SR 1-1 (**E**), and SR 1-2 (**F**).

Figure 2. Genotypes of Japanese quince species: SR1-3 (**A**), SR 1-4 (**B**), SR 1-5 (**C**), SR 1-6 (**D**), and Alfa (**E**).

Table 3. Characterization of Japanese quince fruits.

Genotype	Average Fruit Weight (g)	Maximum Fruit Weight (g)	Characteristics of the Fruit
SR1-1	53	130	Round and slightly flattened with a smooth surface, exhibiting mild ribbing and a notably deep inflorescence.
SR1-2	45	78	Bright yellow and homogeneous in appearance, these are barrel-shaped with significant puncture and rust characteristics.
SR1-3	64	122	Dark yellow, round, and slightly flattened; characterized by prominent red dots and brown dotted rust; they also display a ribbed texture.
SR1-4	34	71	Predominantly bright yellow, round, and barrel-shaped, with some assuming a pear-shaped (pyriform) form. They have a very smooth surface and are mostly free from puncture.
SR1-5	42	110	Yellow, round, and barrel-shaped with a smooth texture; slight ribbing at the tip, aesthetically pleasing, and with a few red dots; near the inflorescence, there is slight brown rust.
SR1-6	56	105	Smooth, attractive, and yellow, varying from round or oval, to bottle-shaped. Some exhibit pronounced red dots and slight russeting in the form of small brown dots or stripes.
Rasa	48	75	Yellow and rounded, exhibiting mild ribbing. In some years, they assume a pear-shaped (pyriform) appearance.
Darius	34	45	Oblong and yellow, characterized by a smooth and homogeneous surface.
Rondo	52	67	Yellow and oblong, featuring a deep flower bed and generally homogeneous in appearance.
Ada	55	78	Dark yellow with a pink wreath, oblong, and maintaining a homogeneous texture.
Alfa	53	67	Yellow with pronounced rust spots, rounded, slightly ribbed, and featuring a deep flower bed.

3.2. Characterization of Japanese Quince Fruits Utilizing a 3D Imaging-Based Methodology

This section presents data acquired through 3D camera imaging, subsequently processed using the algorithms detailed in the Methodology section. The scans encompass the same species and quantity of fruits as those measured manually, ensuring a direct comparison. Statistical analyses of the 3D scanned and postprocessed data have been conducted to provide a comprehensive understanding of the fruits' characteristics (Table 4).

Table 4. Characterization of Japanese quince fruits utilizing a 3D imaging-based methodology.

	Genotype	Fruit Length (mm)	Fruit Width (mm)
N	Ada	19	19
	Alfa	19	19
	Darius	15	15
	Rasa	23	23
	Rondo	20	20
	SR1-1	16	16
	SR1-2	29	29
	SR1-3	25	25
	SR1-4	29	29
	SR1-5	17	17
	SR1-6	29	29

Table 4. *Cont.*

	Genotype	Fruit Length (mm)	Fruit Width (mm)
Median	Ada	48	46
	Alfa	42	46
	Darius	38	41
	Rasa	45	50
	Rondo	50	46
	SR1-1	42	48
	SR1-2	39	39
	SR1-3	45	48
	SR1-4	39	42
	SR1-5	50	48
	SR1-6	46	46
Standard deviation	Ada	3	4
	Alfa	3	4
	Darius	2	4
	Rasa	5	5
	Rondo	10	6
	SR1-1	2	6
	SR1-2	3	7
	SR1-3	3	4
	SR1-4	4	4
	SR1-5	3	6
	SR1-6	5	3

In its turn, Table 5 presents a comparative analysis, showcasing the numerical differences between the ground truth—represented by manual measurements—and the data obtained through the 3D-based methodology. This table serves as a critical tool for evaluating the accuracy and precision of the 3D imaging technique in relation to traditional manual measurement approaches.

Table 5. Comparative analysis of fruit dimensions: manual calliper-derived ground truth measurements versus 3D data estimations for length and width across various genotypes.

	Genotype	Fruit Length (mm)	Fruit Width (mm)
Median	Ada	−2	3
	Alfa	−3	0
	Darius	−2	2
	Rasa	0	−1
	Rondo	−7	2
	SR1-1	3	−2
	SR1-2	2	6
	SR1-3	−3	2
	SR1-4	−2	−3
	SR1-5	−5	−5
	SR1-6	0	1

Table 5. *Cont.*

	Genotype	Fruit Length (mm)	Fruit Width (mm)
Standard deviation	Ada	4	3
	Alfa	5	4
	Darius	3	6
	Rasa	5	4
	Rondo	13	6
	SR1-1	5	5
	SR1-2	4	6
	SR1-3	4	3
	SR1-4	3	4
	SR1-5	4	5
	SR1-6	5	3

Figure 3 presents a concise visual comparison between manual measurements, which serve as the ground truth, and the data acquired from 3D imaging techniques. This juxtaposition effectively highlights the variances and correlations between these two measurement methodologies.

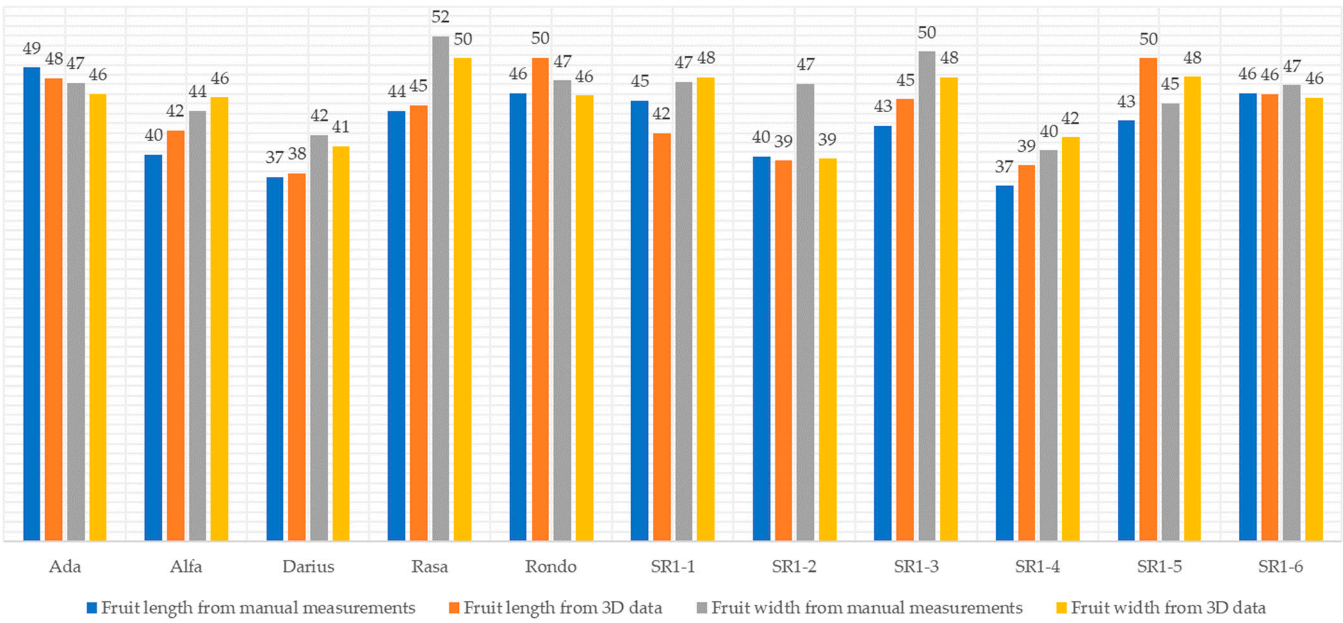


Figure 3. Comparative analysis of fruit parameters: manual versus 3D data-based measurement techniques for length and width assessments (mm).

Figure 4 displays the distribution of points in the point cloud generated from the 3D scanner. Care was taken to place all fruits while maintaining a consistent distance between them, estimated visually. Additionally, efforts were made to preserve the same angle and orientation for each fruit wherever feasible, ensuring uniformity in the scanning process.

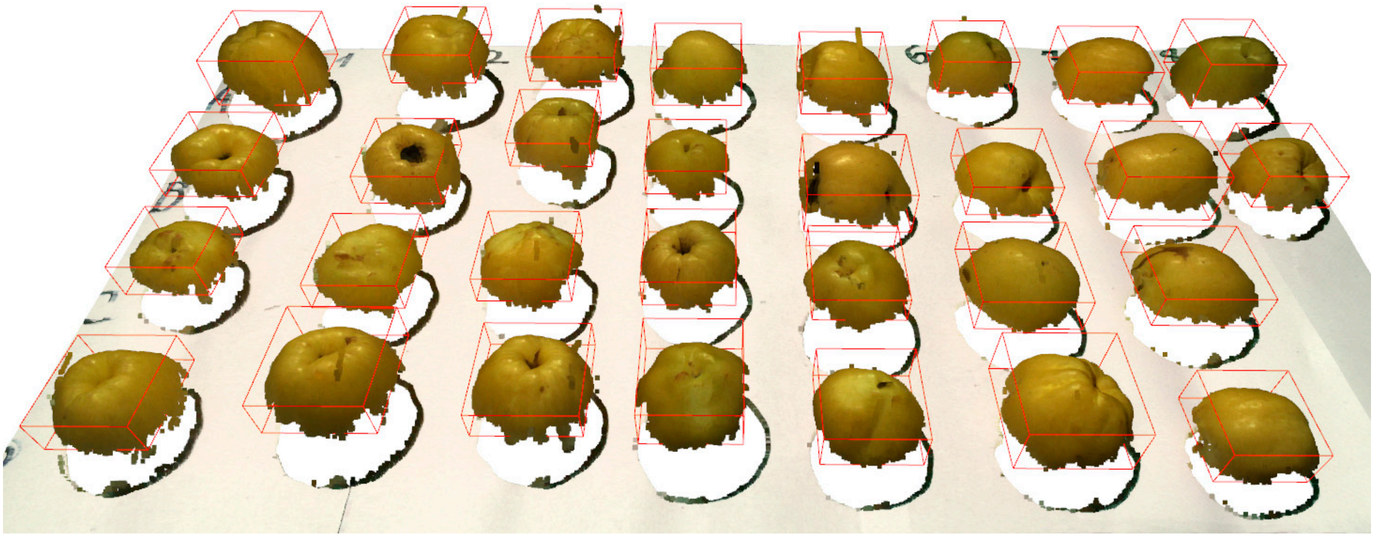


Figure 4. Volumetric data of various Japanese quince species captured using a 3D camera.

The program was developed to facilitate the automation of all preprocessing steps and associated calculations, as depicted in Figure 5.

Figure 5. Graphical user interface (GUI) of the developed program based on PyQt5.

4. Discussion

The analysis revealed that the data obtained from the 3D scanner, which was later utilized in calculations, unfortunately lacked the desired level of precision and accuracy when compared to the results from manual methodologies. It was evident that the effectiveness of 3D data calculations varied significantly among different species, with some experiencing a notably low rate of successful scans. This inconsistency in successful scanning adversely affected the algorithm's ability to accurately calculate fruit length and width. Furthermore, the limited number of successful samples from the 3D scans had a substantial impact on the standard deviation, indicating variability in the data. A primary concern highlighted in this study is the low rate of successfully processed 3D data, particularly in terms of the final calculated parameters of the fruits. This issue underscores the need for further refinement of 3D scanning techniques to enhance their reliability and accuracy for such applications.

This study represents a pioneering effort in exploring the phenotyping of Japanese quince using 3D technologies, an area where modern research is notably sparse. The algorithms developed herein demonstrate promising potential; however, they require further refinement to match the efficiency and accuracy of traditional manual methods. The exploration should not be confined to the current methodologies alone. Incorporating additional novel 3D scanning techniques, along with the integration of artificial intelligence, could provide a more comprehensive insight into the most effective approaches for this specific species. This broader approach is critical for advancing our understanding and capabilities in precision agriculture, particularly for Japanese quince phenotyping [23]. However, the understanding of limitations within the study is paramount for a comprehensive understanding of the tool's applicability and scope. Two primary constraints have been identified:

Inherent variability in fruit positioning: One of the salient limitations arises from the inability of the tool to uniformly calculate measurements for all fruits. This challenge is predominantly due to the variable positioning of fruits on the scanning platform. The irregular morphologies of different fruits often result in their placement at diverse angles on the scanning board, thereby complicating the uniformity of measurement. This angular variance can significantly affect 3D point cloud data interpretation, leading to potential discrepancies in dimensional assessment. The irregular orientation of the fruits introduces a degree of spatial heterogeneity that the current algorithmic framework struggles to normalize, thereby restricting the tool's efficacy in uniformly measuring fruits with complex or asymmetrical shapes.

Proximity-induced measurement challenges: A second limitation pertains to the difficulty in accurately distinguishing and measuring individual fruits when they are in close proximity to one another. In instances where fruits are positioned adjacent to each other, the tool's algorithms may erroneously interpret them as a singular entity. This conflation is primarily a consequence of the overlapping spatial data points in the 3D point cloud, which the system fails to segregate into distinct fruit entities. This limitation is particularly pronounced in densely packed fruit arrangements where the physical boundaries between adjacent fruits are minimal, leading to significant challenges in individual fruit identification and measurement.

It is crucial to enhance the algorithms to more accurately discern and measure fruits in varying spatial orientations and close proximities. This enhancement would involve refining the tool's capabilities to differentiate individual fruits, even when they are clustered closely together or obscured by foliage and other environmental factors. Such refinements could include advanced image processing techniques, improved depth perception algorithms, and more sophisticated machine learning models that are trained on a diverse set of scenarios representing different fruit orientations and clustering patterns.

Moreover, the challenges of the use of 3D technologies in horticulture extend beyond just the algorithmic enhancements. These encompass a range of issues, such as the scalability of these technologies for large-scale agricultural settings, their integration with existing agricultural management systems, the cost-effectiveness of their deployment, and their robustness under different environmental conditions. Each of these aspects presents unique challenges that require dedicated research and development efforts [37]. Addressing these challenges is indeed critical to expanding the applicability and reliability of 3D scanning tools in a variety of fruit measurement scenarios. This will not only facilitate more accurate phenotyping and breeding decisions but also enhance yield estimation, quality control, and disease detection in agricultural practices. It will allow for more precise and efficient agricultural operations, ultimately contributing to sustainable and productive farming practices, as non-destructive measurement techniques are pivotal in fruit phenotyping, providing superior advantages over traditional destructive methods. Currently, our research necessitates harvesting the fruit for analysis, but we are actively working towards enhancing our methodologies to transition to non-destructive approaches allowing for non-invasive, repeated quality assessments of individual fruits, thereby reducing waste and enhancing efficiency [38]. In contrast to the time-consuming nature of destructive methods, non-destructive techniques facilitate rapid, accurate analysis of fruit internal quality, essential for maintaining consistent product standards [39]. The advent of advanced electronics and computing has spurred the development of diverse non-destructive tools like NIR, NMR, X-ray, computed tomography, and ultrasound, proving invaluable in commercial harvest, handling, distribution, and breeding programs for their cost-effectiveness and efficiency [40]. Additionally, the use of non-destructive spectroscopy for pigment assessment in supply chains exemplifies the broad applicability of these techniques in ensuring fruit quality across various stages. We are currently planning to adopt these innovative, non-destructive methods into our research, a move that could revolutionize fruit phenotyping by enabling more precise, efficient, and sustainable quality assessments and thereby significantly benefit postharvest processes and breeding programs.

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