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Crop height monitoring with digital imagery from Unmanned Aerial System (UAS)

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ABSTRACT

Crop height is a very important attribute to assess overall crop condition, irrigation, and estimation of terminal yield. In this study, a novel method to monitor crop height of Sorghum (*Sorghum bicolor*) using an Unmanned Aerial System (UAS) is proposed. UAS data were acquired seven times over the growing season and each aerial acquisition included over 200 images with significant image overlap at an altitude of 50 m above ground. Ortho-mosaic image and 3D point cloud were generated by applying the Structure from Motion (SfM) algorithm to the images. Ground control points (GCPs) were installed around the study area and they were surveyed using a real time kinematic (RTK) GPS unit for accurate georeferencing of the geospatial data products. A Digital Terrain Model (DTM) and Digital Surface Model (DSM) were generated from the 3D point cloud data, and a Crop Height Model (CHM) was then created by subtracting DTM from DSM. Uniform crop grids along the center line of each variety were defined for further processing. The maximum CHM value within each individual grid was taken to represent crop height of the grid, and average of all grid heights over the whole area of each variety was calculated as crop height of individual variety. These measurements were compared with manual crop height measurements. Root Mean Square Error (RMSE) between field measurements and the proposed approach was 0.33 m. In addition, the height estimates from both field measurement and the proposed approach could be used to derive a growth curve by fitting a sigmoidal curve. The residual RMSEs between the observed and predicted value of the curve established from UAS and field measurements were calculated as 0.05 m and 0.1 m, respectively. The growth curve results showed that the proposed approach indicated less RMSE and generated more reliable growth curves for monitoring sorghum height.

1. Introduction

Crop monitoring is an important component in precision agriculture since it is used to assess overall crop condition, determine when to irrigate, and estimate terminal yield. In addition, understanding crop growth pattern is a critical component in crop monitoring (Cloutis et al., 1996; Hunt et al., 2010; Poenaru et al., 2015). Previous crop monitoring studies have used field measurements or airborne/space-borne data to effectively cover wide areas. However, the field-based method has disadvantages to collect data because it is often destructive, labour-intensive, expensive, time-consuming, and variable in their implementation (Hollinger, 1997; Chang et al., 2011).

Remote sensing techniques from manned airborne and space-borne systems have been widely adopted for crop monitoring purposes (Migdall et al., 2009; Mulla, 2013) since measurements are non-destructive and non-invasive and enable scalable implementation in space and time (Araus and Cairns, 2014). Although many have explored crop monitoring using remote sensing technologies, they have been limited to only a small dataset or low spatial resolution images for time-series analysis. Migdall et al. (2009) derived crop properties such as green leaf area index, fraction of senescent material, and grain yield for precision agriculture from airborne hyperspectral imagery and satellite images. Esquerdo et al. (2011) studied the potential use of Normalized Difference Vegetation Index (NDVI) temporal analysis in soybean crop monitoring with Advanced Very High Resolution Radiometer (AVHRR) imagery in Brazil. Moderate Resolution Imaging Spectro-radiometer (MODIS) NDVI temporal profile was analysed for rice and high

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correlation was observed between remote sensing estimates and ground data (Boschetti et al., 2009).

However, traditional remote sensing platforms have not been widely utilized in the precision agriculture discipline due to several logistical challenges; (1) data acquisition can be costly from these platforms, and (2) they have limited flexibility in terms of temporal and spatial resolution of the data. Fine spatial and high temporal resolution data is required to monitor crops accurately through the growing season for biomass estimation, yield prediction, and early detection of harmful insects and disease. In this regard, advances in UAS technology and sensor miniaturization can provide great opportunities to tackle the challenges encountered with the traditional remote sensing platforms (Anthony et al., 2014; Bendig et al., 2014; Rey-Carames et al., 2015). In addition, the cost of the UAS platform and sensors are rapidly decreasing, making it much more feasible to develop a low-cost UAS system so that finer spatial and higher temporal resolution remote sensing data can be collected (Anthony et al., 2014). This is the reason why UAS technologies are gaining great attention from agriculture research scientists, hence they can be an alternative solution to address the limitations of the traditional remote sensing platforms.

Baluja et al. (2012) analysed the relationships between various indices derived from the UAS imagery, leaf stomatal conductance, and stem water potential for assessing the water status variability of a commercial vineyard. The visible spectral indices were calculated for multi-temporal mapping of the vegetation fraction from UAV images and the automatic object-based method was proposed to detect vegetation in herbaceous crops by Torres-Sánchez et al. (2014, 2015). Rey-Carames et al. (2015) utilized a quadrotor system to acquire multispectral images and derived spectral indices for precision viticulture management. Furthermore, Bendig et al. (2014) estimated biomass of barley using crop height derived from UAS imagery, while Anthony et al. (2014) presented a Micro-UAS system mounted with a laser scanner to measure crop heights. Previous studies with UAS system for agriculture have not focused on time-series data, but analysed spatial and spectral information from UAS data acquired at once.

Among various phenotypic characteristics, crop height is a critical indicator of crop evapotranspiration (Allen et al., 1998), crop yield (Lazcano and Dominguez, 2011), crop biomass (Bendig et al., 2014), and crop health (Anthony et al., 2014). It was shown that UAS platforms can provide height estimates even with only an optical sensor (Harwin et al., 2015), but use of UAS data for monitoring crop growth over the whole growing season has not been leveraged in the plant breeding discipline. Therefore, the main aim of this study is to test a novel method to monitor crop height growth throughout the life cycle of the biomass sorghum using UAS data. The crop height and growth curve extracted from UAS data and field measurements were compared to validate the accuracy and reliability.

2. Study area and data collection

The study area was located at the Texas A&M (Agricultural and Mechanical) AgriLife Research and Extension Center in Corpus Christi, Texas, USA, at a latitude of 27°46′35″N and a longitude of 97°33′38″W (Fig. 1). The sorghum crop was planted on May 1st, 2015 in east-west oriented rows. A plot was 4 rows wide by 120 m long. A total of 41 plots with 35 different genotypes of biomass sorghum were planted, for a total of 164 rows. Aerial images were acquired from a DJI Phantom 2 Vision Plus platform, which is manufactured by DJI (Shenzhen, China), on a weekly basis from June 3rd, 2015 to August 27th, 2015. The RGB camera mounted on the Phantom 2 Vision Plus take the 14 Megapixels image with 1/2.3 in. We adopted the grid style mission to fly UAS and nadir (90° vertical) view only to generated ortho-mosaic image and 3D point cloud for mapping in study area (Fig. 1) (Su and Chou, 2015). Although 11 data sets were acquired during this time period, only seven dates were used in this study since the quality of the other data sets was inadequate for analysis due to windy conditions at the time of flights. The wind could cause image blurring and crop swaying to make difficulty for finding matched points between images. All data sets, except June 3rd, resulted in over 200 raw images with 90% forward and side overlap at an altitude of 50 m (Table 1). Approximate locations of raw images (longitude, latitude, and altitude) were recorded by an onboard GPS, however, its accuracy is not high enough for direct georeferencing. Eight Ground Control Points (GCPs) were installed around the study area for accurate geo-referencing, geo-correction, and co-registration of UAS data. Four GCP were located on each corner and an additional 4 GCP were installed between the corner targets (Fig. 1). Since the study area was approximately 2.21 ha in size, the number and location of GCP were reasonable and enough to remove bowling effects from UAS data (Mesas-Carrascosa et al., 2015). The coordinates of all GCP were surveyed using an APS-3 RTK GPS, manufactured by Altus Positioning Systems Incorporated (California, USA). The horizontal and vertical accuracy of the GCP coordinates were 0.3 and 0.7 cm, respectively.

The field measurement data were also collected every 10-day from June 16th to August 27th, 2015 by removing plants from the field and measuring crop information including heights in the lab. There were 5 field measurements for 41 varieties and 3 measurements for 32 varieties since 9 varieties were harvested earlier (Table 1). Each sampling was conducted on a 1 m long along the center line and 2 locations (east and west) were sampled for each variety. Ten plants from each sampling location were randomly selected for height measurements, and average crop height was calculated for each variety. Among multiple UAS data collection and field measurements, the data collected on August 27th is the only date when both UAS data and field measurements were acquired on the same date because flying UAS and collecting field measurement had conducted separately according to the conditions such as weather and growth level. The data on August 27th were used in this study to evaluate crop height measurements estimated from UAS data.

3. Data analysis

The proposed method is composed of four major steps: (1) preprocessing of UAS data; (2) Crop Height Model (CHM) generation; (3) plant height extraction; and (4) growth analysis with growth curve. The last step is based on time-series analysis of crop heights calculated from UAS data. The growth curve could be drawn by fitting a non-linear curve from high temporal time-series data acquired from an UAS platform. The time-series analysis fills the gap between each flight date and provides estimated data. Crop height of each genotype was estimated using the individual grid height information generated by the Structure from Motion (SfM) algorithm. Crop growth curve was fitted and Root Mean Square Error (RMSE) between the result of this study and field measurement obtained were calculated.

In the pre-processing step, an ortho-mosaic image and 3D point cloud data are generated using the Structure from Motion (SfM) algorithm. The SfM performs a bundle adjustment among images acquired from the UAS based on matching features between the overlapped images to estimate interior and exterior orientation of the onboard sensor. First step of the SfM algorithm is to extract features in each image that can be matched to their corresponding features in other images for establishing relative location and parameters of the sensor (Lowe, 2004; Snavely et al., 2008). After