Development of an Unmanned Aerial Vehicle (UAV) for hyper resolution vineyard mapping based on visible, multispectral, and thermal imagery

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Abstract – Unmanned Aerial Vehicles (UAVs) are an exciting new remote sensing tool capable of acquiring high resolution spatial data. This study has developed a UAV capable of collecting hyper resolution visible, multispectral and thermal imagery for application to Precision Viticulture (PV). Traditional modes of data collection are not well suited to the detection of subtle but important changes in vineyard structure given low temporal and spatial resolutions. Mapping with UAVs has the potential to provide imagery at an unprecedented spatial and temporal resolution. We present a technical description of our UAV and its payload options including visible imagery which is processed using feature matching and photogrammetric techniques to create Digital Surface Models (DSMs) of the vineyards. A thermal infrared camera is used to map soil moisture enabling assessment of irrigation efficiency, and a six-band multispectral camera enables the calculation of vegetation indices that relate to vineyard vigour and health.

Keywords: UAV, Precision Viticulture, Multispectral, Vegetation Indices, Thermal Infrared

1. INTRODUCTION

Historically, Unmanned Aerial Vehicles (UAVs) have primarily been used for military applications. More recently, the use of UAVs in the civilian domain as remote sensing tools presents new and exciting opportunities. Improvements in the availability of accurate and miniature Global Positioning System (GPS) units and Inertial Measurement Units (IMUs), along with the availability of quality off the shelf consumer grade digital cameras has resulted in an increased use of civilian UAVs (Nebikera *et al*., 2008).

The highest spatial resolution data available from conventional platforms such as satellites and manned aircraft is typically in the range of 20-50 cm/pixel. UAVs are capable of flying much lower and hence can collect imagery at a much higher resolution (Scaioni *et al*., 2009; Hunt *et al*., 2010), often at a sub-decimetre resolution, even as detailed as 1 cm/pixel.

The temporal resolution of conventional systems is limited by the availability of aircraft platforms and orbit coverage patterns of satellites. For the purpose of monitoring highly dynamic vegetation such as that within vineyards, satellite sensors are very much limited due to unfavourable re-visit times (Berni *et al*., 2009).

Precision Viticulture (PV) is defined as monitoring and managing spatial variations in physical, chemical, biological variables related to productivity of vineyards (Hall *et al*., 2002). Extensive research has been undertaken to determine if traditional sources of remote sensing data (satellite and aerial photography imagery) can be used to assist with PV, Hall (2008) provides one example. Much of this research has been based around calculating vegetation indices such as Plant Cell Density (PCD) and Normalised Difference Vegetation Index (NDVI), and subsequently relating these to bio-geophysical properties of the vines such as Leaf Area Index (LAI).

Proffitt and Pearse, (2004) used ground truth data to demonstrate that PCD provides a good indication of vine vigour that correlates well to yield and wine quality. Berni *et al*.(2009) discovered that the Photochemical Reflective Index is a much better indication of plant water stress than NDVI when looking at orchard crops such peaches and olives.

However, vineyards are not a homogeneous crop and data from traditional aerial photography or high resolution satellite sensors are not able to accurately differentiate between individual vines and the between row vegetation. This dictates that at the edges of the vines, pixels will exhibit the reflectance properties of both the vine itself and the adjacent vegetation. Hyper resolution UAV imagery of vineyards does not have this limitation, hence there is an exciting potential for development of a UAV system to map vineyards and thus assist with PV.

This paper describes our UAV platform and the sensors that are used to collect data. We demonstrate the processing algorithms that are used to process and ortho-rectify data from each of our sensor types. Some vegetation indices will then be examined to qualitatively assess their ability to differentiate differences within vineyard imagery.

2. METHODS

Our UAV is based on the Oktokopter platform (Mikrokopter, 2011), a multi-rotor electric powered system purpose designed for aerial photography (Figure 1). The Oktokopter has been fitted with a stabilised camera mount to which we mount our sensor systems. The Oktokopter has a payload limit of approximately one kilogram, hence we are limited to flying each of our sensors individually.

Figure 1. Oktokopter fitted with multispectral camera.

A Canon 550D digital SLR camera is used to capture visible imagery which is then processed with feature matching and photogrammetric software to create Digital Surface Models (DSMs). The same camera mount has been adapted to carry a Tetracam mini-MCA (Multi Camera Array) (Tetracam, 2011) multispectral camera that operates in six bands set by fitting specific filters. This imagery is used to examine vegetation

reflectance in critical wavelengths allowing the calculation of vegetation indices. Finally, a FLIR (FLIR, 2011) Thermal Infrared (TIR) camera can be attached to the Oktokopter to measure surface temperature.

The Oktokopter has an onboard navigation system based on a GPS receiver and an IMU. A defined set of waypoints can be pre-programmed to form a set flight path. Flight planning software has been developed that calculates the spacing and layout of waypoints to acquire data over a region of interest at a nominated image scale (Figure 2). Imagery is typically acquired at the maximum rate allowed on the device, thereby providing redundancy to account for elimination of imagery with excessive tilt, motion blur or bad exposure.

Figure 2. Flight planning software. Flight grid is approximately 200 x 100 m which represents a single flight sequence (5 mins flight duration)

3.   TEST CASES

We have tested our UAV system at the Frogmore Creek vineyard near Richmond in southern Tasmania. This is a large vineyard containing many blocks of vines of different varieties. We have identified one block of particular interest for use in this study – it consists of highly variable topography that affects the surface moisture and thus is one of the influences the vigour of the vines.

A significant challenge associated with UAV imagery is the large volume of data that is produced; to deal with this automated processing systems are required. We have developed a semi-automated system to ortho-rectify the imagery with or without Ground Control Points (GCPs).

To ortho-rectify the imagery we initially manually select the most appropriate photos from the dataset collected. The selected images are processed with the Bundler software (Snavely, 2010) which uses the SIFT algorithm (Lowe, 2005) to detect matching features across the images.

Bundler then runs a bundle block adjustment to align the images within its own coordinate system. An output file is generated that lists the calculated position of each exposure station in the bundler coordinate system along with the location of each matched feature in both the bundler and original image based coordinate system. A point cloud is also produced in which the x, y, z position (in the bundler coordinate system) of each

matched feature is listed along with its RGB colour from the original imagery.

These bundler point clouds are sparse, however, denser point clouds but can be generated by use of PMVS2 software (Furukawa and Ponce, 2009) to produce point clouds containing many millions of points. (Figures 3 and 4)

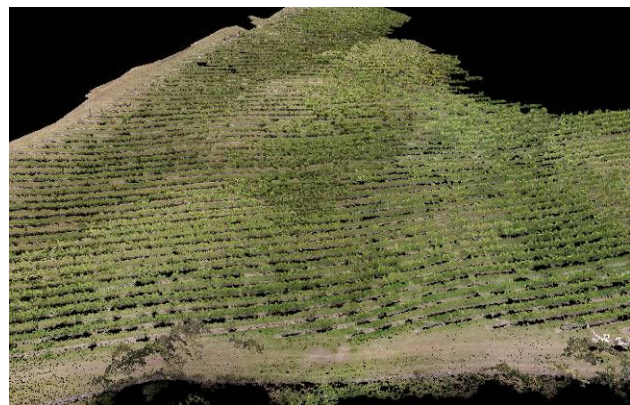Figure 3. Vineyard point cloud, before vine canopy growth

Figure 4. Vineyard point cloud, vines with full canopy

If GCPs are present in the imagery we use a simple filtering algorithm (based on thresholding to identify the bright orange colour of the control points) to extract the location of the GCPs from the point cloud and subsequently match them to the locations measured in situ with survey-grade, carrier phase differential GPS equipment. This provides a list of x, y, z points in the bundler coordinate system with a corresponding northing, easting and elevation coordinate in a real world coordinate system, in our case the Map Grid of Australia (MGA). The point cloud is transformed into MGA following the solution for Helmert transformation parameters (three translations, three rotations and one scale parameter) using a least squares algorithm.

When no GCPs are present in the image the camera locations in the Bundler output file are matched to the onboard GPS logs from the Oktokopter based on the time at which the image was captured. This again gives us a list of coordinates matched to their real world equivalents allowing Helmert transformation parameters to be determined. This technique is presently limited to the inaccuracy of the onboard GPS unit that is a navigation grade single frequency GPS device.

Initial validation of the point cloud transformed with the aid of GCPs yields an RMS error of approximately 10 cm. Without GCPs, the RMS increases to ~2 m given the quality of the GPS unit on board.

The calculated Helmert parameters can also be applied to the Bundler output file to create control points for each image. That is, for each matched feature in an image we have an x, y, z coordinate which can be transformed into a northing, easting and elevation coordinate. For a given matched feature, we also have an image coordinate, this means there is now a list of control points for each image (usually in the order of thousands) for which we have real world 3D coordinates (Figure 5)
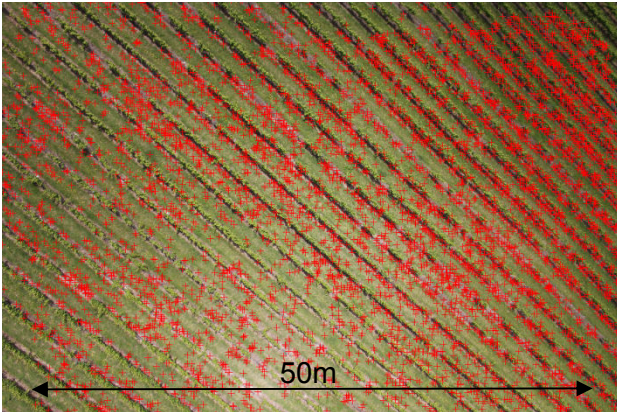

Figure 5. Control points from bundler shown in red.

These control points can now be used with a rubber sheet transformation to orthorectify each image. Once all images are orthorectified it is a simple task to mosaic them together with a geo-referenced based stitching software such as ENVI (ITTVIS, 2011). (Figure 6)

Figure 6. Example ortho-mosaic of visible vineyard imagery made up from 48 images. Area is approximately 200x150m

Further data processing algorithms have been developed to convert the raw data collected by the multispectral and TIR camera into usable imagery. The TIR images indicate the soil and surface temperature which is generally related to moisture content. Figure 7 provides a TIR example that highlights a temperature gradient up to the bottom right of the image where temperatures are higher than in other areas. Inspection of the study region shows that this region is less vigorous (both vines and between row vegetation), hence more soil is exposed and the ground is warmer.
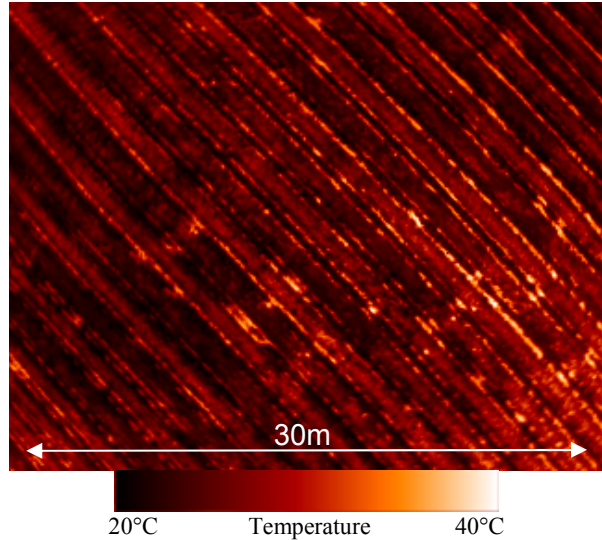

Figure 7. Example TIR image of vineyard

Data from the multispectral camera can be viewed as a false colour composite. We use this to generate a set of "quicklooks" allowing us to find regions of specific interest. Figure 8 is of the same area as the TIR image and demonstrates that the less vigorous area is also well defined in the multispectral imagery.
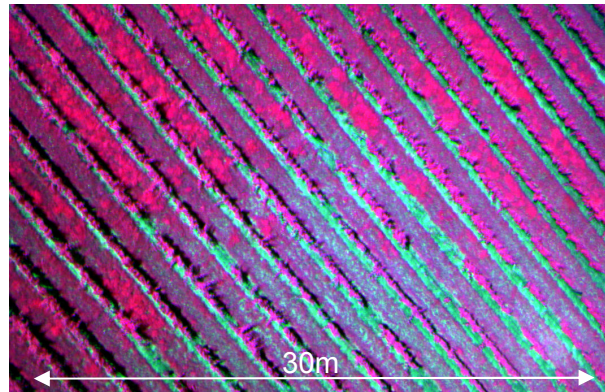

Figure 8. False colour composite of vineyard area where Red = 800 nm, Green=670 nm and Blue=550 nm

A commonly used vegetation index is NDVI which provides a general measure of vegetation vigour and biomass. NDVI is a ratio and has the advantage that an object under shadow will reflect light reduced by the same amount across the entire spectrum, thus it is not severely affected by shadows in the image (Hall, 2002). NDVI is commonly used in PV applications, for example, Lamb *et al*. (2001) found a correlation between image derived NDVI values and subsequent grape yields. Figure 9 displays the NDVI generated from the multispectral image display in Figure 8, again the less vigorous area is well defined.
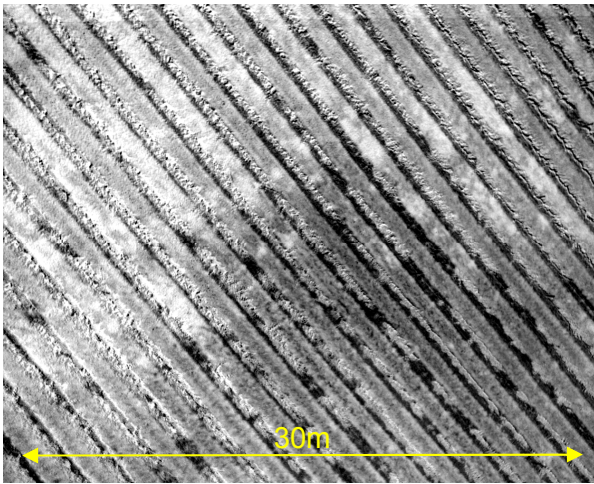
Figure 9. NDVI for same section of the vineyard

Another commonly used vegetation index is the Photochemical Reflectance Index (PRI) that is an indicator of chlorophyll fluorescence which changes under water stress conditions (Suárez *et al*., 2008). Berni *et al* (2009) demonstrated that PRI generated from UAV multispectral imagery could be used for water stress detection. Figure 10 shows how PRI can be used to differentiate between the vines and the background surface. It is possible to see that the vines in the upper left are vigorous and leafy (i.e. brighter in the PRI image) whilst in the bottom right there are far fewer leaves and areas where you can see the trellis wires in the absence of any significant vines.
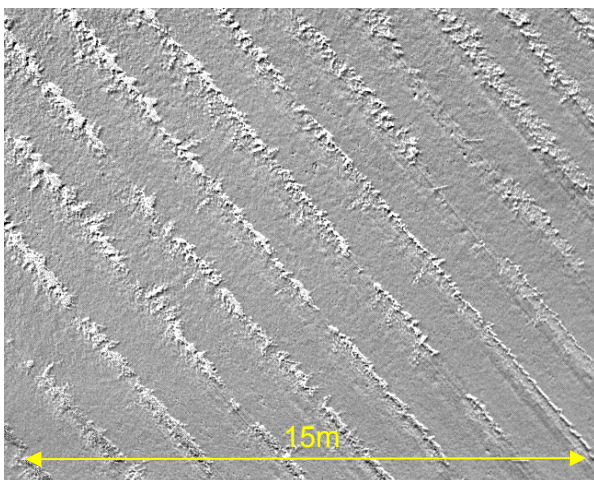

Figure 10. PRI for zoomed in section of the vineyard

4.   CONCLUSIONS

These initial results presented in this study further highlight the potential for multi-sensor UAV systems in the application of PV. The versatility of the UAV system is further enhanced by the fact that these data sets can be collected "on-demand", providing unprecedented temporal resolution that spans the critical times in the crop growing season.

The imagery produced from UAV collected data in this study has a spatial resolution up to 1 cm/pixel. The accuracy of the ortho-mosaics produced depends on the use of GCPs, however, a dual frequency survey grade onboard GPS has the potential to eliminate the need for GCPs and thus greatly improve the efficiency of the UAV field to finish system.

Further studies will be undertaken to determine how these datasets can best be used by vineyard managers to implement decisions that improve operational efficiency, productivity and sustainability.

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