Computer Vision Based Autonomous Robotic System for 3D Plant Growth Measurement

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***Abstract*—Research on increasing the production of crops is increasingly important these days. This research needs a way to quantitatively measure the 3D growth of plants under controlled environments to allow a cost versus benefits analysis. Plant scientists need a non-invasive, non-destructive method to quantitatively measure the 3D growth of plants. Traditional methods, for example, measuring weight, area or volume, often negatively affects the future plant growth. Also the manual nature of this measurement can be quite time consuming, tedious and error prone. Some recent effort have been reported in the literature about the construction of autonomous systems for plant phenotyping, but these are not practical for large scale accurate 3D plant growth computation. To the best of our knowledge, we are the first in the world to attempt truly 3D approach via robot assisted plant growth analysis using 3D imaging and laser scanning technology. We describe an automated system to perform 3D plant modelling using a laser scanner mounted on a robot arm to capture 3D plant data. We present a detailed overview of the system integration, including the robotic arm, laser scanner and a programmable growth chamber. We also show some results on reconstructing the 3D model of a growing plant which is better than the current state of the art.**

***Keywords*-Robotic Imaging; Gantry Robot; Autonomous System; 3D Plant Growth; Multiview Reconstruction;**

Autonomous robotic imaging systems are emerging as an important research area for different kind of bio-engineering applications. Analyzing different properties of plants is of fundamental interest in plant science research. Some of the most common applications include measuring the growth of a growing plant, tracking a specific organ over time, *phenotyping* (analyzing biological properties), etc. The naive methods used by biologists for measuring plant growth are often destructive in nature, preventing the growth analysis of a growing plant. Also, considering the manual effort required and the chances of measurement error are severe restrictions for real time analysis. With the advancements of robotic technologies and low cost near-infrared laser scanners, 3D automatic non-invasive analysis of growing plants is becoming possible. One motivation of this work is to introduce a system which is capable of capturing 3D plant data and which can process the captured data in real time.[1] Such a system would be beneficial for large scale *phenotyping* and crop monitoring in future. Usually a crop monitoring system involves growth chamber, inside which the plant is grown and monitored over time. We believe that the functionality of the chamber is an integral part of a automation system. More specifically, apart from the data capture using the robot, the system should be integrated as a whole. We present such a system below.

Due to its non-invasive non-contact nature, imaging techniques are now being used extensively for analysis in various fields including medical science, biology, etc. Most applications still involve 2D image analysis and exhibits the inherent limitations of 2D analysis. A 3D laser scanner offers the best chance for the purpose of reconstructing the original model. This is especially true for a growing plant, as capturing the plant's detailed structure is important to accurately compute parameters such as volume and surface area, as well as individual leaf area. This will allow a more accurate assessment of photosynthetic capacity, photosynthetic efficiency and biomass production as a function of plant development. Laser scanning allows the surface data to be captured as raw 3D coordinates or point cloud form from

[1]Real time means processing the current data fully before the next dataset is captured.

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a real object. Multiple views of such data allow the full 3D reconstruction of the plant's surface. We use a near-infrared laser scanner rather than a visible spectrum laser scanner, as the former has no effect on a plant growth. In plant science research, large scale *phenotyping* is of great importance for obtaining growth measurements in a plant scene over time. If the number of plants is large and the plants have complex morphological properties, manual processing is not possible in real-time. While most of the existing 3D reconstruction focus on standard models, 3D reconstruction of plant like structures have rarely been studied.

In this interdisciplinary work among Computer Vision, Robotics and Biology, we propose a novel system for automated and non-invasive plant growth measurement. We exploit the recent advancements of sophisticated robotic technologies and near infrared laser scanners to build a 3D imaging system and use state of the art Computer Vision algorithms to fully automate growth measurement. We have set up a 2-DOF gantry robot system having 7-DOF modular robotic arm (manufactured by *Schunk Inc., Germany*) hanging from the roof. The payload is the ShapeGrabber laser (range) scanner which can measure dense depth maps of the visible surface of a plant. This scanner uses near-infrared light at 825 nm (versus visible red light at 660 nm for most scanners) which is believed to not affect plant growth. The scanner can be moved around the plant to scan from different viewpoints by programming the robot arm with a specific trajectory. Note that, hand-held or fixed position scanners can't be used for automation, especially when the position of the scanner needs to be changed for dynamic or adaptive scanning. Then, the sequence of overlapping images can be aligned and triangulated to obtain a full 3D structure which mimics the original plant. The idea is that the 3D volume and surface area of the plant's mesh measured over time might serve as good growth metrics for the plant. That is, we would be able to measure the plant's growth quantitatively through it's life cycle without touching or damaging the plant. The plant is grown in a controlled environment in a growth chamber (manufactured by *BioChambers Inc., Canada*), which can be monitored remotely and is fully programmable to control the light, air and humidity. All robot arm, environment control and scanning operations are fully integrated and are capable of operating independently for the whole life time of a plant. We are currently experimenting on *Arabidopsis thaliana L.* wild type, whose life-time is about 6 weeks.

We present a literature survey in next section, followed by a system overview. Next we present some experimental results on multi-view reconstruction and discuss about the scope of the proposed system.

I. Related Work

Attempts to automated plant growth measurement are not new. Subramanian *et al.* [24] reported a gantry robot system to analyze root growth of a growing plant in an automated manner. They have shown results of high throughput *phenotyping* for *Arabidopsis thaliana L.* plants. However, their 2D image based analysis has inherent limitations in capturing complete and accurate information of a 3D object. Recently, a body of literature has been proposed on point cloud imaging based plant analysis. A robotic system for automatic fruit recognition was proposed by Jimenez *et al.* [11]. The proposed computer vision system is capable of capturing raw data using a 3D laser scanner. The system can process the data using efficient image analysis algorithms and is capable of recognizing fruits from colour and morphological properties. This kind of automated system has great demand for fruit harvesting and agricultural engineering applications. Plant *phenotyping* software has become very popular in recent years. Clark *et al.* [7] proposed a high throughput phenotyping software system. Plant imaging and meshing application software platforms are also being reported in recent literature [7]. Recently imaging techniques have been employed to build machine vision system for various kind of applications ([23], [1]) including shape recognition and segmentation of plant organs in controlled atmosphere ([21], [28]). Paproki *et al.* [17] demonstrated a 3D mesh based approach for measuring plant growth in the vegetative stage in a non-invasive manner. However the technique is not fully 3D, they generated 3D meshes from 2D images using 3DSOM software. Recently, some work on plant organ classification and parameterization ([18], [19]), tracking budding and bifurcation events [14] have also used 3D laser scanning technology for plant analysis.

II. System Description

The robotic quantitative laser imaging platform (QLIP) shown in Figure 1 consists of a ShapeGraber 1002 near-infrared (825 nm) laser scanner mounted on a lightweight 7-DOF robotic arm that is moved around the plant by an overhead 2-axis gantry. The robotic imaging platform is housed in a bio-chamber that provides a controlled growth environment for the plant in which the light, humidity, temperature and air quality can all be controlled and monitored remotely. The 7-DOF robotic arm provides a high level of flexibility for controlling the position and orientation of the 3D scan head, while the 2-axis gantry provides an extended workspace. The 3D laser scanner captures point cloud data of the surface of the plant from multiple viewpoints.

Next we outline the use of the QLIP for acquiring multiple discrete views of a plant along a circular trajectory. For each view, the scan head is positioned 0.26 m above the base of the plant at a distance of 0.56 m from its centre, and is configured to be parallel to the floor. This set-up is shown below in Figure 2.

Before performing a high-resolution multi-view scan, a pre-scan procedure is performed in which the plant is imaged at low resolution from the front and side as depicted

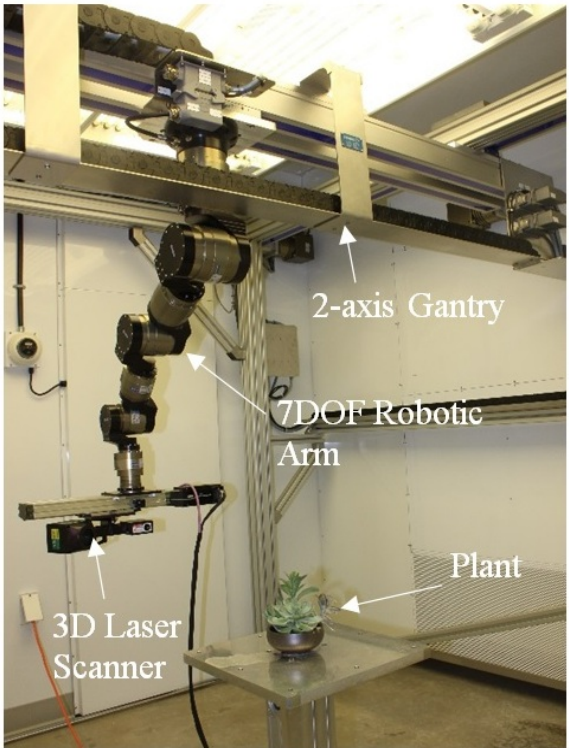

Figure 1. Robotic quantitative laser imaging platform (QLIP)

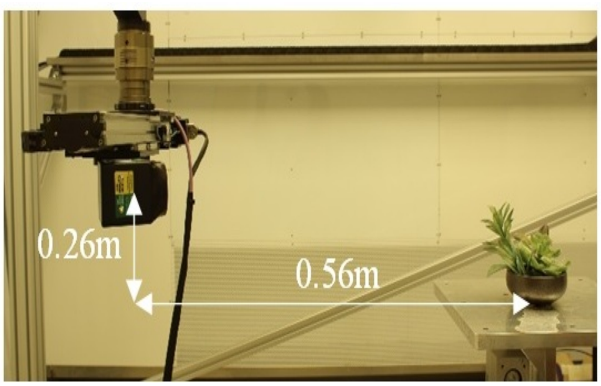

Figure 2. Scan head position relative to plant

in Figure 3. From these scans, the centre of the plant's bounding box is approximated and used to update the centre of rotation for the circular scanning trajectory. This is an important feature that allows the system to adjust to non-symmetrical plant growth, or small shifts in plant position (that may result during plant watering etc.) when scanning over extended periods of time.

Once the plant centre has been determined, the system causes the gantry and robotic arm to translate and rotate the scan head to (specified) discrete positions around the plant

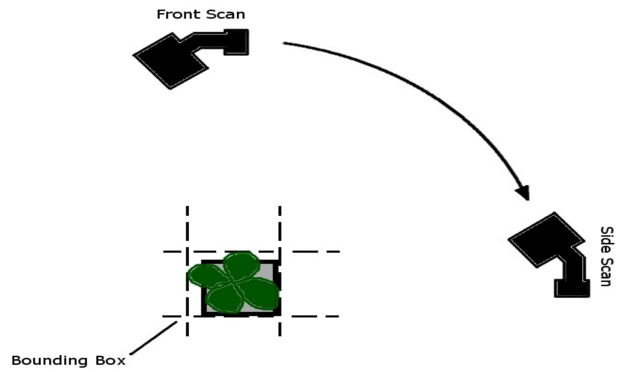

Figure 3. Pre-scan of plant from front and side

as shown in Figure 4. This is how a trajectory of the robot arm and scanner payload is executed.

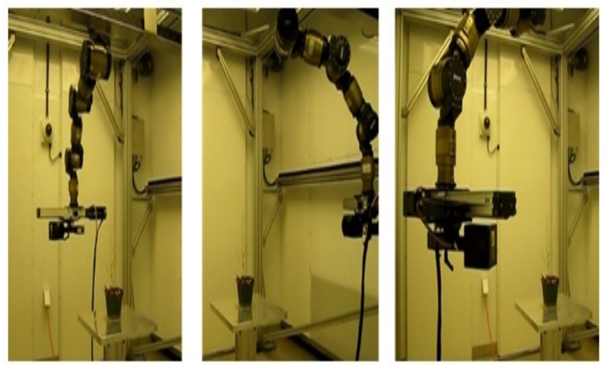

Figure 4. Scan head is rotated around plant to discrete positions

At each position, the system waits 10 seconds to allow the plant and the scanner to settle before initiating a scan. Once a scan has finished, the resulting scan data is analyzed to ensure that the plant has been fully captured (i.e. there is no clipping). If clipping is detected as in Figure 5, the scanner moves sideways in the direction of clipping and another scan is taken. This ensures that the entire plant is imaged, even if it is too large to fit in the scanner's FOV or if the approximated plant centre is not accurate for every view.

We have written a single script which communicates among all devices: robot, scanner and the chamber. The overview of the system is shown in the block diagram of Figure 6. The scanner and the robot control software operate from different machines, which are connected by network cables. The bio-chamber is a dedicated embedded system and can be controlled via wireless connection. We have intentionally designed the system in a modular way for ease of operation. The home position of the robot is chosen to be at the corner of the chamber. Every time while

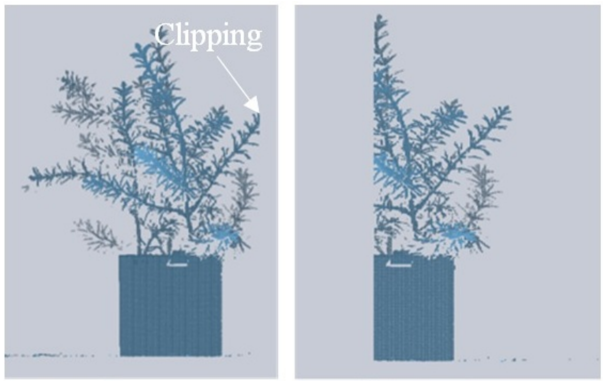

Figure 5. Scanning bounding box ensures full plant data is captured. The left and right images show clipped images, requiring a second scan.

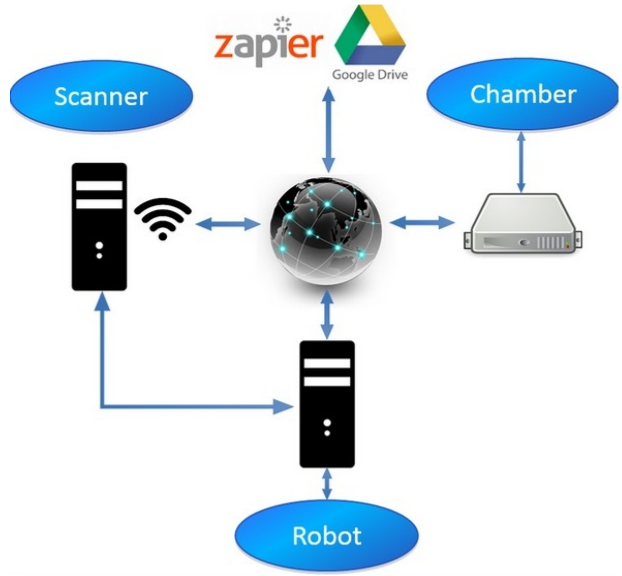

Figure 6. System connections

scanning, the robot moves from the home position to the desired scan position, communicates with the scanner via a network cable, performs a scan and waits for the scanner computer to respond. Then the robot moves to the next location. Before scanner/computer communication, the state of the chamber can be modified (if needed) via wireless network. For example, if we need to investigate the effect of light or wind, these factors can be controlled by sending specific commands to the chamber. We plan to investigate the growth behaviour of a plant over it's lifetime, which is about 6 weeks for a typical Arabidopsis plant. In this scenario, the plant might need to be scanned a large number of times a day and the huge amount of data at the end of the experiment should be backed up periodically. We have synchronized the local storage of the scanner with Google drive. At the beginning of the experiment, the user is asked to enter various parameters that include the number of days the experiment is roughly intended to run, the number of scans per day, the required laser intensity (coarse or dense depending on the application), the lighting conditions of the chamber, the distance of the scanner head from the plant (if it's different from the default value), etc. Also, installed cameras in the chamber allows us to remotely monitor the status at any time.

III. Experimental Results of Reconstruction

The next phase of the proposed automated system is to analyze the data. As we discussed previously, one application of the system is to study plant growth over time. Currently, we are investigating the change in volume and surface area of a plant over time as growth metrics. Having 3D point cloud data (or simply raw 3D coordinate points) of multiple views of a 3D object, the actual plant model can be reconstructed by aligning all the views via a **Multiview Reconstruction** method. The reconstructed point cloud can be triangulated to obtain a surface of the model. Subsequently, both the volume and overall plant surface area can be computed easily from the mesh triangles. However, reconstructing the 3D model of a standard object like Stanford bunny [13] or Buddha statue [9] is less demanding than reconstructing a thin plant structure. Moreover, considering the case of jittering of the plant by wind makes the problem more complicated(although we can shut down the wind in the chamber automatically, but we are considering the case of an outdoor experiment). Registration is a very basic step in 3D reconstruction, where we compute the 3D coordinate transformation to align two views. This is referred to as *pairwise registration*. Although the primitive algorithm for rigid reconstruction, for example Iterative Closest Point (ICP) algorithm [2] and some of it's variants ([27], [8], [3]) have been shown to be effective in many applications, these algorithms don't perform well on non-rigid datasets. Among several robust methods for registration, some notable work can be found in [6], [26], [29], [22]. These algorithms belong to a similar class of approaches. We found that various non-rigid registration methods are reasonably effective for registering adjacent scans, but any attempt to merge multiple registrations into a single point cloud was problematic.

Recently, Gaussian Mixture Models (GMM) [10] were used for non-rigid registration. However, for our plant data, which is extremely sparse with long stems, a few leaves and some flowers (at the end of the plant's life cycle), it is necessary to use a large area of support to construct the GMMs so that we can obtain a smooth solution space. A notable work was presented by Myronenko *et al.* [16], an algorithm called the Coherent Point Drift (CPD) was proposed where all the Gaussians were assumed moving simultaneously as a group (called the *drift*). Brophy *et al.* [4] show that CPD actually works best among existing pairwise registration algorithms for plant data.

However, Myronenko *et al.* [16] didn't consider multiple view alignment. Brophy *et al.* [4] have extended their algorithm to handle the alignment of multiple views. We use the basic idea of moving the centroids of Gaussians together. Given two point clouds, $\mathcal{M} = (x_1, x_2, ..., x_m)^T$ and $\mathcal{S} = (y_1, y_2, ..., y_n)^T$, in general for a point x, the GMM probability density function will be $p(x) = \sum_{i=1}^{M+1} P(i)p(x|i)$, where:

$$p(x|i) = \frac{1}{(2\pi\sigma^2)^{D/2}}\ exp[-\frac{||x - x_i||^2}{2\sigma^2}]. \tag{1}$$

Instead of maximizing the GMM posterior probability, the negative log-likelihood function can be minimized to obtain the optimal alignment:

$$E(\theta, \sigma^2) = -\sum_{j=1}^{N} log \sum_{i=1}^{M+1} P(i)p(x|i). \tag{2}$$

Then the Expectation Maximization algorithm can be used iteratively to optimize the cost function.

Inspired by Toldo et. al.'s work in rigid registration [25], this problem is solved by constructing an "average" scan to which we register all other scans. For a scan X, we find the set of points that are the Mutual Nearest Neighbors (MNN) to a point in the scan, and then we calculate a scan that is composed of the calculated centroids from each point. Although CPD alone is effective in registering pairs with a fair amount of overlap, when registering multiple scans, especially scans that have not been pre-aligned, our method achieves a much better fit than CPD by itself, utilizing sequential pairwise registration. The method is a two step process, beginning with aligning the scans approximately. We then register a single scan to the "average" shape, constructed from all other scans, and update the set to include the newly registered result. We perform the same process with all other sets of scans.

In this way, we avoid accumulation of merging error. Once the initial registration is complete, we use CPD in conjunction with MNN to recover the non-rigid deformation field that the plant undergoes between the capture of each scan. At this point, the scans should be approximately aligned to one another. We then construct the centroid/average scan and then register to it.

We have captured 12 views of the plant in 30° increments. The aligned data is shown in Figure 7. The graph in Figure 8 (from Brophy *et al.* [4]). shows the performance over pairwise registration technique.

We have triangulated the reconstructed plant point cloud using simple Delaunay triangulation, the result is shown in Figure 9. Note that, efficient triangulation algorithm is not in the scope of this paper. Interested readers are encouraged to see recent works on general surface reconstruction ([15], [12]) and surface reconstruction for plant shoots ([20]). We have computed the surface area from the mesh triangles, and we have obtained $1.3653 \times 10^5 mm^2$ as the mesh surface area. However, area of the mesh is highly dependent on selection of triangle size. We have tested with different

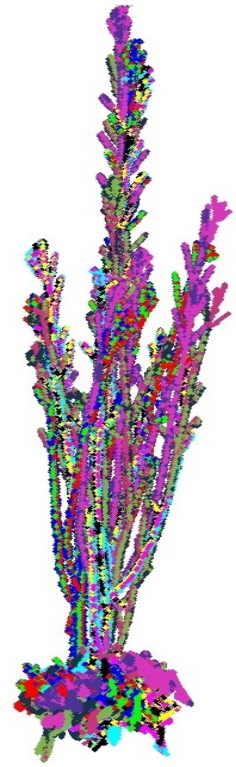

Figure 7. Aligned result: the different colours indicate which views the data comes from.

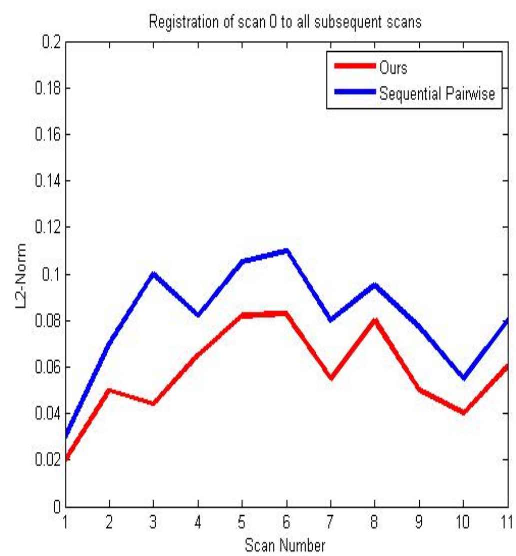

Figure 8. Performance over pairwise registration

parameters and obtained the surface area in the range of $1.0-4.2\times10^5 mm^2$. We believe that there exists a correlation between the actual volume of the plant and the volume measured from the 3D mesh. This can be an interesting research direction which we plan to investigate in future.

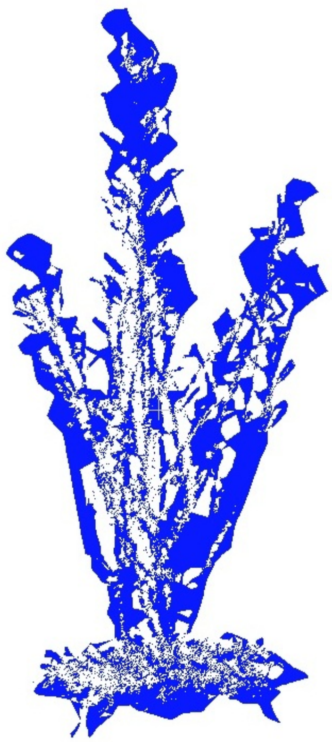

Figure 9. Triangulated plant data

IV. Conclusion and Future Work

We have presented an integrated system overview that can perform 3D plant growth measurement in an automated manner. We also show some basic results of multi-view reconstruction of a complex plant. We have described many details of the system and we believe that this description will be helpful in building similar autonomous system for various applications. The purpose of this paper is not to tell a story of different individual system parts, but to discuss the system as a whole.

An aspect of real time operation is the processing time. Existing reconstruction algorithms are far from operating in real time. It takes more than a day to register 12 views of a plant. That means, for data collected over a period of a month, it will take another month just to obtain results from reconstruction. One approach to this problem is to process our datasets on the SharcNet computer network (where multiple parallel processing machines are available). Another approach (to be done simultaneously) is to find junction points that can be used as good feature points instead of typical local descriptors (see Chaudhury *et al.* [5]). Using these points can be useful to estimate the initial rotation and translation matrices that can be used as pre-alignment of two views. This kind of feature point based technique could drastically reduce the computation time and the system can be used to operate in real time.

With a fully operational system, we plan to perform experiments to quantify growth rates of wild type as well as mutants of Arabidopsis thaliana over their vegetative and reproductive lifetimes. This will be coupled to measurements of photosynthetic efficiency and capacity in order link growth performance and biomass productivity with photosynthetic performance.

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