Soybean plant phenotyping using low-cost sensors

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Abstract. Plant phenotyping techniques are important to present the performance of a crop and it interaction with the environment. The phenotype information is important for plant breeders to analyze and understand the plant responses from the ambient conditions and the inputs offered for it. However, for conclusive analysis it is necessary a large number of individuals. Thus, phenotyping is the bottleneck of plant breeding, a consequence of the labor intensive and costly nature of the classical phenotyping. Consequently, efficient high throughput phenotyping (HPP) is needed. In this scenario, many studies have evaluated the use of sensors for the development of an efficient HPP. Therefore, the aim of this study was to develop a greenhouse structure for plant phenotyping and to test sensors in order to evaluate the advantages and disadvantages of it for plant phenotyping. A structure with three rails was developed for scanning two vases with soybean plants. A camera T3 Canon, a LMS-200 (LiDAR) and a Kinect version 1 (K1) were used to generate the 3D models of the plants. According to the results, the LiDAR sensor generated the point cloud with the other two sensors. On the other hand, Kinect and T3 RGB cameras are very affected by the ambient light. Moreover, the sun light limits outdoor uses of the K1 sensor because the infrared from the sun amess with the infrared pattern generated by K1 used to measure the depth distances. In terms of processing time consuming, the Structure From Motion 3D reconstruction is the most time consuming. In general, LiDAR creates a robust result but still is a more expensive sensor, K1 is not very suitable for field conditions (sun light exposure) and RGB cameras can be used all conditions but processing is computer intensive.

Keywords. High throughput phenotyping; 3D imaging; Microsoft Kinect; Depth Camera.

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Introduction

According to Fiorani and Schurr (2013), plant phenotyping could be considered as the set of methodologies and protocols to evaluate plant parameters with certain accuracy and precision. These plant parameters obtained by phenotyping techniques are important to present the performance of a crop and the interaction between a plant genotype and its environment (Walter, Liebisch and Hund, 2015). Therefore, phenotype is an important analysis within plant breeding, because it is the only way to understand the real plant responses from the environmental conditions.

Plant breeding improvement demands experiments using large plant population in strictly controlled environment or in field and more details on phenotype analyses. Therefore, plant phenotyping is considered a bottleneck for plant breeding. This is a consequence of labor-intensive and costly nature of the classical phenotyping (FURBANKER and TESTER, 2011). Many researches related to the development of high throughput phenotyping processes have been done in order to find an efficient way to get plant phenotype information. However, according to Araus et al. (2015) the development of an effective high throughput phenotyping (HPP) still is a limitation for plant breeding. Thus, according to these authors, the progress in technologies, such as sensors and high-performance computing, will help to get through an effective HPP.

In this scenario, many studies have been developed in order to use different technologies for HPP. Nevertheless, some authors (HÄMMERLE and HÖFLE, 2017; JAY et al., 2015; AZZARI, GOULDEN and RUSU, 2013) pointed that the three-dimensional (3D) model of plants has a great potential for plant phenotyping and generates important information, such as plant architecture, height, volume and leaf area index and accurate results have been obtained for crop height and leaf area.

3D modeling of plants can be generated by using some sensors such as laser scanning systems (e.g. LiDAR), RGB cameras, depth cameras and low cost sensors (e.g. Microsoft Kinect). Sun, Li and Paterson (2017) used LiDAR for HPP in cotton, obtaining accurate measures of cotton plant height in field. However, according to Azzari, Goulden and Rusu (2013), LiDAR is still an expensive technology.

Therefore, many researches have been evaluating the use of low cost sensors for HPP. Azzari, Goulden and Rusu (2013) evaluated the use of the Microsoft Kinect to obtain geometric parameters of a plant and concluded that the Kinect has a potential for plant structure measurements. Paulus et al. (2014) evaluated the use of Microsoft Kinect for Xbox 360 (K1; Microsoft, Redmond, USA) for plant phenotyping comparing it with expansive sensors, which according to their results, could be replaced by Kinect.

However, a comparison between camera, LiDAR and Kinect results and applications for HPP would be an interesting and important information. Therefore, the aim of this study was to develop a greenhouse structure for plant phenotyping and test these different types of sensors in order to evaluate the advantages and disadvantages and the results that can be obtained for plant phenotyping.

Methodology

- Sensors characterization

Three different kinds of sensors were tested. RGB camera T3 (Canon, Tokyo, Japan), LMS-200 (Sick, Waldkirch, Germany) and Kinect version 1 (K1; Microsoft, Redmond, USA). Table 1 presents some specifications of these sensors. Prices of the sensors is contrasting and the difference can be higher if different LiDAR sensors are listed, such as the Hokuyo UTM-30LX model (Hokuyo, Osaka, Japan) that has a market price around $4500.

Table 1. Specifications for the sensors evaluated

Sensor	Measuring Range	Resolution	Acquisition Rate	Voltage	Price
LMS -200	0 to 8m	1°@180°	75hz	24v	$2000
T3 Canon	90° X 67°	5184 x 3456 (pixels)	1 frame/s	7.4 v (battery)	$200
Kinect V1	0.8 to 4m	640 x 480 (pixels)	10 frames/s	12v	$25

- Structure development

A data collection structure was developed (Figure 1), with 2.5m height, 1.5m width and 5m of length, dimensions determined by the measuring range of the sensors. Therefore, the three sensors would be able to create 3D model of the plants. Two different acrylic vases with 1.160m height by 0.305m width and 2.0m of length were positioning exactly in the middle of the structure. As the sensors required different voltage (12V and 24V), power supply and connections for each sensors were available.

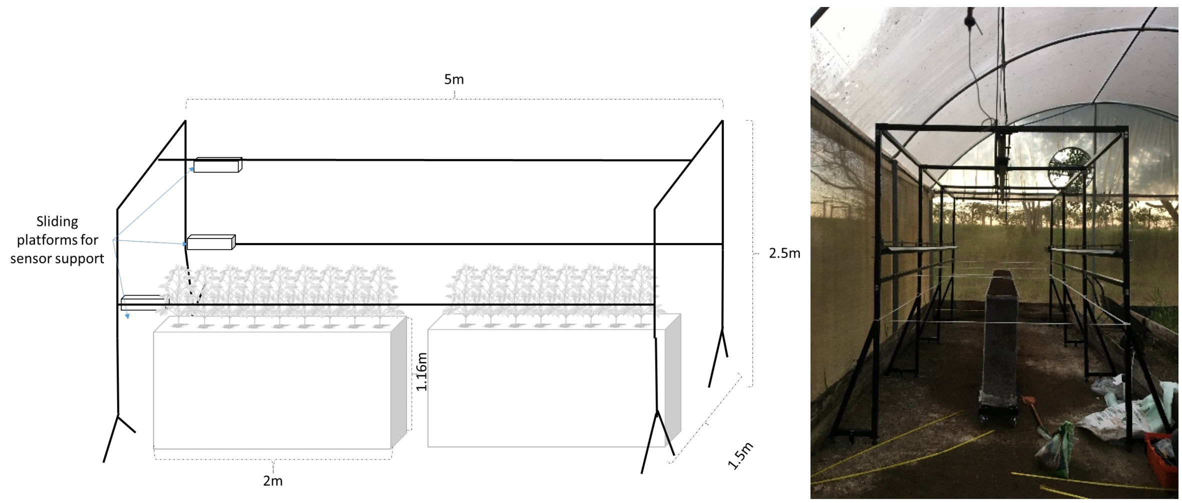

Figure 1. Structure assembled to support the sensors.

Nevertheless, just the sensor K1 is able to create a 3D model in a static mode, but still it would not be able to scan all the plants. Therefore, three rails were developed to move the sensor along one of their axis, allowing to create a 3D model for the LiDAR and camera and scan all the plants. To move the sensors, three electric 12v DC motors were used. In addition, an optical rotary encoder (400 PPR) was installed in each sensor holster platform. This encoder was used for georeferencing the data acquired by the K1 and the LiDAR sensor. The camera was georeferenced using bar codes with known coordinates, attached to the side of the vases (Figure 2). All the motors and sensor could be activated by a web-page interface accessible through the computer or smartphone, allowing remote control of the data collection. Illumination was also present in the greenhouse, making it possible to collect data even during the night.

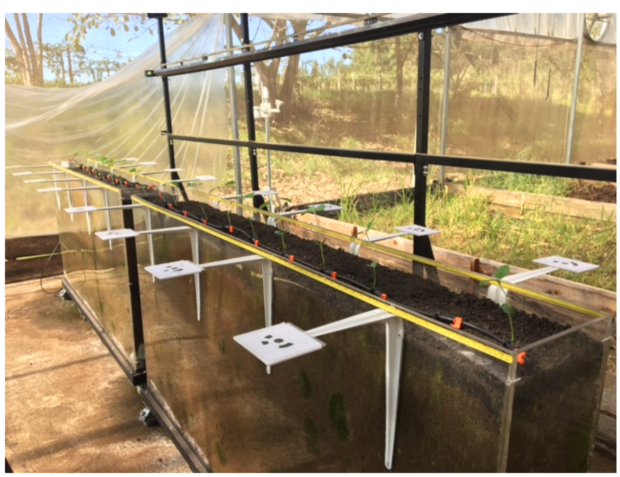

Figure 2. Bar codes used to overlap and geo-reference the images

- Data acquisition and processing

Soybeans were sown in the vases in order to evaluate the performance of the sensors in a representative crop, on which new varieties have been developed and HPP could help and be effective.

For data acquisition a Raspberry PI3 (Raspberry, United Kingdom) with a customized data acquisition software, using Python 2 programming language, was developed to collect the LiDAR and Kinect synchronously with the encoder. Camera data was acquired by setting an automatic shooting time interval of one frame per second. All data was transferred through the Wi-Fi network to a desktop computer with better computing capabilities, where the data was processed. The RGB images from the camera were used to create a 3D model by stereoscopy (Structure From Motion – SFM); it was possible because there were overlaps between two different images with different points (LLC, 2016) in which the bar codes were read and the 3D model georeferenced. RGB images were also evaluated individually, in order to preserve the resolution of the photo. In addition, a customized data processing software, using Python 2 programming language, processed the K1 and LiDAR data. This software joined the depth and RGB images from K1, creating a RGB-D image and georeferenced the K1 and LiDAR data.

Results and Discussion

As seen in the examples on Figure 3, LiDAR sensor data has the poorest resolution because fewer information is obtained each time (2D sensor) and it has no overlap in sequence as it has in the image sensors. On the other hand, varying light conditions can affect image acquisition and even more the SFM 3D reconstruction.

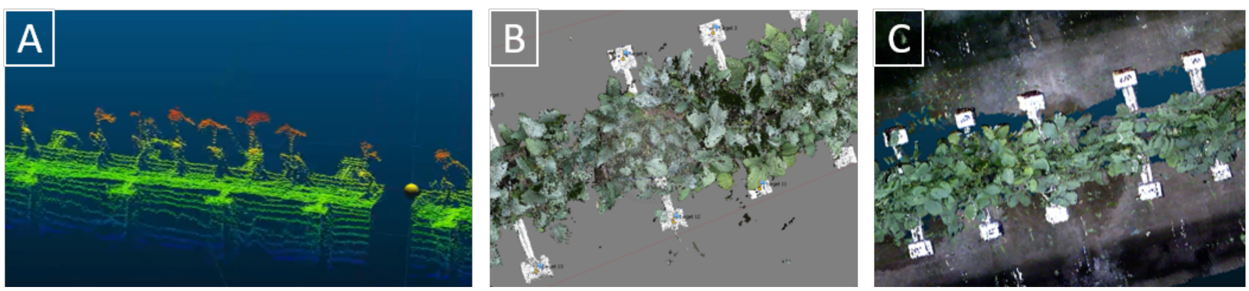

Figure 3. Examples of point cloud obtained with: a) LMS -200 b) T3 Canon and c) Kinect V1

K1 depth sensor uses a pattern of infrared light to measure distances, when the ambient infrared light is high. When the plants are direct exposed to sunlight, the sensor generates low quality depth information. Therefore, K1 has restricted outdoor applications. Another ambient restriction for K1 is the RGB dependence of ambient light to capture good images. Therefore, according to Jiang et al., 2018 the way to overcome this problem in field conditions can be to construct and move a chamber with its own source of light, like in the GPhenoVision system proposed by these authors. Also, including artificial light on the structure allowed K1 night data acquisition, avoiding the sun infrared wavelength that do not allows good data quality. Figure 4 present the influence of sun light in depth image from K1. On the very intense sun light exposure, the depth camera can just identify a very small object that is shadowed. Even in the less intense sun light exposure, the depth camera cannot produce reliable results.

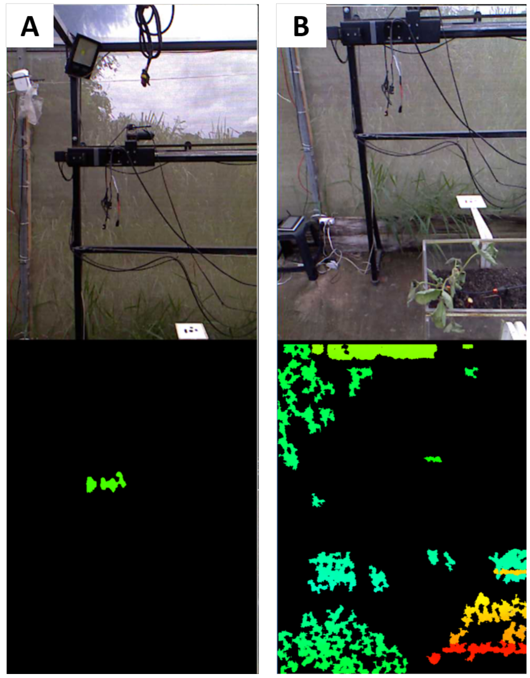

Figure 4. RGB (top) and depth (bottom) images from K1 on a very intense sunlight exposure (A) and on a less intense sun light exposure (B)

Wind has also a great impact on SFM 3D reconstruction. This method depends on common points found in two or more images, if the objects move between images, poor results will be produced and shadows of the plant tissues that were moved by the wind. The RGB-D and LiDAR sensor are also affected by the wind when more than one perspective (e.g. from different rails in the structure) of the same plants are acquired. If the plants change the position, the different perspective point clouds will not match.

Table 1 presents a summary of different conditions and a 0-10 scale showing how good the methods are on the aspect of each condition. This scale was developed by the experience phenotyping using the structure developed and comparing the sensors evaluated in this work. Thus, 10 is the highest score that a technique could be classified on that condition. It is interesting to point that, hand and LiDAR are most robust methods for ambient conditions, but they have the poorest data resolution. Another point is the RGB-D from K1 not been suitable for field conditions, this related with the effect of sun light already commented.

Table 1. General characteristics of different methods for extracting phenotypic information from soybean plants.

Condition	Hand	RGB	SFM RGB	RGB-D	LiDAR
Light	8	5	3	2	9
Wind	9	8	1	4	5
Resolution	1	6	5	4	2
Accuracy	7	8	8	8	9
Data acquisition time	0	9	7	9	9
Data processing time	6	8	1	5	7
Positioning precision	4	2	8	7	7
Positioning accuracy	3	1	6	5	5
General Cost*	1	9	8	7	5
Field	6	8	7	2	8
Greenhouse	8	8	7	4	8
Individual plants	9	9	9	8	8

*General Cost = costs related with data acquisition such as people, sensor cost, structure, time consuming, data processing and others

The resolution of LiDAR and RGB-D sensors, in terms of number of data points acquired per plant in normal operation, can be a limitation to identify small parts of the plants. The accuracy of the systems, which can be calculated taking measurements of the same plant in different times, are all similar. Acquisition time for all sensors are also similar, and usually a phenotyping platform can acquire data from all sensors at once. When compared by data acquisition time, sensors are much more efficient than manual measurements. Therefore, this is the reason by evaluating sensors for plant phenotype, because it allows a HPP.

The SFM 3D reconstruction is computer intensive and time consuming. Processing 1000 images can take more than 24 h in a normal computer. Extracting features from single RGB images is much faster and can even be done in real time if a good processor is used.

At field level, positioning precision and accuracy can be obtained using a RTK GPS and an inertial measurement unit to get the sensor coordinates, associated with ground control points. Usually, millimeter level precision is desired, which is a difficult task. Most of the methods will produce centimeter or decimeter level precision in field conditions, which is sufficient for plot level evaluation, but may not be enough for temporal comparisons of individual plants. In greenhouse, different methods of relative positioning can be used and millimeter level accuracy is more likely to be obtained.

The costs associated with imaging techniques are more related to data processing than the sensor itself. LiDAR sensors are still more expensive, but due to their popularity in self-driving vehicles applications, the mass production of these sensors will force prices down in the near future.

Considering the general score, the Kinect v1 sensor is not well suited for field conditions, while the RGB cameras can be applied in all conditions. The most suitable sensor will depend on what is the phenotypic information wanted and how fast it is required. Table 2 summarize the general performance of the different methods for extracting phenotypic traits from soybean plants.

Table 2. General performance of different methods for extracting phenotypic information from soybean plants.

Feature	Hand	RGB	SFM RGB	RGB-D	LiDAR
Crop height	9	5	8	9	10
Canopy volume	6	5	8	8	9
Canopy mass	7	5	8	8	9
Canopy porosity	5	5	8	8	7
Stem diameter	9	8	5	2	1
Stem bending angle	7	5	6	6	4
Nodes count	9	8	3	2	1
Internodes distance	9	7	4	2	1
Secondary stems	9	8	4	2	2
Leaf Area	7	8	7	9	5
Leaf count	9	7	6	8	4
Leaf vegetation index	3	9	8	8	1
Diseased leaves	8	8	7	6	1
Flowers count	8	6	4	4	1
Flowers position	6	6	5	5	1
Pods count	9	8	5	6	1
Pods position	7	6	6	6	2
Grains per pod	9	3	3	3	1
Grain Yield	9	5	6	6	4

Conclusion

The study showed the reliability of low-cost data for the parametrization of plant organs in phenotyping setups. We observed that RGB cameras have a great potential to extract phenotypic information from soybeans. Kinect V1 has an important limitation for field conditions as it uses a pattern of infrared light to measure distances, and this pattern cannot be seen when the ambient infrared light is greater than that from the sensor. LiDAR technology, the most expensive sensor tested showed the worse resolution to measure phenotyping parameters, on the other hand, the data is faster to process and is not influenced by light conditions.

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