IMPLEMENTATION OF UAV-BASED LIDAR FOR HIGH THROUGHPUT PHENOTYPING

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ABSTRACT

High throughput phenotyping is rapidly gaining widespread popularity due to its ability to non-destructively extract plant traits, such as plant height, canopy density, leaf and plant structure, and so on. In this study, we focus on developing a UAV-based LiDAR system to acquire accurate time-series 3D point clouds for monitoring two specific plant traits – plant height and canopy cover – which are integral for enhancing crop genetic improvement to meet the needs of future generations. Furthermore, the obtained estimates are validated by comparing the results with those obtained from wheel-based LiDAR data.

***Index Terms*—** High throughput phenotyping, plant height, canopy cover, UAV, LiDAR system.

1. INTRODUCTION

According to a recent study, an increase of 100-110% is forecast in global crop demand by 2050 as compared to 2005 [1]. In order to meet this demand with minimal environmental impacts, attainment of high yields on existing croplands is of great importance. In [2], the author stated genetic improvement of staples has accounted for more than half of the past increases in yields. The continuing advances in technology enable the development of more efficacious breeding schemes. High throughput phenotyping is one of such advances that is gaining wide recognition as it has proven to be an efficient method to non-destructively capture plant traits. The authors of [3] conducted a detailed study on the advancement of field high throughput phenotyping that is required for increasing the efficiency of crop genetic improvement to meet the needs of future generations. They concluded that the capacity for undertaking precision phenotyping, particularly under repeatable and representative growing conditions in the field, is lagging far behind the capacity to generate genomic information, thus constraining breeding advances. So, it is imperative to have adequate low-cost and easy-to-handle data collection platforms that facilitate repetitive data acquisition for extracting accurate phenotyping information. In this regard, airborne (UAV-based) mobile mapping systems consisting of LiDAR unit(s) and a GNSS/INS unit can be used to successfully acquire time-series 3D point clouds over agricultural fields, thus facilitating the monitoring of various plant characteristics, such as plant height, canopy density (or, canopy coverage), leaf and plant structure, and so on. Currently, there are commercially available LiDAR units that are capable of emitting more than a quarter million pulses per second at a cost of less than $10k. Also, there are GNSS/INS units that are designed to provide highly accurate position and orientation information while meeting the size, weight, power, and cost constraints of small UAVs. Such availability renders UAV-based mobile mapping systems as a feasible alternative for high throughput phenotyping. However, the accuracy of the acquired information is contingent upon the integration of various system components – such as a LiDAR unit and a GNSS/INS unit – followed by an accurate calibration of the mobile mapping system as a whole. In this paper, we propose a development of a LiDAR-based mobile mapping system by – 1) choosing system components whose specifications indicate that these would be adequate for our intended application of UAV-based high throughput phenotyping and integrating the hardware components involved in the mobile mapping system, and 2) developing a novel calibration approach to ensure the acquisition of highly accurate 3D point clouds using the UAV-based mobile mapping system. Then, we also propose an approach for estimating important traits for plant phenotyping – plant height and canopy cover – using LiDAR data acquired by a calibrated UAV-based mobile mapping system. The proposed calibration strategy is validated by a set of experimental results. Finally, we present some preliminary results derived for plant height and canopy cover evaluation using the data captured by the calibrated UAV-based mobile mapping system for an agricultural field situated at the Agronomy Center for Research and Education (ACRE), Purdue University.

2. SYSTEM INTEGRATION AND CALIBRATION

To build an operational UAV-based mapping system, which satisfies all the demands of a certain application, an adequate platform, and mission sensors should be selected [4]. The key attributes of the proposed system design are low cost, ease of use, and flexibility to fulfill precision agriculture applications. In this research, the developed system includes a position and orientation (POS) unit, an RGB camera and a LiDAR unit. All

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these components are rigidly fixed within the UAV platform as shown in **Error! Reference source not found.**.

Fig. 1. UAV-based mapping system configuration

The DJI M600 as the UAV platform is designed for professional aerial mapping applications. Its total weight with batteries is 9.6 kg and maximum take-off weight is 15.5 kg, thus allowing around 6 kg payload of sensors/equipment to be installed onboard. As a POS unit, the Applanix APX-15 UAV is considered due to its low weight, compact size, and precise positioning and orientation information. In post-processing mode, it can attain an accuracy of 0.025º for pitch/roll and 0.08º for heading (yaw), and the position accuracy is 0.02-0.05 m [5]. The Sony alpha 7R is a 36.4 MP off-the-shelf camera, which is selected as a passive imaging sensor onboard the developed mapping system [6]. The LiDAR unit used in this research is a Velodyne VLP-16 Puck HI-RES. It is a small LiDAR unit, which has 16 lasers beams that are aligned over the range of +10.00º to -10.00º that provides the vertical field of view, and it delivers a 360º horizontal field of view. It can scan up to 300,000 points per second with a range of 100 meters and typical accuracy of ± 3 cm [7]. For storing the collected data, a Raspberry Pi 3 with 1.2 GHz 64-bit quad-core ARMv8 CPU is used with around 50 gm weight. Its small size and light weight eases its installation on the UAV.

System calibration is a vital step in order to have an accurate geospatial information. The system calibration encompasses estimating the mounting parameters of the camera and LiDAR unit with respect to the onboard GNSS/INS unit using geometric tie points as well as features (e.g., planar, and linear/cylindrical features). The conceptual basis for a simultaneous LiDAR/camera system calibration is to minimize the discrepancies among points, linear features, and/or planar features obtained from different laser scanners, cameras, and/or flight lines.

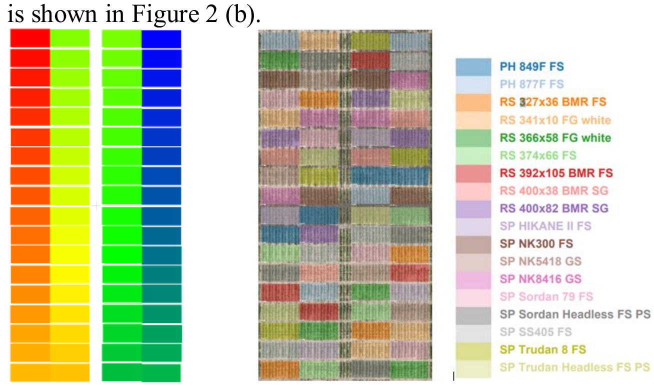
3. PLANT HEIGHT AND CANOPY COVER ESTIMATION

The temporal variation of plant height is an important trait to be used in phenotyping. In order to monitor plant growth over time, we generate Crop Surface Models (CSMs) for different days, which are rasterized maps depicting the maximum height over each user-defined grid cell within the region of interest. Owing to the noisy nature of LiDAR data, the CSMs are generated for 90th percentile heights within each grid cell, which would still represent the effective plant height while eliminating any potential impact of noisy LiDAR points. Also, in order to consider the variation of entire plant structures, we also generate the 30th and 60th percentile height maps. Note that the 30th, 60th, or 90th percentile height maps are generated by sorting all the points within a grid cell by height and assigning the height value for the 0.3nth, 0.6nth, and 0.9nth points to the grid cell, respectively, where n denotes the total number of points within the grid cell. Finally, a nearest neighbor interpolation is applied to all the grids within the plots to account for the grids where no points have been captured.

In this study, the agricultural field of interest is divided into plots consisting of different genotypes of the same crop. Hence, the focus of this paper is to study the plant height and canopy cover variation across various plots within an agricultural field for different days. The first step in canopy cover estimation is to obtain the Digital Terrain Model (DTM) for the area of interest, which would yield information regarding the bare earth height for the region. The DTM is obtained using LiDAR data captured for barren land, which is then used to derive the average bare earth height for each plot within an agricultural field. Now, the canopy cover is estimated for each grid cell as the ratio of number of points with a height value more than 10 cm above the bare earth height for the respective plot to the total number of points captured within the cell. Finally, a plot's canopy cover is determined by averaging the estimated canopy cover for each of the grid cells contained in the plot.

4. EXPERIMENTAL RESULTS

The calibrated UAV-based mobile mapping system was used to for multiple data acquisitions over an agricultural field at ACRE, Purdue University, where different genotypes of Sorghum are planted. In this research, we aim to use the LiDAR point cloud acquired for three different days (7th, 14th, and 25th July, 2017) and analyze the plant height and canopy cover variation with time over various plots (each plot consisting of a different genotype of the same crop). The plant height variation can be extracted by creating a Crop Surface Model (CSM) using the LiDAR point cloud for each data acquisition and extracting the average plant growth between consecutive data acquisition days for each plot. The plots of interest are indicated in Figure 2 (a) with blue denoting Plot 4101, red denoting Plot 4172, and the intermediate colors denoting the intermediate plots. The color-coded map of the different genotypes planted in each plot is shown in Figure 2 (b).



(a) (b)

Fig. 2 Plots of interest – (a) colored by the plot numbers from blue denoting Plot 4101 to red denoting Plot 4172, and (b) colored by genotypes of Sorghum

The 30th, 60th, and 90th percentile height maps for the three days are shown in Figures 3, 4, and 5 for 7th July, 14th July, and

25th July, respectively. The corresponding point density maps for the three days are also shown along with the flight trajectory in Figure 6. Further, the canopy cover is estimated by integrating the CSM with the Digital Terrain Model (DTM) obtained for the agricultural field from a data acquisition conducted before any plant growth.

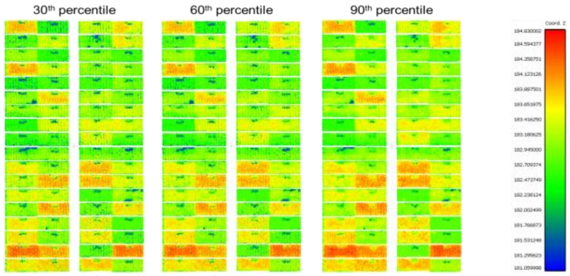


Fig. 3. 30th, 60th, and 90th percentile height maps for 7th July, 2017

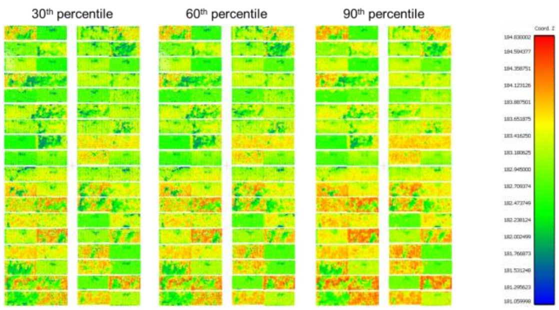


Fig. 4. 30th, 60th, and 90th percentile height maps for 14th July, 2017

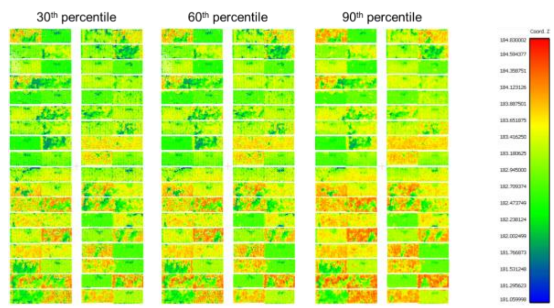


Fig. 5. 30th, 60th, and 90th percentile height maps for 25th July, 2017

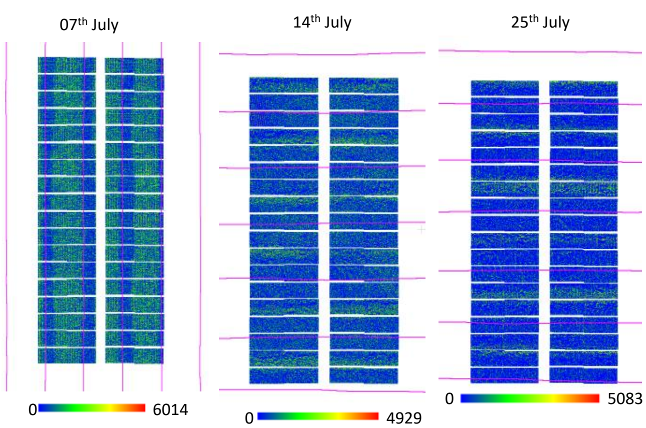
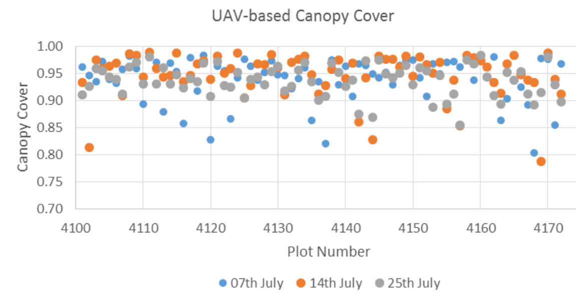
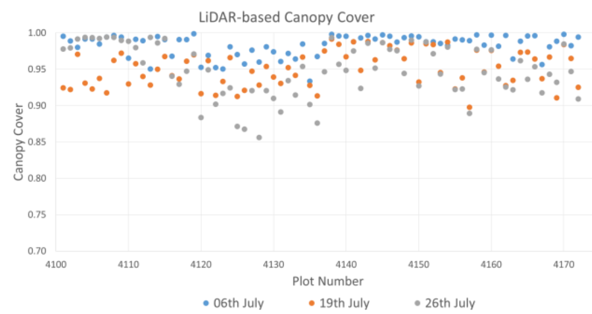


Fig. 6. Point Density Maps for 7th, 14th, and 25th July, 2017

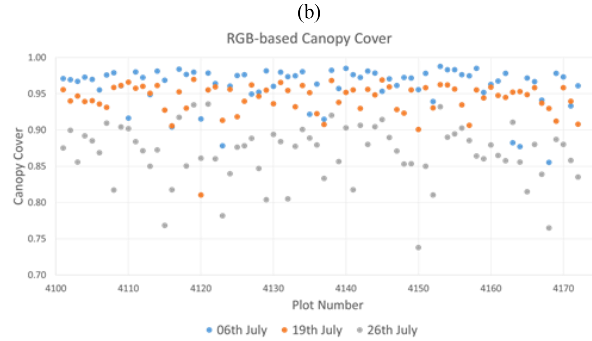
The canopy cover for each 4 cm x 4 cm grid cell is shown in Figure 7 and the quantitative results for canopy cover of each plot as obtained from UAV-based LiDAR data are shown in Figure 8 (a). From the UAV-based LiDAR data, the average canopy cover for all the plots was found to be 93.97%, 94.76%, and 93.66% for 7th, 14th, and 25th July, respectively. Similarly, the canopy cover estimates of each plot as obtained from wheel-based LiDAR data and RGB-orthophoto are shown in Figures 8 (b) and 8 (c), respectively. Note that the average canopy cover increases from 7th to 14th July, which is intuitive as the canopy cover should increase with plant growth. However, there is a decrease in canopy cover from 14th to 25th July. This is attributed to an intermediate destructive sampling conducted on 18th July within each plot for a direct biomass prediction. The average canopy cover estimates obtained from wheel-based LiDAR data and RGB-orthophoto for nearby dates are listed in Figure 9. The slight mismatch in the estimates from different modalities for close dates can be attributed to the intermediate destructive sampling, as discussed before, as well as the varying ability of the different modalities to penetrate through the canopy. These preliminary results indicate that UAV-based LiDAR data is a feasible and highly efficient method for conducting high throughput phenotyping.



(a)



(b)



(c)

Fig. 8. Canopy cover estimates for all plots from: (a) UAV-based LiDAR data, (b) wheel-based LiDAR data, and (c) RGB-orthophoto

5. RECOMMENDATIONS FOR FUTURE WORK

In the future, we plan to improve the suggested approach for canopy cover estimation by taking into account the areas where destructive sampling is done in order to mitigate the counter-intuitive results showing a reduction in canopy cover.

Furthermore, we plan to conduct a comparative analysis of the canopy cover estimated using UAV-based LiDAR data with the ones estimated using wheel-based LiDAR data and UAV-based RGB imagery data acquired for the same dates in order to eliminate the effect of intermediate plant growth or destructive sampling.

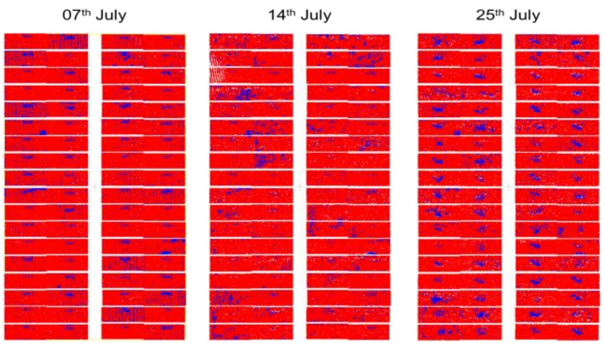


Fig. 7. Rasterized Canopy Cover Maps for 7th, 14th, and 25th July, 2017 – Colored by canopy cover with blue denoting 0% and red denoting 100%

	06th July	07th July	14th July	19th July	25th July	26th July
UAV-based LiDAR	NA	0.9397	0.9476	NA	0.9366	NA
Wheel-based LiDAR	0.9830	NA	NA	0.9511	NA	0.9480
RGB-orthophoto	0.9606	NA	NA	0.9428	NA	0.8672

Fig. 9. Average canopy cover estimates from UAV-based LiDAR, wheel-based LiDAR and RGB-orthophoto for different dates

6. REFERENCES

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