Estimation of canopy height using an unmanned aerial vehicle in the field during wheat growth season

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Abstract
Canopy height is a simple trait to represent status of plant growth and development and potentially biomass production, as well as having an influence on lodging susceptibility. Measurement is labour-intensive and time consuming, especially in the large breeding trials, which involve thousands of plots. In this study, we developed a methodology to estimate canopy height using a high resolution camera which was mounted on an Unmanned Aerial Vehicle (UAV). Aerial images were captured during a wheat growth season with contrasting canopy height at four time points. Digital surface models (DSMs) were generated using structure from motion (SfM) algorithm after 3D reconstruction of the whole field (e.g. phenocopter.csiro.au). Three methods were used to estimate soil surface and canopy heights at plot level after segmentation of DSM into individual plots including 1) background extraction after segmentation mosaic into vegetation; 2) interpolation of soil surface using soil surface around field edges; 3) measured soil DSM by a flight immediately after planting. Estimates of canopy heights were compared to manual measurements close to the flight times. The results indicated Method 2 had the best performance for wheat canopy (R^2 = 0.88; RMSE = 4.5 cm). The proposed method can been integrated into the high throughput phenotyping platform to apply UAV technologies in the breeding program.

Keywords
High-throughput phenotyping, LiDAR.

Introduction
Canopy height is a useful trait to indicate growth status (Bendig et al. 2014; Freeman et al. 2007; Holman et al. 2016). The traditional method to measure plant height with a ruler is labour-intensive and inefficient in the large breeding trials which involving thousands of plots.

With recent advances, consumable unmanned aerial vehicles (UAVs) costing less than $1000 are available for general usage and have been used in multiple high throughput platforms to collect aerial imagery through mounting multiple sensors, e.g. laser scanner (Anthony et al. 2014; Wallace et al. 2014), colour infrared camera (Zarco-Tejada et al. 2014), RGB camera (Geipel et al. 2014; Holman et al. 2016; Weiss and Baret 2017). Aerial imagery were collected in a short period (10 to 20 min) and reconstructed the 3 dimensional structure of whole field using image analysis, e.g. the structure from motion (SfM) algorithm.

A digital surface model (DSM) is generated after reconstruction to represent the viewable surface of field from the air. Canopy height can be determined through difference between soil surface and DSM. The upper boundary of canopy at plot level can be calculated through 99th percentile of DSM to decrease the errors introduced by outliers (Holman et al., 2016; Khanna et al., 2015), and local maxima or statistical methods (Anthony et al. 2014; Torres-Sánchez et al. 2017; Zarco-Tejada et al. 2014). To develop sufficient precision (< 5 cm), methods need to account for issues related to the shape and slope of the field, the effectiveness of the mosaic and structure algorithms and poor accuracy of GPS positioning, especially in the Z dimension.

It is challenging to find soil surface under field conditions, especially with dense canopies and spatial variation of ground level. Some methods had been proposed to estimate the soil surface, e.g. statistical methods (Anthony et al. 2014; Khanna et al. 2015) , fitting or interpolating a ground plane with a portion of lowest or soil points at gaps (Holman et al. 2016; Weiss and Baret 2017), soil surface without crops with the same set of ground control points (GCPs) (Geipel et al. 2014). However, these methods have not been compared for dense canopies.

In this study we compared three methods to determine the soil surface and estimate canopy height during wheat growth season with contrasting canopy height. The performance of three methods were compared with manual measurement.

Methods

Wheat experiments were conducted in 2016 at the experimental station of Gatton Campus, the University of Queensland (27.50°S, 153.01°E). Contrasting canopy structures were established by two irrigation treatments (irrigation and rain-fed) and two nitrogen treatments (high and low nitrogen). Fertiliser was applied at sowing with 205 kg ha^{-1} for high nitrogen and 50 kg ha^{-1} for low nitrogen (Urea, 46% N) after measuring the pre-planting soil nitrogen being ca 32.3 kg ha^{-1} (0 to 60 cm). The experimental field has a gentle slope along the long sides of the field and was 54 m wide and 161 m long, and split into four blocks and totally 522 plots including the fillers in the whole field. Plots contained seven rows and were 2 m wide and 7 m long. The planting data was 21th May and plant density was 150 plants m^{-2} by machine. Canopy height were manually measured for sampling plots by rulers within 3 days at each flight to validate and calibrate the estimated canopy height from UAV. In each plot, canopy height of 5 average plants were manually measured through measuring the height from canopy top and ground in the natural conditions.

A low cost unmanned aerial vehicle UAV-based phenotyping platform was used to capture the RGB images in the field at four time points during the growing season following protocols developed by Chapman et al. (2014). The flight dates were 11th July, 19th July, 1st August and 9th August, 2016.

An unmanned aerial vehicle (Iris+ quadcopter (discontinued product), 3DR Robotic Systems, Palo Alta CA, USA) was flown over the field with controlled flight pattern as substantial image overlap is required to obtain a satisfactory reconstruction results. Autonomous flight plans ('lawnmower' designs) were constructed using Mission Planner (open-source flight planning software for Pix Hawk autopilot) to have substantial overlap (i.e. 70% forward and 80% side) at flight heights of 20 m and with a flight speed of 3 meters per second. The UAV carried a Sony camera (DSC-RX100M3 with 24 mm focal length and resolution 5472 × 3648) and was flown over the experiment field. The ground sampling distance (GSD) was about 4 mm in all flights, with the camera triggered at 1 second intervals, with a fast shutter speed (<1/1200th second), ISO of 100 (sunny) or 200 (cloudy) and automatic aperture. GCPs were lay out in the whole field from the start of the season (15 in total). Coordinates of GCPs were recorded before the first flight using the Trimble Geo 7X GPS (http://www.trimble.com). In addition, five height references were installed around field (0.5 and 1 m).

Pix4DMapper software (Pix4D SA, Switzerland) was used to generate ortho-mosaic and DSM for each flight. Ortho-mosaics and DSMs were segmented into individual plots according to experiment design and four corners of field using the method developed by (Duan et al. 2016) with data being managed via a customised workflow (see phenocopter.csiro.au for examples). The same segmentation could be used for ortho-mosaic and DSM in all flights after adding GCPs.

The key issue to estimate canopy height is to approximate the soil surface of whole field. The canopy height was calculated as the elevation difference between soil surface and top of the canopy. The top of canopy was represented by the 99th percentile of vegetation for each plot. We presented three methods to determine soil surface including 1) background extraction after segmentation mosaic into vegetation; 2) interpolation of soil surface around field; 3) measured DSM immediately after planting.

Method 1: For each flight, the ortho-mosaic of each plot was segmented into two classes, i.e. vegetation and background using a machine learning method (Duan et al. 2016; Guo et al. 2013). The plots didn't have any trimming around 4 edges, so this method detected the inter-row area between adjacent plots. The 1st percentile of background was used to represent the soil surface.

Method 2: For each flight, two virtual lines were positioned along the two longer sides of field in the unplanted gaps. Elevations of 50 points were extracted from the DSM at each line with an even distribution. An inverse distance weighted interpolation algorithm was applied to predict elevation of soil surface as an underlying plane under the trial.

Method 3: All flights were fitted with the 15 GCPs, which we expected to have the same elevations for soil surface. The first flight was conducted immediately after planting without any plants and could be used to represent the soil surface of the whole field.

Results

Manually measured canopy heights were used to evaluate the performance of three methods. There were totally 384 observations for 4 flights (96 observations in each flight). Method 1 was the poorest performance (R^2 = 0.30, RMSE = 9.09 cm, Figure 1) with a better performance in the early stage when wheat canopy coverage was small. When canopies were close to full coverage, only small portions of soil were visible to the camera mounted on the UAV, so that the inaccurate reconstructions of soil pixels made these pixels float in the air or mix with plant pixels. The canopy heights were significantly underestimated at later stages (Figure 1). Method 2 had the best performance among three methods (R^2 = 0.88, RMSE = 4.48 cm). However, this method is depending on the gradient of soil surface in the field. Our field was a long rectangle (161 m long and 54 m wide) with relatively constant gradient. For other fields with an undulating gradient, a different method should be studied to estimate canopy heights. Method 3 had the medium performance among three methods (R^2 = 0.82), but significantly underestimated canopy height (RMSE = 9.57 cm, Figure 1). The underestimation by Method 3 was related to the accuracy of GCPs in all flights. The horizontal errors of GCPs were about 2 cm after reconstruction of Pix4D, but vertical errors of GCPs were up to above 20 cm (data not shown), when compared with the manually measured positions of GCPs using Trimble GPS.

Several methods have been developed to estimate canopy height using UAV, but the accuracies of these methods depend on several factors (e.g. shape and slope of field, image quality, ortho-mosaic and DSM reconstruction, and GPS accuracy) and need to further study to improve the performance of UAV technologies.

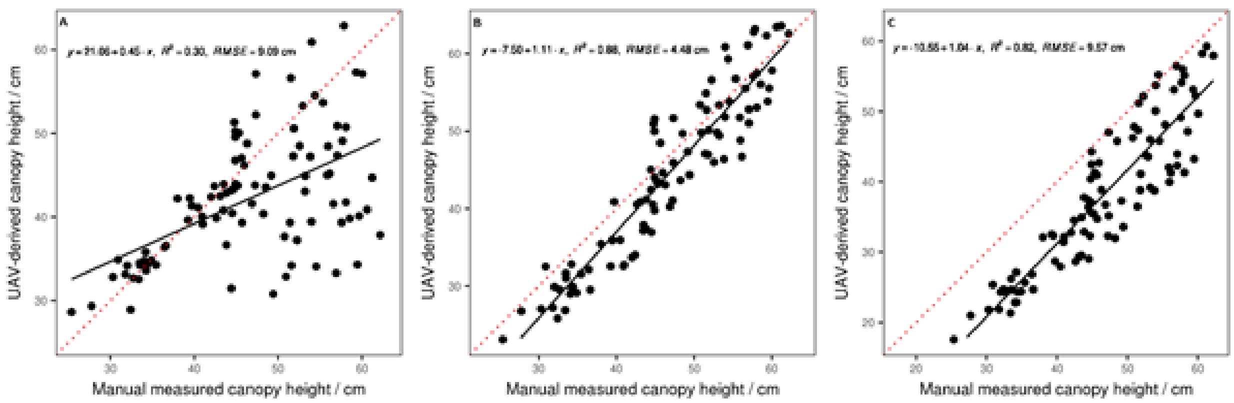

Figure 1. Comparison of canopy height measured by ruler (X-axis) and estimated by UAV (Y-axis) at four time points. Three methods were used to represent soil surface and then estimate canopy heights (1. background extraction after segmentation mosaic into vegetation (A); 2. interpolation of soil surface around field (B); 3. measured soil DSM immediately after planting). The red dashed lines are 1:1 lines. The black lines are linear regression lines.

Conclusion

In this study, we compared three methods to estimate canopy heights using a UAV-based phenotyping platform, PhenoCopter. The performance of three methods were compared with manually measured values during a wheat growing season with contrasting canopy height at plot scale. The results indicated the soil masking (Method 1) was not suitable for canopy with high coverage. Gaps around field edges (Method 2) can be used to represent soil surface for fields with a constant spatial gradient. Soil surface after planting plus GCPs (Method 3) may be suitable for tall crops that should have smaller relative errors. These methods can be integrated to high throughput phenotyping platform in the breeding program.

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