Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-16 (2016) 398–403

Non-Productive Vine Canopy Estimation through Proximal and Remote Sensing ⋆

Julie Tang * Michael Woods ** Stephen Cossell * Scarlett Liu *
Mark Whitty *

* University of New South Wales, Australia (e-mail: {julie.tang; s.cossell; sisi.liu; m.whitty}@unsw.edu.au).
** e-mail: m.woods1987@gmail.com

Abstract: Non-productive canopy detection in a viticultural block is a key factor in reducing the drain on infrastructure and improving management practices. However, current methods are significant in cost, biased, and do not provide information on location of non-productive canopy. This paper proposes both a proximal and remote sensing method for assisting in decision support and yield estimation from available technologies. The proximal method utilizes two different measures of green pixel thresholding in video frames, with results providing a useful relative measure of productivity across a vineyard block at the phenological stage of shoots. The remote sensing method utilizes local thresholding and Self-Organizing-Maps on aerial imagery to identify missing vines and total non-productive canopy on a block level. Results indicate the success of this semi-supervised method in providing a useful measure of non-productive canopy at the phenological stage of veraison; laying the groundwork for improved methods in this area. These methods provide practical outputs that lay the foundations for improving management decisions in an automatic and low-cost manner at different times in the season.

Keywords: NDVI, yield estimation, decision support systems, automation, mapping, machine learning

1. INTRODUCTION

An area that is of great importance, but has not been not at the forefront of research is in classification of productive and non-productive land; using both proximal as well as aerial imagery. Non-productive land represents a drain on infrastructure and inputs such as irrigation and spraying. Although research in grapevines through spectral indices, photogrammetry, as well as proximal sensors such as Laser Range Finders (LiDAR) is comprehensive; much of the research has been in estimating and improving vine vigour Mathews and Jensen (2013); Llorens et al. (2011), fruit yield Nuske et al. (2014), and maturity Hall et al. (2011); Serrano et al. (2012).

The majority of existing methods for vine row extraction has been used in identifying variation in measures of vine health through Normalized Difference Vegetation Index (NDVI), Plant Cell Density (PCD), or Leaf Area Index (LAI) and obtaining relationships with the above mentioned research areas. The techniques previously used include spectral band thresholding Hall et al. (2003), skeletonization Nolan et al. (2015), and variations of Hough lines Comba et al. (2015).

Grapevines represent a high value crop and by providing information about productive and non-productive land within a vineyard to the farmer this can allow for the land to be better managed, so as to optimise the land use within each vineyard. With this information the farmer can make informed management decisions on vine replanting, however, current methods are costly and do not provide accurate locations of non-productive canopy within a vineyard.

The current methods for estimating productive and non-productive canopy include a rough estimation by the farmer, as well as manual counting to a lesser extent. Estimation by farmers is anecdotally known to have significant errors with large variation, as the approximation is based on their knowledge of missing vines. Manual counting techniques can also be error prone if taken at a very early phenological stage which is otherwise referred to as Modified Eichhorn-Lorenz (E-L) Coombe (1995) stage. This occurs when canopy has not yet fully developed. Thus, care needs to be taken in the timing of measurements as this can result in a large variation between actual non-productive canopy and estimated canopy extent of each vine.

In manual counting, regions with approximately 50cm of missing vines, dead vine arms, and "bare-wire" are recorded as a count to obtain a percentage of non-productive canopy per vine row or block. The estimation of non-productive canopy may be difficult if the vine canopy is not fully developed, especially early in the season. Currently, manual counting only reports the total distance or percentage of non-productive canopy per vine row or per block; reducing the manual counting effectiveness as localization of non-productive canopy from this data alone is difficult. Thus, manual measurements are often significant in cost and ineffectual. Therefore, an automated method is required to reduce the discrepancies in identification of the productive and non-productive vines with geo-location

⋆ This work was supported by Wine Australia

10.1016/j.ifacol.2016.10.073

mapping which greatly assists with vine block management.

Identification of non-productive areas on other broadacre crops generally utilise a combination of multispectral, hyperspectral and thermal imagery such as Calderón et al. (2013); Turner et al. (2011) mounted on an Unmanned Aerial System (UAS). This allows for enough spatial resolution in the image to be obtained and thus an analysis on the non-productive areas.

This paper presents a novel method for sensing and classifying non-productive vine canopies from a combination of proximal camera data as well as multispectral aerial photography. The proposed aerial method firstly identifies missing vines and 'bare-wire' through thresholding techniques and then utilizes this information to further classify all non-productive canopy. The objective of the proximal method is to provide a comparison between ground-based and aerial techniques at an early stage in the season.

2. DATA COLLECTION

Aerial photography was obtained around veraison in 2015, across four different vineyard blocks and two trellis systems, situated in contrasting climatic regions. The site at Clare, South Australia contained one Chardonnay (40A) and one Shiraz (47A) block, both with sprawling canopies. The cool climate site at Orange, New South Wales, contained one Chardonnay (B12) and one Shiraz (B4) block, both with Vertically Shoot Positioned (VSP) canopies. The spatial resolution of the aerial imagery was 0.4m for the Clare vineyard blocks and 0.25m for the Orange vineyard blocks.

Proximal data for all vineyard blocks in the study was also captured at each phenologically significant stage; the data consists of vehicle mounted Go-Pro footage, which was collected in the same manner as prior work by Liu et al. (2015).

Manual counting of 50cm segments of non-productive canopy and number of missing vines per row were only available for the two Clare experimental blocks. These were taken at E-L stages 4 for Block 40A and 7 for Block 47A.

3. EXPERIMENTAL APPROACH

Using the approach of Hall et al. (2003), vines are segmented in an attempt to locate the edges of a vineyard block. Although such approaches are suitable for identifying existing rows, they are not suitable for obtaining the outline of a concave shaped block, as shown in Fig. 1. The idea of automatically determining row-end post locations from visible vines tends to under-represent the amount of non-productive canopy due to the possibility of missing vines at each row-end, as shown in Fig. 2. Thus, row-ends of each experimental block were marked with GPS locations and used for localizing rows.

3.1 Identifying missing vines from aerial imagery

Two methods were considered for segmenting vines. Supervised learning methods were found to perform well if at least 10 % of a block was labelled, however, this can't be considered automatic. Local thresholding was found to perform best, with a much easier implementation when used together with a large local neighbourhood. The local thresholding was performed by firstly re-sampling all aerial data to 0.1m spatial resolution using bi-linear sampling and then applying a tuned threshold parameter to segment the vines.

Fig. 1. Convex Hull (red) of a vineyard block which does not follow actual block outline (yellow)

Fig. 2. Missing vines at the row-end of a vineyard block results in misrepresentation of end-post location

Similar to Nolan et al. (2015), we found a neighbourhood of vine row spacing, 3m in our case, was sufficient to prevent over-segmentation. However, the method we employed was that of Sauvola and Pietikäinen (2000) on the green spectral band as the histogram filtering method used by Nolan et al. (2015) required imagery of sufficiently high resolution, decimeter or less, which was not available for our study blocks. The histogram filtering method resulted in over-segmentation of thin or unhealthy vines which were present in one of our study blocks.

Although each vine-row end post was labelled, vines were not always situated along the straight line formed between the two opposite vine-row end posts. The vines that do exist on the straight line are herein referred to as row-centered pixels. Thus, in the case of straight rows, vines deviating from row-centered pixels need to be accounted for, this variation could be due to vine posts being damaged or the vine growing at different angles.

An indication of missing vines can be obtained by taking vine pixels within a 1 meter buffer on either side of the row-centered pixels, as shown in Fig. 3, on the green spectral band thresholded image. This can be found by taking the sum of the number of non-zero pixels in the thresholded