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Portable device for contactless, non-destructive and in situ outdoor individual leaf area measurement

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ABSTRACT

Plant phenotyping is a research area concerned with the quantitative measurement of a plant's structural and functional properties. In the case of measuring a leaf's surface area, it is more often than not laborious as well as stressful to the plant. In this paper, we present the use of the RGB-D sensor, Kinect v2 as part of a portable device for non-destructive measurements of individual leaf areas (cm^2/leaf) outdoors in daylight. The Kinect v2 was utilized to capture a single viewpoint 2.5D frame of plant foliage. An unsupervised clustering method, HDBSCAN was used to segment out individual leaves from the captured 2.5D frame of the subject plant. Performance of the leaf segmentation was measured by evaluating the 10 nearest (max) clusters from the sensor for each frame into 3 different categories, individual leaves (non-occluded, occluded), under-segmented and over-segmented. Probability of segmenting individual leaves differs from plant to plant, ranging from a low of 0.7178 to a high of 0.8975. The surface area of all individual non-occluded leaves obtained via the segmentation method was calculated and compared to its ground truth. The calculated individual leaf surface areas R^2 was recorded to range from 0.792 to 0.911 with respect to its best fit regression line while the RMSE range from 4.9482 to 14.4941 cm^2. The proposed system and method was shown to be capable of segmenting individual leaves from dense foliage and measuring its surface area.

1. Introduction

Plant phenotyping refers to the quantitative measurement of a plant's anatomical, ontogenetical, physiological and biochemical properties. It plays a very critical part in plant management, ranging from agronomy to plant breeding (Walter et al., 2015). More specifically, the study measuring plant total leaf area were linked to performance measurements of plant mechanisms such as radiation interception, water and energy exchange, crop growth and bio productivity of its parent plants (AiPing et al., 2013). In addition to that, studies by (AiPing et al., 2013; Gyves et al., 2008) indicated that measuring individual leaf surface area can be useful to provide a wide range of information for plant growth studies and plant-environment interactions. Common methods for individual leaf area measurement of outdoor crops require a lot of human labour and is time consuming as demonstrated by (Córcoles et al., 2015). Therefore, there's great interest in the development and implementation of less labour intensive methods to measure a plant's phenotypic traits, in particular using imaging and image processing as reported in (Dhondt et al., 2013). This research is specifically focused at measuring a plant's individual leaf surface area (cm^2/leaf) using a vision-based system.

1.1. 2D Imaging

Advancement in computer vision provide great opportunities for developing new methods to collect information on plants. Fixed setups utilizing 2D sensors like a camera or scanner (Lin et al., 2014) required removal of leaves from its parent plant. Non-destructive leaf area measurement using a camera as done by (Baker et al., 1996) required a fixed camera pose relative to the target leaves which was placed over a reference background. To overcome this issue, (AiPing et al., 2013) paired an ultrasound sensor with a camera to measure individual leaf surface area. However, the leaf-of-interest still needs to be placed over a reference background and the system cannot handle occlusions.

1.2. 3D Imaging

As discussed previously, there are limitations regarding 2D vision

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systems. Those limitations can be overcome by utilizing 3D positional data which can be obtained using depth sensors.

1.2.1. 2.5D Sensors

One of the common depth sensors are stereo-vision (SV) and time-of-flight (ToF) sensors. ToF has been used in a hybrid system (Alenya et al., 2013) with a color camera for plant probing. Due to older ToF sensor's low resolution, it cannot be used as a standalone sensor for plant phenotyping but complements the 2D camera with depth information.

Researches by (Xiong et al., 2017; Li et al., 2017) used SV to capture 2.5D point cloud of plants for plant phenotyping. In (Xiong et al., 2017), the authors highlighted the weakness of SV related to stereo-image mismatch due to the lack of texture. Both researches highlighted the slower processing time for obtaining real-time depth data compared to active depth sensors like the ToF. This concurs with the results obtained by comparing SV and ToF sensors of (Kazmi et al., 2014).

Comparison between SV and ToF for monitoring plant leaves done by (Kazmi et al., 2014) showed SV was more robust to different lighting, particularly with regards to sunlight and has a higher resolution than the ToF. The higher resolution of the SV preserved edge discontinuity better. Plus, the ToF sensor's low resolution also required for closer range observations to reduce SNR. However the ToF sensor was proven to be better at extracting the leaf shape, runs at a higher frame rate and was more robust to object texture.

Affordable consumer grade RGB-D sensors like the Kinect v1 has been used effectively in various crop husbandry practives such as 3D scanning plant organs for measurements (Paulus et al., 2014). For such applications, the Kinect v1 was utilized under little to no external NIR interference agreeing with the work by (Kuan et al., 2019) that Primesense-based sensors cannot work in significant natural sunlight NIR interference. Kinect v1 was used for in situ individual leaf segmentation and area measurement by (Xia et al., 2015), focused on a single plant type in a controlled greenhouse lighting setting. Authors state that the Kinect v1 functioned admirably for measuring plant physical trait but suffers due to limited accuracy, precision and spatial resolution leading to the sensor missing out small sized objects and gaps which can frustrate leaf segmentation.

Older generation ToF sensors were limited due to its low resolution and high cost. ToF sensor's resolution have been improving while its cost continue to drop making it more viable for use in agricultural monitoring and management applications. For example the Kinect v2, a ToF-based consumer sensor was used as a standalone sensor by (Li et al., 2018) to capture depth images of plants indoors. The authors determined from the results of their individual leaf segmentation method that the Kinect v2 was capable at capturing accurate plant point cloud.

There were recurring weaknesses of single viewframe 2.5D image of plants. First is the incomplete 3D plant model stemming from the limited viewpoint of the subject plant and significant plant organ occlusion. Next, is the change in point density with distance from sensor.

1.2.2. 3D Scanning - 2D/2.5D Sensors

This section lists methods to obtain full 3D models of plants from many different viewframe as opposed to just a 2.5D point cloud. By capturing images (depth or color) of plants from various viewpoints, a more complete 3D model of the plant can be reconstructed. This is applicable when utilizing 2D or 2.5D sensors and LiDAR-based sensors.

There are two general methods used to obtain multiple viewpoint images of a subject. First is with fixed rigs such as a multi-camera setup or a single-camera setup and a turntable. These setups provide the benefit whereby the camera poses relative to each other and the test subject are known beforehand. In order to reconstruct 3D plant models, (Golbach et al., 2016) used shape-from-sihouette method while multi-view stereo (MVS) method was used in (Zhang et al., 2016). Based on (Golbach et al., 2016), shape-from-silhouette was faster than other 3D reconstruction methods but at the expense of the quality of the plant's 3D model. Common issues related to MVS from (Zhang et al., 2016) were the high computational cost, difficult to use in uncontrolled lighting situations and large unportable setups.

Second is moving a single color camera around the subject to capture from different viewpoints. Due to the unfixed setup of the camera, the camera poses for each captured images respective to each other and the subject need to be calculated. Structure-from-motion (SfM) was used to infer camera pose and to reconstruct the subject plant from images captured from 360^{o} around the plant (Itakura and Hosoi, 2018). Meanwhile (Pound et al., 2016) used a 2 step-method for 3D plant model reconstruction; SfM for inferring camera poses and MVS for 3D reconstruction. The aforementioned works relate the successes of their plant organ segmentation and measurement as indicators that the obtained 3D plant reconstructed models were accurate. These methods are less restrictive than the traditional MVS setups but require manual maneuvering of the camera around the target subject and the computational power to generate the 3D model using the camera images.

1.2.3. 3D Scanning - Terrestial Laser Scanners

Terrestial laser scanners (TLS) is a ToF-based laser scanning (LiDAR) sensor that was used by (Yun et al., 2017; Li et al., 2018; Xu et al., 2019) to 3D scan plants and mid size trees outdoors for quantifying plant physical traits. TLS was placed on tripods in multiple location around the subject plant to obtain point cloud of the subject plant from various viewpoints. The point clouds are then stitched together with a co-registration method, obtaining an extremely accurate 3D model of the plant. TLS have much longer range than any other 2.5D sensor and outputs a very high density scan necessary for capturing small objects such as leaves. However, TLS are expensive and suffer from foliage jitters due to winds causing noise and ghost points in the captured point cloud. RPLiDAR sensor, a cheaper variant of LiDAR sensors was used to 3D scan plants indoors in (Wang et al., 2017). However it is less accurate, shorter ranged and only effective indoors.

As with other 3D scanning methods, TLS also suffer from the loss of point density with distance albeit less due to its larger operational range. All 3D scanning methods will suffer from self-occlusion issues due to the complex structure of plants. 3D reconstructing an object/scene using information from the different sensor viewpoints not only takes time to set-up to capture but are computationally expensive to merge in order to output the final 3D point cloud. For certain applications, there isn't a need for completely 3D scanning plants which can be time consuming and impractical to setup.

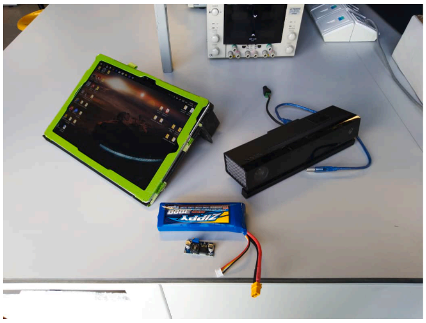
The research objective was to develop a portable point-and-shoot-then-analyze device for non-destructive measurement of leaf area outdoors in daylight. The device must be able to capture plant point clouds outdoors, segment out individual leaves from the point cloud and measure its surface area. Based on the aforementioned literature review, there are some current gaps in the literature. One, utilizing a consumer-grade RGB-D sensor as part of a hand portable system to measure individual leaf surface area outdoors in daylight. Two, develop a data processing pipeline that do not require difficult parameter tuning and is capable of segmenting individual leaves from plant point cloud without the need of any training stage which would require a large training dataset. This research work aims to address these gaps.

2. Materials and Methods

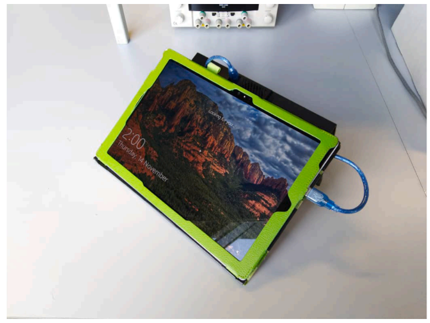
2.1. Hardware Platform

The prototype device is a point-and-shoot-then-analyze system for onsite measurement of individual leaf surface area outdoors in daylight. Fig. 1a, b shows the prototype portable device that was used to capture RGB-D image of various plants, process the acquired raw data, segment out individual leaves and measure its surface area. The device is divided into three key individual component devices.

Three different RGB-D sensors, Asus Xtion Pro Live, Kinect v2 and the Intel R200 capable of capturing depth data at high frame rates were



(a) Device setup break down of the portable 2.5D imaging device



(b) Device setup for utilizing the Kinect v2 as a portable 2.5D imaging device

(c) Device used in-field to capture a 2.5D point cloud of a subject plant's ROI

Fig. 1. Finalized Device for Measuring Leaf Area In-Field.

considered. Given that these sensors are consumer-grade devices, the sensors were relatively cost effective when compared to professional depth sensors at the time of purchase, costing between $100 to $220 each. All three sensors utilizes different methods to obtain depth information, namely structured light (Asus Xtion), active SV (R200) and ToF (Kinect v2). Both the Kinect v2 and the Asus Xtion was designed for an indoor use case while the Intel R200 was designed to be able to work indoors and outdoors under sunlight. Despite that, results from our prior work (Kuan et al., 2019) showed that the Kinect v2 was able to outperform both the Asus Xtion and Intel R200 at capturing dense surface data outdoors under various levels of sunlight as well as indoors. Based on that, we selected the Kinect v2 as the primary sensor for integrating into the prototype device to capture dense surface depth data of plants.

The Kinect v2 was packaged with a Surface Pro 4 and an external battery. The Surface Pro 4 runs Windows 10 with the necessary software required to perform the capture and process 3D data. The Kinect v2 was modified to take in a 12 V DC input from a portable source. To provide the required power to the sensor, a 11.1 V, 3000mAh Li-Po battery was used in conjunction with a step-up adjustable DC-DC switching boost converter to provide a consistent 12 V DC power input.

3. Methodology

3.1. Experimental Setup

3.1.1. Experimental Conditions

This research work was centered on putting together a portable hand-held platform for contactless measurement of individual leaf surface area outdoors. In order to evaluate the device's robustness in difficult situations, the device was used to capture RGB-D images of plants outdoors during midday without any artificial shade. As previously mentioned, the chosen RGB-D sensor, the Kinect v2 was shown to be able to capture dense surface depth data under those conditions. However there were some limitations with regards to its precision and working effective range (for more details, refer to our prior work in (Kuan et al., 2019)).

However, depending on cloud cover and natural shades, the lux range may vary even though the period of testing was roughly set around midday. General testing of lux ranges at several experimental locations where subject plants were located showed that with light-medium canopy cover during a clear midday, lux ranges from 10–25 kLux. That measured lux range corresponds to medium–high cloud cover during midday within the experimental location as shown from our prior work (Kuan et al., 2019). Given the availability and location of subject plants as well as the intermittent weather (cloud cover) during the experimental period, it was decided that capturing RGB-D images of plant foliage with the developed device would be done at midday within the lux range of 10 to 25 kLux. Lux range was measured with a lux meter in proximity to the observed plant foliage.

3.1.2. Experimental Subjects

Each frame captured of each and every plant of different type must be independent. Given that parameter and the availability of plants in the testing environment, 6 variety of plants species were used as test subjects. Specifically the plants used were mulberry (*Morus rubra*), jackfruit (*Artocarpus heterophyllus*), mango (*Mangifera.*), council tree (*Ficus altissima*), hibiscus (*Hibiscus rosa-sinensis*), queen's crape-myrtle (*Lagerstroemia speciosa*).

For each species of plant, a minimum of 10–15 independent RGB-D frames were captured. The number of frames for each plant species was listed in Table 1.

3.1.3. Data Capture

As the platform was designed to be used as a hand-held device, all plant point clouds were captured from a variety of angles relative to the user depending on the location of the region-of-interest (ROI) of a subject plant. The ROI must be roughly centered within the Kinect v2's viewpoint. Therefore, if the ROI was at ground level, it would be captured from a relatively top-down view as shown in Fig. 1c. Conversely, if the ROI is higher, it can only be captured by the user from the side. It is also important to highlight that the plant point cloud was captured such that the leaves-of-interest within the captured ROI of a plant were relatively front-facing with regards to the Kinect v2 sensor and at the very minimum 0.7 m away (minimum effective distance of the Kinect v2).

Depth and color image frames were captured from the Kinect v2. The depth image has a narrower field of view than the color image. RGB image has a 1080p resolution while the depth image comes in at 512 x 424 resolution.

3.2. Data Processing Pipelines, Analysis and Evaluation

There are 3 general stages of the entire pipeline from grabbing frame of sensor and pre-processing the data to cluster-segmentation and finally surface reconstruction and measurement. These steps are shown in detail in Fig. 2.

3.2.1. Data Pre-processing

The depth and color image frames captured from the Kinect v2 were correlated and merged to obtain a single view 512 x 424 RGB-D point cloud of scene with position and color data. All further data pre-processing and analysis works directly with the point cloud data.

Filtering: The obtained raw point cloud data will be passed through a series of filtering process to remove unwanted data points such as those too far from the sensor as well as Kinect v2-related artifacts and data outliers.

Table 1
Result of Leaves Segmentation (Probability of Leaf Segmentation - Individual Leaf, Over-segmented, Under-segmented).

	Mulberry - 15 Frames				Jackfruit - 10 Frames			
		Probability		Avg. Leaves (Under-Seg)		Probability		Avg. Leaves (Under-Seg)
	Ind. Leaf	Over-Seg	Under-Seg		Ind. Leaf	Over-Seg	Under-Seg	
Mean	0.8805	0.0333	0.0862	2.5	0.82	0.03	0.15	3.1852
Std Dev.	0.0769	0.0699	0.0823	0.9428	0.0748	0.0458	0.0922	1.3436
	Council tree - 10 Frames				**Queen's crape-myrtle - 10 Frames**			
		Probability		**Avg. Leaves (Under-Seg)**		**Probability**		**Avg. Leaves (Under-Seg)**
	Ind. Leaf	**Over-Seg**	**Under-Seg**		**Ind. Leaf**	**Over-Seg**	**Under-Seg**	
Mean	0.8975	0.04	0.0625	2.4	0.7178	0.03	0.2522	3.9333
Std Dev.	0.1186	0.0917	0.0515	0.7638	0.0964	0.064	0.0795	2.4857
	Mango - 10 Frames				**Hibiscus - 10 Frames**			
		Probability		**Avg. Leaves (Under-Seg)**		**Probability**		**Avg. Leaves (Under-Seg)**
	Ind. Leaf	**Over-Seg**	**Under-Seg**		**Ind. Leaf**	**Over-Seg**	**Under-Seg**	
Mean	0.83	0.03	0.14	2.0952	0.77	0.02	0.21	2.1481
Std Dev.	0.1005	0.064	0.12	0.2333	0.11	0.04	0.1221	0.5903

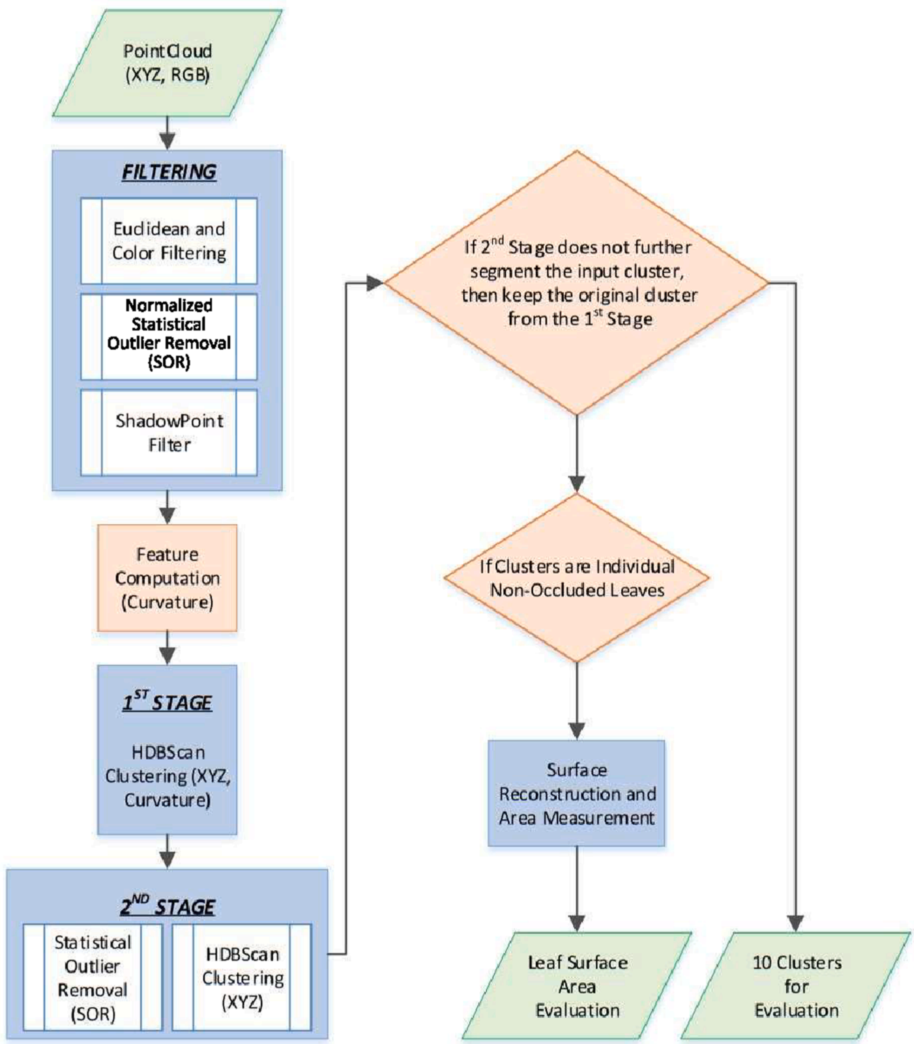


Fig. 2. Process Pipeline for Leaf Area Measurement. **(1)** *Filtering*, **(2)** *Feature Computation*, **(3)** *1st Stage [HDBSCAN - XYZ, Curvature]*, **(4)** *2nd Stage [SOR + HDBSCAN - XYZ]*, **(5)** *Surface Reconstruction*, **(6)** *Cluster-Segment Evaluation and Leaf Surface Area Measurement Evaluation.*

- Euclidean Filter: To crop out points in the point cloud that are too far away from the sensor in Euclidean space based on a user-set distance threshold on the X,Y and Z-axis.
- Color Filter: To remove data points from the captured plant point cloud based on its color using the user-set threshold of the point's color channels.

- ShadowPoint Filter: To remove ToF-based sensor (i.e Kinect v2) point data artifacts at object edges based on the angle between the point's normal vector and its coordinate vector from origin (sensor).
- Statistical Outlier Removal: Remove noisy sensor measurements and data outliers in the point cloud data based on the statistical analysis of the average distances of each point and its neighbors.

A more thorough description of these pre-processing and filtering steps is available in Section 4.1, since various parameters and thresholds were determined experimentally.

Feature Computation: Aside from the original Euclidean coordinate of X,Y,Z, the local curvature feature is also used. Small-sample testing of the employed method for individual leaf cluster-segmentation was used to identify this feature as being suitable for use.

Curvature is a scalar value that measures the amount a surface deviates from a flat plane or line. Curvature of each point can be estimated from its neighboring points and is calculated by first obtaining the covariance matrix for each point. The output surface curvature for a single point can be estimated from the eigenvalues of its calculated covariance matrix (Rusu and Cousins, 2011). Curvature data was calculated for each individual data point in the point cloud. The final features used for clustering were the point coordinates and the calculated curvature of each point.

3.2.2. Individual Leaf Segmentation

In order to extract plant leaf traits such as surface area, automatic leaf segmentation from the obtained 2.5D point cloud was essential.

Supervised methods used in previous works (Yun et al., 2017; Li et al., 2018) require labelled training datasets or templates for plant organ segmentation. Most supervised methods results in semantic segmentation, classifying plant point cloud to branches and leaves. In order to measure individual leaf area, there's a need to perform instance segmentation as opposed to semantic segmentation. Instance segmentation via supervised methods is harder to perform than semantic segmentation, requiring not only more volume but more details in the dataset. However, there's an unavailability of a large amount of labeled data-set for training due to the large number of plant subjects and species tested.

Plant foliage data was collected in situ in a single frame with no fixed positions. Therefore, there's no way to exploit the structural layout of the plants. Due to that, our focus was on utilizing unsupervised clustering methods which works without any pre-known structural layout of plant in order to segment out individual leaves such as in (Golbach et al., 2016; Li and Tang, 2017).

Therefore, an unsupervised clustering-based method was considered for the task. The experimental assumption for individual leaves to be clustered out from the larger plant point cloud is data-points correlating to each and every individual leaves are high density data-point islands amid a sea of sparser data-points (noise, outliers, artifacts) in the specified feature space. The plant point cloud would be cluster-segmented in a 4-D feature space covering the Euclidean coordinates and Curvature. Curvature data was used to differentiate surfaces that are in close physical proximity but have different surface curvature.

Each individual leaf's data points in this 4-D feature space forms high density islands which have some physical spatial separation (X,Y,Z) and/or surface curvature differences between each individual 'data-point islands' for successful cluster-segmentation of individual leaves from the plant point cloud.

Based on this assumption, an unsupervised density-based clustering method, HDBSCAN was chosen to cluster-segment out individual leaves from the point cloud. From (McInnes and Healy, 2017), the accelerated HDBSCAN has the following advantages over several other clustering algorithms:

- Doesn't assume clusters are globular/spherical
- Capable of clustering variable density clusters
- Not a partitioning algorithm, in that outliers and noise are not clustered.
- Intuitive algorithm parameters
- Relatively stable across runs, sub-sampling and small changes to parameters
- Fast

In the first stage, HDBSCAN was used to identify and segment out individual clusters from the point cloud in a 4-D feature space (X,Y,Z and Curvature). From there, clusters obtained from the first stage of HDBSCAN (XYZ, Curvature) was passed through a second stage which performs another round of SOR and HDBSCAN (XYZ). The second round SOR was applied to help remove more outliers and edge data points in euclidean feature space (X,Y,Z) to improve inter-leaf clusters physical separation of any undersegmented cluster obtained from the first HDBSCAN (XYZ, Curvature). After filtering, the cluster was passed through another round of HDBSCAN (XYZ) that was configured to identify and segment out individual clusters in a 3-D feature space (X,Y, Z). An important criteria in the second stage was to check whether the input cluster to the second stage gets further segregated into smaller clusters. If the cluster isn't further cluster-segmented, then the cluster (before the second SOR) was kept. HDBSCAN (XYZ) in the second stage was set up to be able to return single clusters.

Most of the subject plants have dense foliage which makes it difficult for a human analyzer to distinguish all the individual leaves due to high occlusion plus low color and depth contrast. Therefore, only the nearest 10 (maximum) clusters from the sensor for each captured frame of a plant were manually evaluated to be either an under-segmented cluster of leaves, an over-segmented leaf or an individual leaf.

3.2.3. Leaf Area Measurement

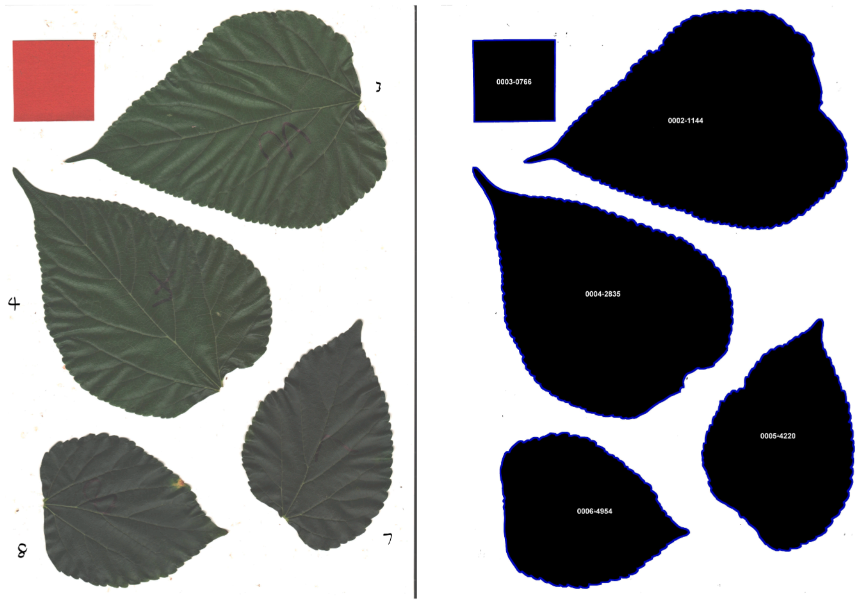
From the clusters obtained via the applied leaf cluster-segmentation method, only individual non-occluded leaf cluster surface areas were manually selected for its surface area to be measured. Each successfully segmented non-occluded leaves were first smoothed with a Mean Least Square (MLS) algorithm to improve surface reconstruction. Leaf surface was reconstructed with the Delaunay triangulation mesh reconstruction algorithm which was setup to reconstruct meshes with a limited edge size. The surface area of the leaves were calculated from summing the area of all the individual triangles that make up the entire surface mesh as shown in Fig. 6. Finally, the calculated leaf area was compared to its ground truth which was measured manually. Manual measurement of leaf size was done off-site destructively using a laser scanner and 2D image processing tool, ImageJ as shown in Fig. 3.

4. Results and Discussions

4.1. Data Capture and Pre-processing

Kinect v2 was more robust under a wider range of daylight illumination intensity opening up a larger variation of working conditions compared to its SL-based predecessor like the Kinect v1. However it can be seen from observations, there's an increase in data fluctuation and noise affecting the spatial resolution necessary for differentiating adjacent objects and surfaces when compared to indoors. These observations are supported by our prior work (Kuan et al., 2019). The quality of data returned by the Kinect v2 under experimental daylight conditions was clearly affected by sunlight but was still capable of producing relatively dense surface depth data of individual leaves of subject plants at closer ranges.

The precision and density of the depth data captured by the Kinect v2 was affected by the distance to the sensor. As the quality of depth data deteriorates with distance from sensor, an Euclidean crop filter in the XYZ was used to limit the field-of-view (XY) to ± 0.5 m and a depth-distance (Z) of 1.5 m from the sensor origin (0,0,0). The filter helps to trim distant imprecise data points and data points that are not within the



(a) Original Scanned Image **(b)** Binary Image - ROI and Labels

Fig. 3. Scanned Image of Leaves for obtaining manual measurements of leaf area using ImageJ software.

ROI of the subject plant and further away from the center of the frame.

The next step was to use a colour filter to remove all brown, black and grey coloured data points. This was done to filter out remaining brown-based wooden branches and grey-black shadow artifacts. From observation, it was clear that some of the grey-black shadow artifacts were results of the slight difference in the Kinect v2's color and depth camera viewpoints and occlusion. This resulted in points in scene being captured by the depth camera but lacking an associated color data as it was occluded from the color camera.

Next, the shadowpoint filter was employed to help remove ToF-based sensor (i.e Kinect v2) data artifacts near edges as shown in Fig. 4. These artifacts typically have a very large angle between their normal vector and coordinate vector. The dot product between two vectors is used. If the absolute value returned is close to 0, the two vectors are close to being perpendicular and if the absolute value returned is close to 1, the two vectors are parallel to each other. Based on visual observation, the shadowpoint filter threshold for the dot product was selected such that points whose dot product between its normal and coordinate vector were above 0.15 was kept.

Finally in the first stage, a distance-scaled SOR filter was used to remove outliers in the data captured by the Kinect v2. SOR filter works by calculating the point cloud's average and standard deviation of all the point-to-neighbors distance. From there, each point is filtered by evaluating the point's average distance from its k-nearest neighbors to the point cloud's average and standard deviation of all its point-to-k-neighbors distance. In our case, the SOR calculations of the average distance between a point and its 25-nearest neighbors were distance-normalized as the density of the point cloud decreases with distance from sensor. This occurs because the Kinect v2 was used to capture from only a single 2.5D viewpoint. For the second stage, the standard SOR filter was also used with a k-nearest neighbors of 25. All the applied filters were employed to help filter the data and improve spatial separation of different surfaces (leaf objects) captured in scene.

Its important to note that each plant is captured via a single view frame. There are two issues that arise from this. One, the Kinect v2 is unlikely to be able to capture every detail of a plant from a single viewpoint given that there can be occlusion among leaves within a dense foliage. Second, the Kinect v2's imaging plane should be parallel to the surface of the leaves in order to obtain the best quality surface depth data. However, no matter how well the Kinect v2 is positioned to capture a subject plant's leaves, there are some issue that can't be avoided. One is the changing curvature of a single leaf. Another is the fact that different leaves will have different surface curvatures. Therefore, some of the leaves surface data will be more noisy or incomplete. These factors

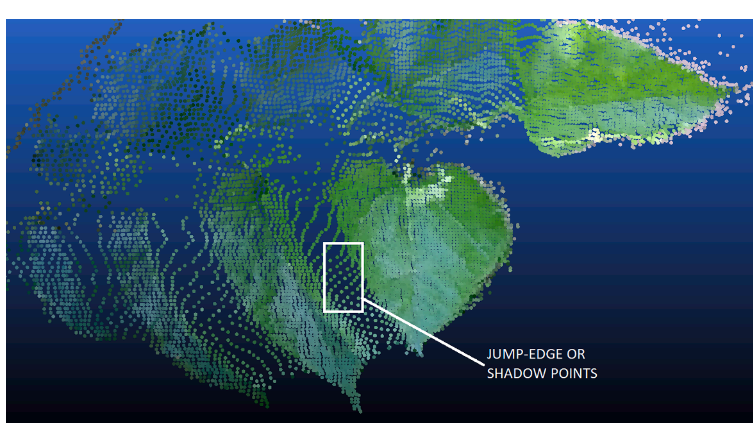


Fig. 4. Shadow Points - Artifacts.

can affect individual leaf segmentation as well as leaf surface area measurements down the line.

4.2. Individual Leaf Segmentation

In Table 1, the average probability of the closest 10 (maximum) clusters being an individual leaf, over-segmented or under-segmented were documented. The average amount of leaves in under-segmented clusters for each plant species were recorded as well. Figs. 5 showed several example frames of the 6 different plants which were cluster-segmented using the developed data processing methodology.

For *Mulberry* leaves, most of the foliage captured were relatively sparse, leading to a high mean (0.88) of individual leaf segmentation. The same was similarly true for *Council tree* where mostly sparse foliage was captured which resulted in a high mean (0.908) for individual leaf segmentation. For denser foliage plants such as the *Jackfruit*, *Queen's crape-myrtle*, *Mango* and *Hibiscus*, the average probability for individual leaf segmentation were 0.8, 0.718, 0.83, 0.75 respectively, which were on the lower end.

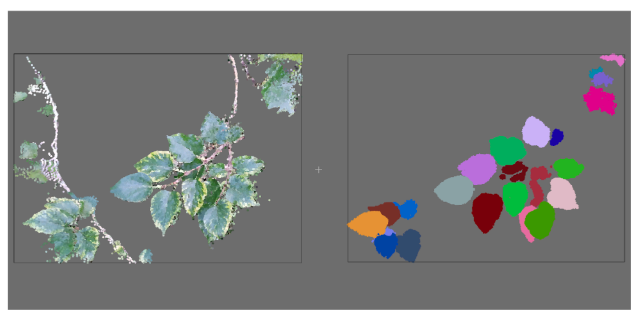
From observation of the captured frames, plants with the densest foliage were Queen's crape-myrtle and Hibiscus. This correlates with the results where both have the lowest average probability for individual leaf segmentation. The Hibiscus has not only dense foliage but its individual leaves were generally smaller which contributed to its low average probability of individual leaf segmentation.

Fig. 7 showed that the second stage (SOR + HDBSCAN-XYZ) led to more individual leaf segmentation. The graph shows the results of surface area measurement of successfully segmented individual non-occluded leaves. We have observed that this stage assists with individual leaf segmentation in general (partially-occluded and non-occluded single leaves). The SOR process in both the first and second stage leads to better inter-cluster separation. It has the effect of removing points close to edges thereby shrinking surfaces and increasing spatial separation between surfaces in Euclidean space.

The probability results from the Table 1 showed that if the obtained clusters weren't of an individual leaf, it was more often an under-segmentation than an over-segmentation. Based on some sample inspection of the obtained data frame, it was observed that under-segmentation commonly occurs due to:

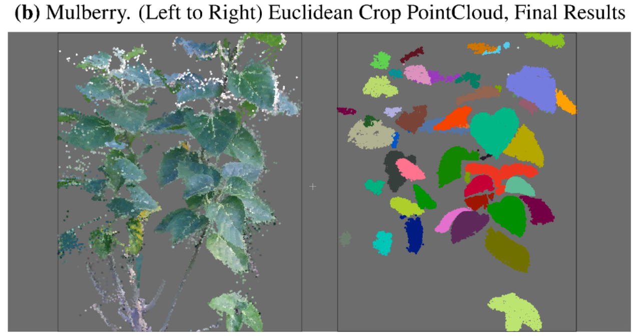
- Insufficient separation between individual leaves in the feature space (XYZ, Curvature). Even a second round of SOR (in the second stage) was not able to provide enough physical (X,Y,Z) separation between data clusters of individual leaves in the plant point cloud data. This can occur due to there not being any actual real world physical separation between leaves. Besides that, the Kinect v2's spatial resolution is limited, more so in daylight. As such, the Kinect v2 may not be able to capture small physical separation between individual leaves.

(a) Mulberry



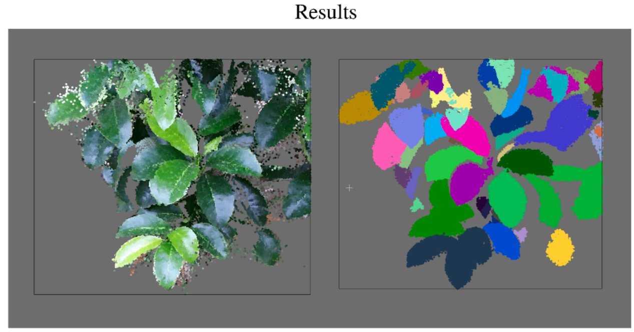
(b) Mulberry. (Left to Right) Euclidean Crop PointCloud, Final Results

(c) Council Tree



(d) Council Tree. (Left to Right) Euclidean Crop PointCloud, Final Results

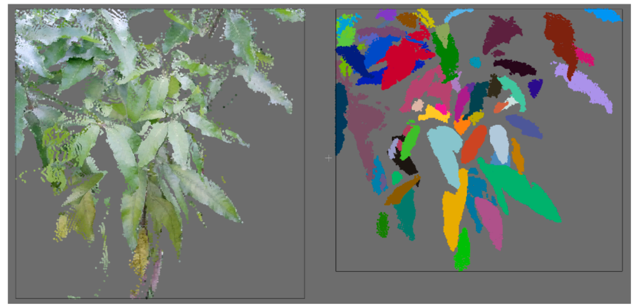
(e) Jackfruit



(f) Jackfruit. (Left to Right) Euclidean Crop PointCloud, Final Results

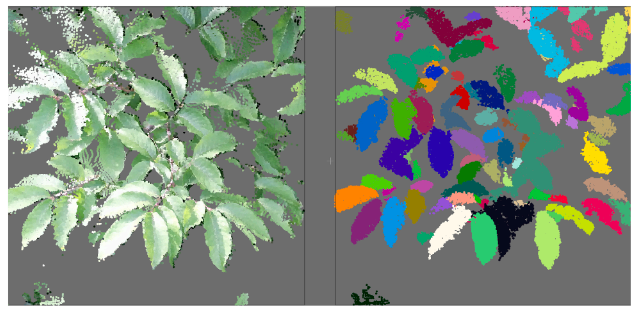
Fig. 5. Example of the Clustering Results for Several Different Frames of Plants.

(g) Mango



(h) Mango. (Left to Right) Euclidean Crop PointCloud, Final Results

(i) Queen's C.myrtle



(j) Queen's C.myrtle. (Left to Right) Euclidean Crop PointCloud, Final Results

(k) Hibiscus

(l) Hibiscus. (Left to Right) Euclidean Crop PointCloud, Final Results

Fig. 5. (*continued*).

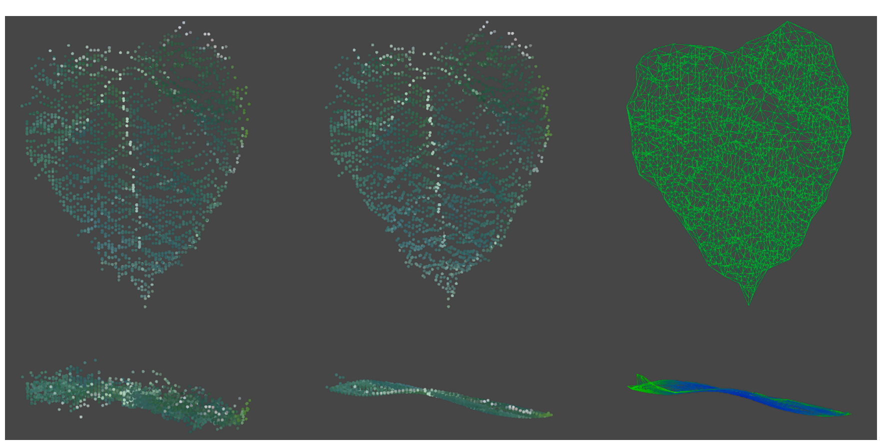
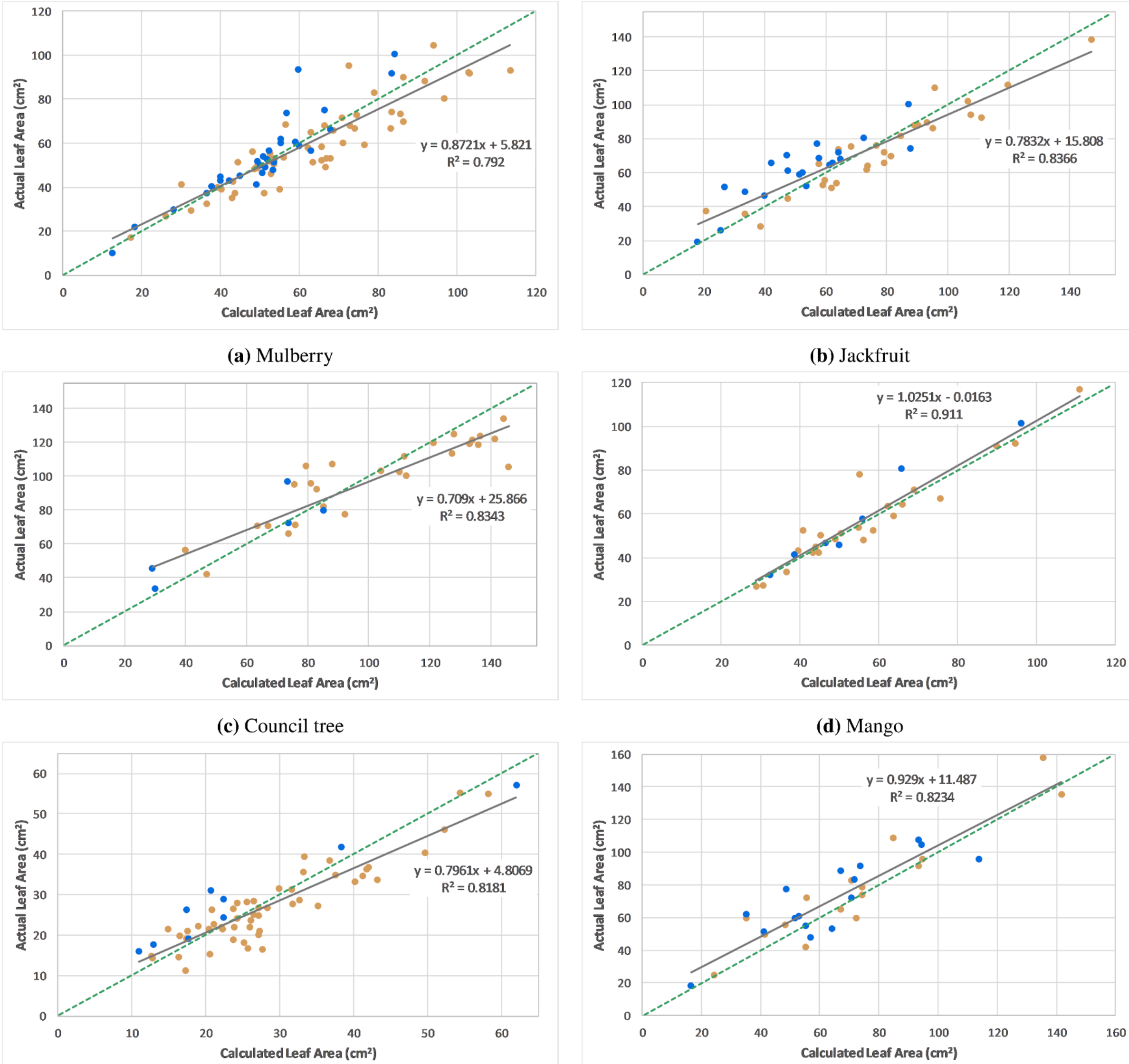


Fig. 6. Example captured individual leaf, MLS smoothed 3D data and its surface reconstructed mesh (from left to right).

Meanwhile over-segmentation was observed to occur due to:

- Occlusion splitting a single leaf into multiple separate dense clusters of data. The larger the leaf, the higher the chance where small occlusions can lead to splitting. This was observed occurring with the mango leaves where occlusion can split the long mango leaves into 2 or even 3 separate segments.
- There's a significant discontinuity of data density for a single leaf point cluster. This can occur due to:



(a) Mulberry **(b)** Jackfruit **(c)** Council tree **(d)** Mango **(e)** Hibiscus **(f)** Queen's crape-myrtle

Fig. 7. Results of All Calculated Individual Segmented Leaf's Surface Area. (*BLUE datapoints indicate individual leaves obtained through the 2nd Stage while the ORANGE datapoints indicate individual leaves obtained through the 1st Stage*).

– Uneven light diffusion on plant leaves leads to variable density of data on its surface. Stronger illumination equals more Kinect v2 interference, leading to a noisier and sparser data.
– Leaves that have severely distorted poses. Kinect v2 has difficulty measuring accurate depth information of leaves in irregular poses. However, cases of this occurrence were hard to determine and may have been categorized as a successful individual leaf segmentation but in return its surface area may be underestimated due to the loss of surface captured.

Based on observations of the data and the knowledge of how HDBSCAN works, the resulting under-segmentation or over-segmentation occurrence happen due to the limitations of the HDBSCAN algorithm at dealing with the following situations:

- Dense foliage with little to no physical separation or any significant surface curvature difference between individual leaves. As a result, HDBSCAN will tend to cluster those individual leaves together resulting in an under-segmentation as it's a density-based clustering method. If the entire foliage point cloud data is equally dense and interconnected, then HDBSCAN will not be able to differentiate.
- When individual leaf cluster is split into several smaller clusters by occlusions and incomplete data, there's no way of merging them as there are no pre-known knowledge of plant organs structure and shape. HDBSCAN is an unsupervised clustering method which works on local data points and segregates them based on similar feature traits (in our case, X,Y,Z and/or Curvature) and as a result does not have any mechanism for merging smaller clusters based on leaf structure or shape.

However we must emphasize that the HDBSCAN algorithm handled data density discontinuity relatively well and was still able to obtain clusters with different densities, sizes and arbitrary shapes that correspond to individual leaves. The developed platform was effective at capturing point cloud data of plants and segmenting individual leaves (occluded and non-occluded) provided the leaves have some physical spatial separation as well as surface curvature differences. This was reflected in our individual leaf segmentation results shown in Section 4.4.1 to be competitive with other researches.

4.3. Leaf Surface Area Measurement

Every successfully segmented individual non-occluded leaf clusters were first surface reconstructed and its resultant surface area measured as described in Section 3.2.3. From the dataset used, there were a total of 85, 32, 48, 32, 30 and 60 non-occluded individual leaves segmented from the mulberry, queen's crape myrtle, jackfruit, council tree, mango and hibiscus frames respectively for comparison with its ground truth surface areas.

In Fig. 7, the resultant surface area for each individual leaf cluster was plotted against its ground truth. The 1:1 reference line of the actual leaf area with respect to the calculated leaf area was plotted in all graphs. Data points below the reference line were leaves whose calculated area were larger than its ground truth while those above it were smaller. The plots also show the best fit regression line and its calculated R^2 for each plant type. For each plant type, the resultant RMSE of calculated area with respect to the 1:1 reference and the R^2 with respect its best fit regression line were tabulated in Table 2. From there, it was recorded that the RMSE of leaf area for each plant type ranged from 4.95 to 14.4941 cm^2 while the calculated MAPE (mean average percentage error) of leaf area from each plant type ranged from 7.31 to 17.02% as shown in Table 4.

As discussed in Section 4.2 and shown in Fig. 7, the second stage in the data processing pipeline helped identify more individual leaves from frames. However, most of the individual leaves obtained from this stage were generally smaller than its ground truth. Individual leaves obtained from the first stage tend to have a larger calculated area from its ground truth.

Based on several sample observations, it was observed that underestimation and overestimation of the calculated leaf surface area occur due to several reasons;

Leaf Area Underestimation:

- Part of a leaf's surface was at a steep angle to the Kinect v2 imaging plane. In this scenario, part of the leaf surface was not captured by the Kinect v2 due to its limitation leading to the loss of leaf surface for calculation.
- Over-shrinking of the leaf point cloud due to the second stage SOR as discussed in Section 4.2.

Leaf Area Overestimation:

- Meshing may lead to holes and gaps on leaf surface being closed when the surface is reconstructed which may not be reflective of the original leaf surface in nature.
- Smoothing was not effective leaving some rough points which lead to an imprecise, rough mesh that when measured is an overestimation of leaf-cluster surface area.

4.4. Comparison with Previous Works

This section will briefly compare the performance of several researches described in the literature review in terms of segmenting individual leaves and measuring leaf surface area in similar setups. The differences in terms of method (2.5D or 3D) or sensor (type of sensors) used to obtain the plant point cloud will affect the availability and quality of 3D data obtained of the subject plant.

4.4.1. Leaf Segmentation

The percentage of successful individual leaf segmentation (%) metric was used as the standard for comparing the different applied methods for segmenting individual leaves from plant point clouds. The following paragraphs will summarize the leaf segmentation method used for each of the respective researches that was compared in Table 3.

The method used in (Glasbey et al., 2014) for individual leaf segmentation was region growing. Region growing starts from seed points obtained from the nearest disparity plane which has the lowest combined edge magnitude (colour, disparity images). The steps were repeated for the next closest disparity plane. Research by (Li et al., 2017) was focused on its SV matching algorithm. However, there was a small section related to leaf segmentation using region growing (point features - position, normal, color information).

The method used in (Xia et al., 2015) for individual leaf segmentation was first using mean shift on the colour space to perform background removal. Next, an active contour model (ACM) was used on the depth space for the plant point cloud to segment plant organs.

Individual leaf segmentation from (Li et al., 2018) began with facet oversegmentation of plant point cloud using region growing followed by k-means to refine the facets. Then, facets were merged together if they were adjacent, meet the threshold for inter-facets distance and do not exceed user-set number of points for a single leaf 'facet'. Each tested plant clouds ran on different thresholds. Parameters were tuned for each plant point cloud resulting in good segmentation results for individual leaves.

The process in (Itakura and Hosoi, 2018) used color data to filter out branches before plant point cloud was simplified by 3D voxelization using a user-set voxel size. Voxel model was projected to its top plane and then distance transformed into a grayscale where contrast represents distance from nearest edges. Next, the image was segmented with a watershed algorithm and the output individual segments were shrunk to create seed regions. Seed regions were projected into the voxel model. From there, the seed voxel regions were expanded cover its closest neighbors until all voxel neighbors were fully assigned into specific regions.

In (Li et al., 2018), the leaves were separated out to estimate leaf angle. First, stem-leaf classification was done to remove woody elements. Then, leaves were voxelized before DBSCAN was applied to cluster-segment out leaves points in each voxel into individual clusters. Clusters are determined to be individual leaves provided their reconstructed surface area meet a user-set criteria.

First step in (Xu et al., 2019) for individual leaf segmentation was stem-leaves classification using local point features. Individual leaf segmentation was done with a 3D watershed algorithm which requires designation of seed points representing the local minima. In order to find the seed points (center of leaves) automatically, a sphere neighbourhood search model was used. The search checks for several user-set criteria. Then, DBSCAN was applied to refine and cluster central area points and passed to the 3D watershed algorithm. The segmentation algorithm parameters were different for all the 3 plant point clouds tested. Comparing the performance of different leaf segmentation methods must be done with caution. There are significant differences in the subject plants used as well as the size of the dataset. Many of the compared works specifically tuned algorithm parameters to provide the best performance for a single point cloud of a single plant, or for multiple point clouds of a single plant. This was not the case for our work, which aims for multi-species individual leaf segmentation and area measurement.

By looking closer at the results of researches that collected plant point clouds in similar outdoor conditions (Li et al., 2017; Li et al., 2018; Xu et al., 2019), we can see that our method for individual leaf

Table 2
Statistical Analysis of Individual Non-Occluded Leaf Area Measurements

	Mulberry	Jackfruit	Council tree	Queen's crape-myrtle	Mango	Hibiscus
R^2	0.792	0.8366	0.8343	0.8234	0.911	0.8181
RMSE (cm^2)	9.2439	10.9523	14.4941	13.9387	6.5826	4.9482

Table 3
Comparison of Percentage of Successful Individual Leaf Segmentation.

Study	Sensors	Viewpoint	Environment	Plant Type Amt.	Sample Size	Acc. Results
Glasbey et al. (2014)	Stereo Camera, ToF Camera	2.5D	Greenhouse	1	3 nearest leaves each from 244 non-unique plant images	100%
Xia et al. (2015)	Kinect v1	2.5D	Greenhouse	1	474 leaves from 37 plant images	87.97%
Li et al. (2017)	Stereo Camera	2.5D	Indoors, Greenhouse, Outdoors	1	37 leaves from 1 plant image	94.59%
Li et al. (2018)	Stereo Camera, Kinect v2	2.5D	Greenhouse	3	51 leaves from 3 plant images	91–100%
Itakura and Hosoi (2018)	Color Camera	3D	Indoors	6	61 leaves total from all plant PCs	75–100%
Li et al. (2018)	TLS	3D	Simulation, Outdoors	2	15–150 leaves (10 simulated PCs), 321–911 leaves (3 scanned PCs)	23–100%
Xu et al. (2019)	TLS	3D	Outdoors	3	168, 1539, 166 leaves from 3 plant PCs	89–94%
Ours	Kinect v2	2.5D	Outdoors	6	10 nearest leaves (max) each from 65 plant imgs	72–90%

segmentation has comparable accuracy results. As previously discussed, the Kinect v2 sensor used grabs a 2.5D point cloud of the target plant, performing similarly to the full 3D scans and expensive industrial TLS sensor used by (Li et al., 2018; Xu et al., 2019). This shows both the capability of the Kinect v2's 2.5D sensing as well as the effectiveness of our leaf segmentation method on the less than ideal 2.5D point cloud. The work in (Li et al., 2017) achieved a higher accuracy result (94.59% versus 72%-91%) utilizing a stereo camera and region growing. However, the test was only performed on a single plant point cloud, as the work in question was more focused on their stereo reconstruction algorithm.

Our individual leaf segmentation method was applied to 65 different plant point clouds. The accuracy achieved for segmenting the closest 10 individual leaves for all clouds was respectable given the circumstances.

4.4.2. Leaf Area Measurement

This section compares several research results of leaf area measurement to determine whether the obtained experimental results were comparable. In the Table 4, comparison of results were done with regards to the root mean square (RMSE), R-squared (R^2) and percentage error of measured leaf area from its ground truth.

As with the leaf segmentation, it was not easy to directly compare the results of the different works which used 2.5/3D data of plants to measure individual leaf surface area. We cross-compared results from authors using different 3D sensors, test environment, method for isolating individual leaves out from the plant point cloud (manual vs semi-automatic vs automatic), subject plant varieties as well as different test sample sizes.

By comparing our method with other outdoor based methods by (Yun et al., 2017; Xu et al., 2019) for measuring individual leaf surface area, it can be seen that the results of our R^2 and RMSE are very comparable. This is impressive considering that we are using a consumer-grade 2.5D sensor to capture the subject plant's point cloud from a single viewpoint whereas the other two methods used an expensive TLS sensor to 3D scan its subject plants. If we were to compare our methods with other methods (Glasbey et al., 2014; Wang et al., 2017; Xiong et al., 2017) that captures 2.5D plant point clouds, the results of our R^2 and RMSE are competitive while operating in a more challenging outdoor

Table 4
Comparison of Individual Leaf Area Measurement.

Study	Sensors	Viewpoint	Environment	Plant Type Amt.	Sample Size	Leaf Area Performance
Glasbey et al. (2014)	Stereo Camera, ToF Sensor	2.5D	Greenhouse	1	149 leaves (59 unique)	RMSE: 10.97 cm^2, R^2: 0.97
Wang et al. (2017)	RPLIDAR	2.5D	Indoors	1	28 leaves	RMSE: 42.04 cm^2 R^2: 0.92
Xiong et al. (2017)	Stereo Camera	2.5D	Indoors	1	n/a	MAPE: 3.68 R^2: 0.984
Golbach et al. (2016)	Multi-Camera	3D	Indoors	2	1082 leaves	RMSE: 0.24–0.28 cm^2 Avg. Size Error: 19–22% R^2: 0.72–0.78
Li and Tang 2017 Li and Tang, 2017	Color Camera, ToF Sensor	3D	Indoors	1	7 leaves	Avg. Error Rate: 10.76%
Itakura and Hosoi (2018) Itakura and Hosoi, 2018	Color Camera	3D	Indoors	6	30 leaves	RMSE: 3.23 cm^2 MAPE: 4.14% R^2: 0.99
Yun et al. (2017)	TLS	3D	Outdoors	2	n/a	Avg. Size Diff.: 3–5%
Xu et al. (2019)	TLS	3D	Outdoors	3	40% of crown total leaves (3 plants)	RMSE: 4.6–9.4 cm^2 RELA: 2.26–16.12% R^2: 0.8–0.98
Ours	Kinect v2	2.5D	Outdoors	6	288 leaves	RMSE: 4.95–13.94 cm^2 MAPE: 7.31–17.02% R^2: 0.79–0.91

daylight scenario. Besides that, we also evaluated our system on a much larger dataset of unique individual leaves. We can see that the leaf area measurement capability of our developed system is competitive with other previous research and validate the methodology for using the Kinect v2 outdoors for leaf area measurements.

5. Conclusion

The Kinect v2 was a very capable depth sensor for capturing 2.5D data of plants outdoor in sunlight conditions albeit with some limitations. As the quality of depth data returned by the Kinect v2 depreciates with distance, an Euclidean distance threshold was used to remove far away datapoints. Filters utilizing color information, statistical outlier analysis and known ToF-based sensor artifacts were used to improve separation between individual leaves. After pre-processing, 2 passes of HDBSCAN clustering was used in succession to segment out individual leaf clusters. Overall, the applied process for segmenting out individual leaves worked well upon analysis of captured frames of plants with sparse foliage while results varied for plants with dense foliage. In cases with a mix of dense and sparse foliage, the sparse foliage section of the captured frame will generally be more successfully segmented. HDBSCAN clustering has proven to a robust and versatile method with simple and intuitive parameters to set. Limitation of the current system is that there's no automatic identification of non-occluded leaves and occluded leaves.

For all obtained individual non-occluded leaves, the data-points were smoothed utilizing a standard Mean Least Square algorithm. After smoothing, Delaunay triangulation meshing method was used to reconstruct the surface of the leaf. From there, the surface area of the leaf can be calculated. Based on the results obtained, the system performed relatively well at measuring leaf area and within range of other computer vision efforts for measuring leaf area in field.

In conclusion, the developed portable device was able to capture, segment and measure individual leaves area from dense foliage outdoors during midday daylight with some constraints. The device was used in-field at midday under low-mid range daylight intensity without any artificial shade. At higher intensity lux range, the device still return depth data albeit with reduced range and precision. This can be circumvented by introducing light shades to cover the target plant.

6. Future works

To reduce the effect of occlusions, the device can be employed as a handheld 3D scanner to scan the subject plants. Given that HDBSCAN is a density-based clustering method, there shouldn't be any problem in applying the subscribed data processing method directly on the reconstructed 3D data. The developed platform can also be used to measure other plant leaf traits like its inclination angle. The device can also be a portable and easy-to-use platform for other plant phenotyping purposes such as measuring flower dimensions (Sunoj et al., 2018) and measuring fruit size (Wang et al., 2018) outdoors in daylight conditions.

Substitution of newer sensors (e.g. Kinect for Azure with 1024 × 1024 depth images) or alternative modalities (modern smartphones are adopting ToF sensors, making it a more portable device) may increase both performance and accessibility for this method. Supervised leaf segmentation methods are also known to be more accurate, should sufficient labeled data be available.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.compag.2021.106278.

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