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Estimating mango crop yield using image analysis using fruit at 'stone hardening' stage and night time imaging

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ABSTRACT

This paper extends a previous study on the use of image analysis to automatically estimate mango crop yield (fruit on tree) (Payne et al., 2013). Images were acquired at night, using artificial lighting of fruit at an earlier stage of maturation ('stone hardening' stage) than for the previous study. Multiple image sets were collected during the 2011 and 2012 seasons. Despite altering the settings of the filters in the algorithm presented in the previous study (based on colour segmentation using RGB and YCbCr, and texture), the less mature fruit were poorly identified, due to a lower extent of red colouration of the skin. The algorithm was altered to reduce its dependence on colour features and to increase its use of texture filtering, hessian filtering in particular, to remove leaves, trunk and stems. Results on a calibration set of images (2011) were significantly improved, with 78.3% of fruit detected, an error rate of 10.6% and an R^2 value (machine vision to manual count) of 0.63. Further application of the approach on validation sets from 2011 and 2012 had mixed results, with issues related to variation in foliage characteristics between sets. It is proposed the detection approaches within both of these algorithms be used as a 'toolkit' for a mango detection system, within an expert system that also uses user input to improve the accuracy of the system.

1. Introduction

The number of fruit on trees in a mango orchard is currently estimated via a manual count of a small number of trees to predict resource requirements for harvest, and to arrange marketing. Crop load is usually estimated at the stone hardening stage of fruit development, about six weeks prior to harvest, as at this stage the majority of fruit drop (fruit self-thinning) has occurred, and fruit numbers will remain relatively constant until harvest. However, fruit colouration (anthocyanin synthesis, chlorophyll breakdown) develops with further maturation on the tree.

In a companion study (Payne et al., 2013) we report the development of an algorithm for identification of fruit within images of a mango canopy, based on the use of an RGB camera in overcast daylight conditions, and the use of filters on shape, texture and colour. However this study dealt with fruit at close to harvest maturity, and consequently with more, and consistent, 'blush' (red colouration) on the fruit than is found at the stone hardening stage. At stone hardening, fruit may be half green and half pale orange colour, or all green.

It is likely that such image characteristics will require a segmentation approach that downplays reliance on a colour filter (e.g. the Normalised Difference Index used in Payne et al., 2013), and increases the weighting on other features, such as texture and edge detection. For example, the border limited mean filter (Image J Wiki, 2011) calculates the average gray scale value over n x m pixels and has been used to filter for the consistent general colour within the mango fruit, rather than for a distinct pixel colour. A hessian filter allows for discrimination between blob, plate and line-like structures. This filter has been used in medical imaging where tube like structures, e.g. veins, need to be identified (Foruzan et al., 2012). In the current application, it may serve to discriminate between line-like leaves and stems, and oval mangoes.

2. Materials and methods

2.1. Imaging hardware

Each image set was collected using the same camera but an improved mounting and lighting system over that used in the previous work (Payne et al., 2013). This previous work showed that diffuse light conditions were optimum for imaging for this computer vision application. With this in mind, we chose in our current work to image at night under artificial lighting. We felt that this approach made it possible to consistently recreate the diffuse conditions of daytime imaging. The camera, a Canon 50D SLR camera

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Fig. 1. Lighting rig as used for image collection. Left image shows rig as used in 2011 (day image). Right image shows rig as used in 2012 (fully illuminated). Only the inner four lights were illuminated during imaging for sets discussed in this paper to maintain consistency between sets.

Fig. 2. Example image, acquired at night under artificial lighting.

with the standard kit 28–135 mm IS zoom lens was mounted on a frame which held four 6 × 3 W LED spotlights (SCA P/L) at a distance 1 m from the camera (positioned above, below, to left and right of camera). The frame was mounted to the tray of a utility and a sonar activated sensor was mounted at 0.6 m height on a bar extending 0.5 m towards the tree line, set to trigger off the passing of a tree trunk. The camera could also be triggered from the front seat of the car without using the sonar. Fig. 1 shows the rig used in 2011 (left side, day) and 2012 (right side, night with lights illuminated). The 2012 rig included an additional four lights, but for consistency, these were not used in the collection of images discussed in this paper. Images were stored in Canon RAW format in RGB colour and at a resolution of 4752 × 3168 pixels.

The car was driven down the plantation rows such that the camera was positioned in the inter-row approximately 2 m from the tree trunk. Each set of images were acquired in the evening (well after sunset) in a single session. Images were acquired with the camera facing the tree row, and aligned to the trunk of a given tree. The night conditions and directed lighting reduced image background features significantly (sample image presented as Fig. 2).

In a preliminary trial, the effect of exposure setting was explored. The colour of fruit in images acquired using the auto-exposure setting was washed out, while a minus three stop setting created images with too great a contrast in lighting between background and foreground fruit. A setting of minus two stops was found to yield images with the best (subjective) quality, and this setting was used for all work in this paper. 2012 imaging varied from 2011 in that greater care was taken in positioning the spotlights to achieve more even illumination of the canopy, Also, trees were imaged on both sides from two distances. Initially, the vehicle was driven at a greater distance from the tree line to ensure imaging of the whole canopy, for comparison of count of fruit in image to in-field total tree counts with results used to calculate relationship to manual tree count. The vehicle was then driven 2 m from the tree to ensure consistency in distance with 2011 sets for the purposes of automated image counts. These two sets are treated as one for the remainder of the paper, and used in the appropriate contexts.

2.2. Plant populations

The current study is based on two different plantations of mango (*Mangifera indica*). The first (2011) is in tropical north Queensland and is the same orchard as used by Payne et al. (2013). The second orchard is in the wide bay region of southern Queensland, some 8° latitude south of the first, and in a subtropical region.

Images of fruit were acquired at stone hardening stage in two seasons (2011, 2012), while the previous paper (Payne et al., 2013) was based on images of fruit near harvest in the 2010 season. The 2011 season produced a different pattern of fruit development than that of 2010, with fruit on tree displaying a wide range of size and colour. Indeed, a number of trees carried panicles ranging from flowering through to stone-hardening fruit. This variation is ascribed to a more variable and colder season in 2011, resulting in multiple flowering events on each tree. The 2012 season was similar to that of 2010.

2.3. Image sets

Four sets of images were collected (Table 1). During season 2011, a set of 100 mango images was collected from 50 trees as a **calibration set**. This set included images of both sides of each tree, and manual counts of all fruit on each tree were undertaken.

The first 10 trees of the calibration set were re-photographed using the same lighting conditions but on a different night (from one side only). This set of images is referred to as **validation set 1**.

On the same night that the calibration set images were acquired, images of a single side of an additional 74 trees were acquired. This set is referred to as **validation set 2.**

In season 2012, images were acquired using the same equipment and under the same conditions as in 2011, of both sides of 21 trees located in a different orchard. These images form **validation set 3**. Manual counts of total tree fruit load were also made.

2.4. Manual total tree crop load counts

For the calibration set and validation set 3, the total number of mature fruit on each tree was manually counted in the field during daylight hours. The approach differed from the companion study in