European Journal of Agronomy 95 (2018) 24–32

Contents lists available at ScienceDirect

European Journal of Agronomy

journal homepage: www.elsevier.com/locate/eja

Estimation of plant height using a high throughput phenotyping platform based on unmanned aerial vehicle and self-calibration: Example for sorghum breeding

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ARTICLE INFO

Keywords:
UAV
High throughput phenotyping
Plant height
Self-calibration
Data fusion

ABSTRACT

Plant height is an essential trait to evaluate in grain sorghum, being positively associated with potential grain yield. Standard manual measures of plant height for large breeding trials are labour-intensive and time-consuming. Due to potential field access issue and the remote nature of breeding trials, Unmanned Aerial vehicles (UAVs) are well-suited to measure plant height if the ground surface can be referenced. In this study, we compared existing algorithms with a new method for estimating plant height for a sorghum breeding trial. Images were captured by a RGB camera mounted on an UAV before emergence and near maturity to generate digital surface models (DSMs). Two existing methods ('point cloud' and 'reference ground') and a new method ('self-calibration') were used to estimate ground level and plant height at the plot level. The self-calibration method required manual measurements of the actual plant height in a sample of plots (fewer than 30), which could be completed during the 30-min flight time. UAV-derived plant heights from each method were compared to manual measurements. The self-calibration method had the best performance (R^2 = 0.63; RMSE = 0.07 m; repeatability = 0.74), with similar repeatability to manual measurement (0.78). The point cloud and reference ground methods had lower repeatabilities (0.34 and 0.38, respectively). For the self-calibration method, we tested different sampling strategies to balance accuracy and the workload of manual measurements, finding that a sample of 30–40 plots from the1440 total could obtain precision similar to manual measurement of the entire trial. The self-calibration method offers a pragmatic, robust and universal approach to high throughput phenotyping of plot plant height with UAV surveys.

1. Introduction

Crop breeding programs have a limited set of resources to phenotype germplasm at different stages of the breeding program. The plot size ranges from single plants to large plots. Accelerating the delivery of new cultivars requires the capacity to more rapidly phenotype of larger numbers of genotypes in the field (Araus and Cairns, 2014; Cabrera-Bosquet et al., 2012; Chapman et al., 2014). However, field phenotyping is expensive, laborious and time-consuming, especially when thousands of plots are being evaluated in multi-environment trials distributed across at target region (Cobb et al., 2013; Sankaran et al., 2015).

Most phenotyping in plant breeding comprises visual scores, quantitative and qualitative measurement of phenotypic traits through non-destructive and destructive methods during growth season and at maturity (*e.g.* height, flowering date, leaf area index, dry mass, grain yield, grain size). A key characteristic of high throughput phenotyping systems is the capability to non-destructively and non-invasively characterise phenotypic traits for thousands of individual plants with high efficiency and precision (Furbank and Tester, 2011; Großkinsky et al.,

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https://doi.org/10.1016/j.eja.2018.02.004
Received 3 November 2017; Received in revised form 31 January 2018; Accepted 17 February 2018

2015; Pauli et al., 2016), and to monitor the same plot in the whole lifecycle to increase the experimental capacity (Fahlgren et al., 2015). Compared with ground-based phenotyping platforms (Busemeyer et al., 2013; Deery et al., 2014; Rebetzke et al., 2016), unmanned aerial vehicles (UAVs) are relatively inexpensive and flexible in the spatial and temporal resolution of data acquisition and can now carry diverse mounted sensors (Chapman et al., 2014; Duan et al., 2017; Sankaran et al., 2015; Tattaris et al., 2016). Depending on the experimental objectives, UAVs are capable of phenotyping an entire field in a short period with the pre-planned routes and specified flight altitudes and speeds (Chapman et al., 2014; Gago et al., 2015; Martínez et al., 2017; Potgieter et al., 2017).

Proximal sensing is being widely adopted in precision agriculture applications, but to date the accuracies of UAV technologies are generally not high enough for the purposes of comparing small differences among genotypes in small plots (López-Granados, 2011; Rathod et al., 2013). However, multiple data sources are potentially available in a field experiment, *e.g.* manual measurements, ground-based sensors and air-based platforms, each source with their own limitations regarding to flexibility, spatial and temporal resolution and accuracy (Großkinsky et al., 2015; Sankaran et al., 2015). Fusion of data from multiple sources has the potential to improve the accuracy for high throughput phenotyping (Berdugo et al., 2014; Dupuis et al., 2014; Rischbeck et al., 2016).

In this study, plant height was taken as an example trait to demonstrate the advantages of data fusion and introduce a method of self-calibration into UAV-based platform of high-throughput phenotyping. Plant height has been related to estimations of shoot biomass and yield (Freeman et al., 2007; Geipel et al., 2014; Li et al., 2016; Schirrmann et al., 2016), characterization of growth rate and health of crops (Holman et al., 2016), crop type identification (Wu et al., 2017) and weed detection (Piron et al., 2011). For sorghum grown in Australia, farmers have a preference for crops in the *ca.* 1.1–1.4 m height range as these relatively short crops have a lower tendency to lodge during poor seasons (low or high rainfall) or when affected by stalk diseases, but are tall enough for efficient harvest by combines.

Plant height is defined here as the shortest distance between the upper boundary of the plant and the ground level (Pérez-Harguindeguy et al., 2013). Manual height measurement is labour-intensive for a large scale breeding trials and can be constrained by weather which may limit access to the plots. Several high throughput technologies have been developed to estimate plant height in field conditions. Ground-based platforms have used various sensors (*e.g.* RGB cameras, RGB-Depth cameras. LiDAR and acoustic sensors) to collect plant height data (Deery et al., 2014; Rebetzke et al., 2016; Shafiekhani et al., 2017; Sharma et al., 2016), although they are typically more constrained from accessing field than manual methods due to difficulties for equipment movement in the field (Araus and Cairns, 2014; Chapman et al., 2014; Sankaran et al., 2015). Aerial-based platforms also have been used to estimate plant heights (Holman et al., 2016; Zarco-Tejada et al., 2014) with methods summarized in Table S1. From these multi-point methods, plant height is usually related to an upper boundary of generated point-cloud or digital surface model (DSM) values (*e.g.* 95th and/or 99th percentiles) (Holman et al., 2016; Madec et al., 2017; Thi Phan et al., 2016; Watanabe et al., 2017). Determination of the ground level (lower boundary) is more difficult with most current methods being based on being able to view the soil surface around and/or in the field to determine ground level, *e.g.* fitting or interpolating a ground plane using a specific percentile of the lowest points (De Souza et al., 2017; Weiss and Baret, 2017) and generating a digital terrain model by segmenting DSM pixels into vegetation and ground (Aasen et al., 2015; Geipel et al., 2014) or by using a reference ground established by flights done pre-sowing or early in the season (Bendig et al., 2013; Holman et al., 2016; Wu et al., 2017). These methods are not suitable for trials where the canopy has full coverage (*i.e.* soil is not viewable from air), and trials without reference ground and/or with complicated spatial terrain.

The aim of this study was to estimate plant height of a sorghum breeding trial using high throughput phenotyping in a UAV based platform. We hypothesized that cameras attached to UAV can accurately estimate the upper boundary of the canopy, but do not accurately measure the soil surface of the field. Therefore, we evaluated two major categories of existing methods to estimate ground level and then plant heights, and developed a new method through fusing sub-samples of manual measurement and UAV survey. Based on the practices of breeders and technicians, sampling strategies were further evaluated to balance accuracy and workload for the self-calibration method.

2. Materials and methods

The workflow comprised several steps (Fig. 1): 1) capturing geo-referenced aerial images using a visual camera (contains three channels, *i.e.* red, green and blue) mounted on an UAV; 2) generating *ortho*-mosaic and DSM using a commercial software; 3) segmenting *ortho*-mosaic (only used in the plot segmentation) and DSM into individual plots according to the experimental design; 4) estimating upper boundary and ground level, and then plant height. For consistency, a single method was used to estimate upper boundary, but three methods were used to estimate ground level (*i.e.* point cloud, reference ground and self-calibration).

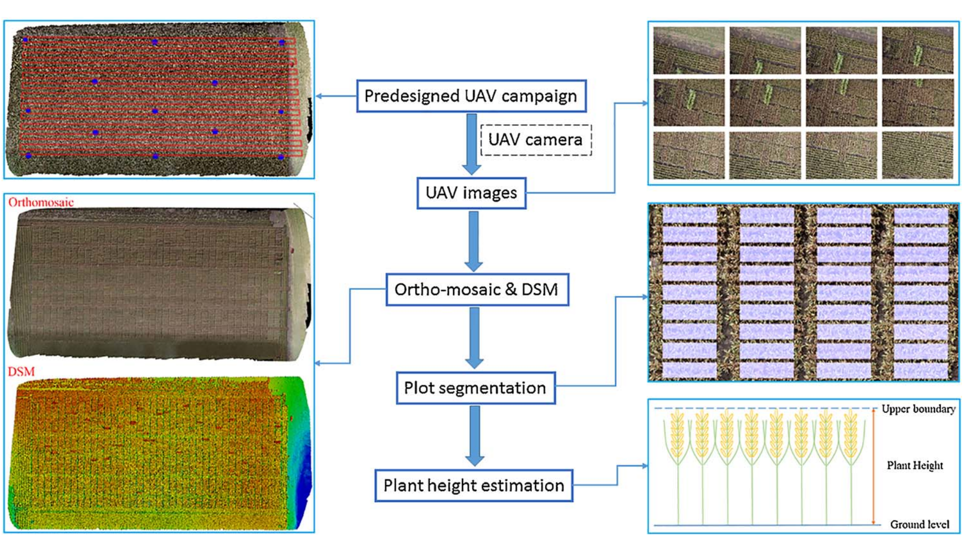

Fig. 1. Pipeline of estimating plant height from UAV images. The pre-designed UAV campaign shows ground control points (GCPs) as blue dots, and flight paths as red lines. The demonstrated UAV images were captured for the breeding trail of sorghum at the maturity stage (29th Apr 2016) by a Sony camera. In DSM (digital surface model), DSM value is represented by fake colour. In plot segmentation, edges of each two-row plot are trimmed by percentage of 15% along the long sides and 10% on the short sides. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)