Digital Image Analysis Based Automated Kiwifruit Counting Technique

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Abstract

*This Paper investigates the use of digital image analysis techniques for developing an automated kiwifruit counting system. Three simple counting methods followed by a minimum distance classifier based segmentation technique in L*a*b colour space were studied. Images were taken prior to harvesting at a New Zealand kiwifruit orchard. Accurate counting of kiwifruit in several sample regions of the orchard is required in order to estimate the fruit harvest. At present, the counting is manually done by hired employees. Manual counting has several issues, such as low accuracy, long duration and higher costs. Automated counting technique facilitates a fast, low cost and potentially more accurate way of counting kiwifruit. Several approaches were trialled and validated on different sets of images. Above 90% accuracy on gold image data and above 60% accuracy on green image data were obtained, showing the potential of using the approach for counting kiwifruit for the harvest estimation purpose. The results, limitations and ongoing research in developing a more robust and consistent technique will be discussed.*

Keywords: Applied image processing, minimum distance classifier, image segmentation, distance transform, automated counting

1 Introduction

Image analysis based automated counting approaches can be found in many fields, such as medical imaging, horticulture & crop industry and soil research [1], [2] and [3]. They show the efficacy of automated counting systems, which are sufficiently reliable, consistent, fast and also more convenient than manual counting. However there are challenges in developing robust, automated counting techniques and they are unique to the specific problem. Some of the challenges for counting are uneven illumination, noise, occluded objects and clumped objects. For example, Sio, S. W. S. et al. developed a clump splitting technique to address the issue of counting clumped red blood cells [3]. The clumped cells adversely affect the accuracy of the parasitimia, because one clumped cell contains a few cells, but it is counted only once.

This paper investigates the use of simple digital image analysis techniques in developing an automated counting approach with application to kiwifruit counting. An accurate harvest estimation system for kiwifruit orchards using the sample digital images taken at the orchard can then be built.

Harvest estimation has importance to the industry in planning market needs and resources, such as packing materials and employees. Furthermore the industry needs to pre-book tractors, trucks and ships to ensure a faster turnaround to lessen wastage. Currently, contractors are used to count the fruit manually. Then the manual counts are used to estimate the harvest. Around \$300,000 to \$500,000 is spent on manual counting per year for a typical pack house. Additionally, there are issues with the accuracy of manual counts due to the higher number of kiwifruit and the exhaustion from continuous and repeated work. Because of the large scale of production, even a 10% error in estimation is a significant loss to the industry. If overestimated, the money on pre-ordering ships and trucks will be lost and another large investment is potentially blocked due to excess packing. If underestimated, the insufficient pickers, packers, packing material and insufficient time for ordering ships can require a bulk sale of products at much lower price. Having a robust automated counting technique facilitates a fast, consistent and convenient way of counting kiwifruit. This further saves the money spent on manual counting as well as the loss due to erroneous estimations.

To our knowledge, there has not been any automated system designed for kiwifruit counting or any digital colour/gray image based automated counting system for counting kiwifruit prior to harvesting. A counting method based on thermal images has been evaluated for counting apples in orchards [4]. However, the method has been tested only on 20 trees and a validation result similar to our result has been achieved. This method has the disadvantage of being highly dependent on weather conditions. A recent work to quantify green apples in an orchard by using hyperspectral images and machine vision techniques

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has been evaluated and shown a detection accuracy between 66.7 % and 100% [5]. A summary of several other reported vision systems for detecting fruit on trees can be found in [6]. Several citrus yield mapping system using machine vision on 3 band images had been developed and the distinctive colour in citrus fruit make the segmentation comparatively easier in that approach [7], [8], [9]. Another fruit counting method has been proposed to estimate fruit in a tree, using randomized branch sampling [10], but is not easily applicable for kiwifruit due to the vigorous tailed growth of the kiwifruit vine. Our study investigates the feasibility to use 3 band digital colour images rather than thermal or hyperspectral images.

In this work, L*a*b colour space, which has been designed to resemble the human visual perceptions, was used. The idea used was to pre-process the image so that the fruit are visually well distinguishable and then to use the L*a*b colour space to segment fruit regions with its perceptually uniform property (i.e. the colours which are visually similar are close to each other in colour space). A good description about L*a*b colour space can be found in [11].

In this paper, the work carried out on kiwifruit images is presented in five sections; data extraction and analysis, segmentation, automated counting, validation, and discussion and future work.

2 Data Extraction and Analysis

Images of the two kiwifruit varieties namely Gold and Green were used. Images were captured using an image capturing system designed by Lincoln Ventures Ltd. In the setup, a Lumenera Le259 camera facing upward is fixed to a tractor with artificial lighting. Pictures of the hanging kiwifruit are taken at night while the tractor moves through the bays of the orchard. Considering the most consistent lighting conditions, the image capturing is done in the night time with the lighting from fluorescent lights. Pictures of the two kiwifruit types are shown in Figure 1. All the images used are 1920x1080 pixels in size.

(a)

(b)

Figure 1. (a) Gold kiwifruit sample image (b) Green kiwifruit sample image

First, randomly selected images from a pool of images were separated into two sets, one for building a model and the other one for validation. 50 images from Gold and 30 images from Green for building the model, and 78 from Gold and 42 from green for validation were used.

Before the data extraction, images were pre-processed as follows. Only the centre window of size 825x540 pixels from original image was considered in order to eliminate poor illumination conditions at the corners. Then the image intensity was transformed non-linearly to contrast darker pixels in a wider range while keeping brighter pixels less affected. Secondly the R, G and B components were rearranged (data in B band was fed to R band, R to G and B remained unchanged), making the image false colour so that the kiwifruit are easily distinguished from the background. Finally the image was filtered using a 3x3 pixels window sized average filter to reduce noise. Resulting image is shown in Figure 2.

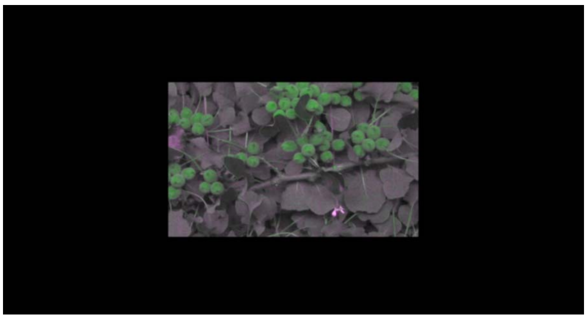


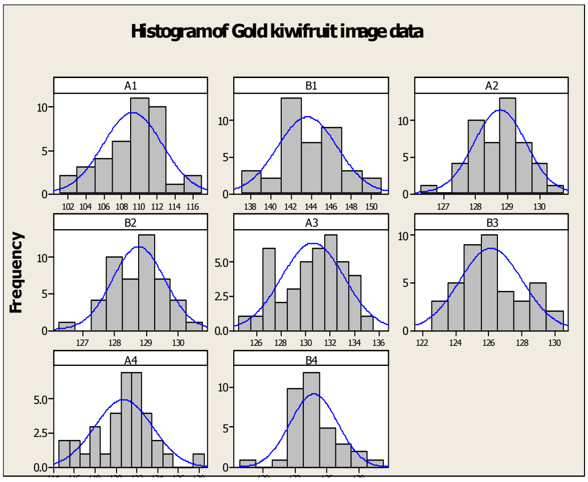
Figure 2. Pre-processed image

Segmentation of a kiwifruit image in to four regions: leaves, kiwifruit, branches and dark background, was empirically found to be more successful than segmenting in to two or three regions.

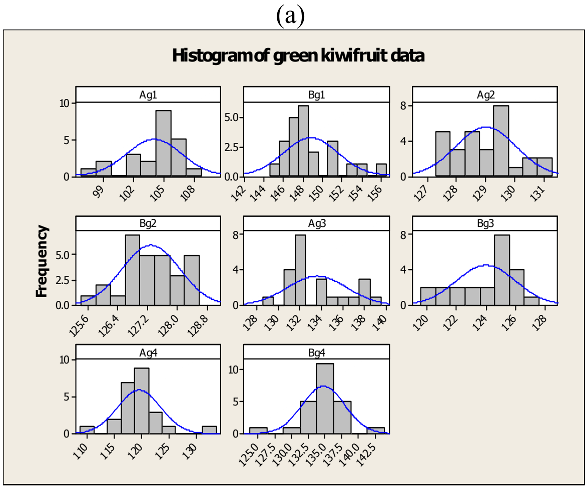
L*a*b colour space, which is one of the two device-independent colour spaces introduced by the Commission International de l'Eclairage (CIE), was used for colour segmentation. Both HLS (Hue, Luminance and Saturation) and RGB colour spaces are device-dependent: that is, the colour coordinates depend on the characteristics of the devices used to capture and display the images. L*a*b space is designed in a way such that colours which are visually similar are adjacent to each other in the colour space. This property makes the L*a*b colour space suitable for colour image segmentation [12]. Considering its advantages, pre-processed images were converted to L*a*b colour space for data extraction and processing.

Sample sub-regions (fruit, leaves, branches and dark background) were selected from each image and average *a* and *b* values of each sample region were extracted for all images. *L* component which indicates the lightness was not taken in to account. A Matlab program was written for extracting data, so that the data of the sample regions can be selected manually using the mouse pointer. The sample regions were of random sizes.

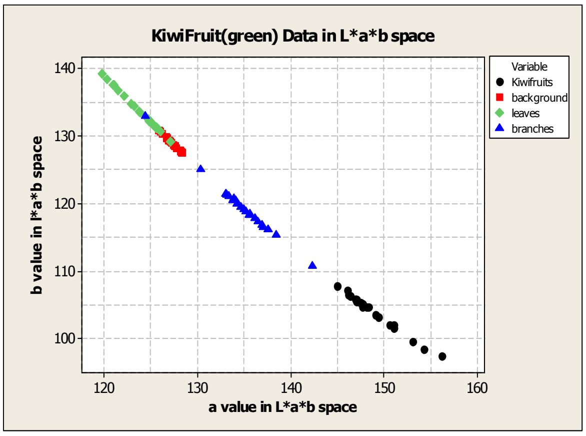
All the 16 data types; *a* and *b* components of the four regions of both gold and green kiwifruit images, were analysed and the mean and variance of each, when fitted to a normal distribution, were extracted. Figure 3 shows the analysed data.



(a)



(b)

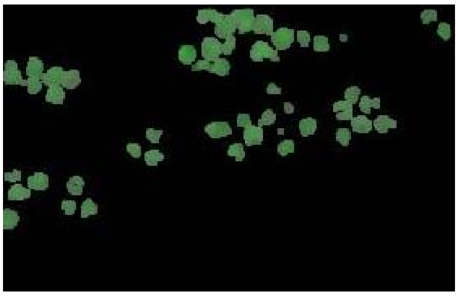


(c)

Figure 3. Data extracted from each region (a) Gold kiwifruit image data, (b) Green kiwifruit image data (c) Scatter plot of green kiwifruit data (A & B stands for the a and b component of L*a*b space, 1, 2, 3 and 4 represents kiwifruit, dark background, leaves and branches respectively)

3. Segmentation

Mean values of two data components; *a* and *b* were considered as the components of the feature vector representing each region. Minimum distance classification was used to classify each pixel into its region. The kiwifruit regions isolated after the segmentation consist of noise. In order to eliminate noise, "morphological open" operation was used. Resulting image is as shown in Figure 4.


(a)


(b)

Figure 4. (a) Segmented kiwifruit region, (b) Boundaries superimposed on the original image

4 Automated Counting

To achieve automatic counting the images were first converted into gray colour images. Next, three simple methods were evaluated to count kiwifruit from the segmented images.

4.1 Regional Maximum (RM)

The pixels from the centre area of kiwifruit take comparatively higher grey values. Therefore the number of regional maximums of the image was used as data to obtain the fruit count.

4.2 Distance Transform (DT)

Before extracting the data for this method, the image was converted into binary. It was then complemented, so that pixels in an object region take the value zero and background pixels take the value one. The distance from each pixel in the object region to the nearest non-zero valued pixel was calculated. The number of regional maximums of the distance matrix were then counted and used as the data for this method.

4.3 Area

The area of all the objects in the image was calculated and considered as the data.

Number of kiwifruit in each image used for model development was manually counted with the help of a program written in Matlab. Then the relationship between the true count and the data obtained in each method was analysed using linear regression. The three regression equations obtained were used as simple models for obtaining the kiwifruit count from images. The linear regression equations for gold and green kiwifruit data are shown in equations (1)-(3) and (4)-(6) respectively, and R^2 values are shown in Table 1.

$$TrueCount = (0.829 * RMcount) - 0.16 \quad (1)$$

$$TrueCount = (1.02 * DTcount) - 0.94 \quad (2)$$

$$TrueCount = (0.000953 * Area) + 2.39 \quad (3)$$

$$TrueCount = (0.80 * RMcount) + 9.1 \quad (4)$$

$$TrueCount = (1.2 * DTcount) + 4.97 \quad (5)$$

$$TrueCount = (0.00157 * Area) + 11.6 \quad (6)$$

Table 1. R^2 values

Kiwifruit variety	R^2 value		
	RM	DT	Area
Gold	97.5	98.6	92.2
Green	67.6	78.2	60.3

Observations showed that the area method gives accurate result when there are no fruit in the image. Therefore that method was used to check whether there are no fruit in the image before proceeding to count fruit using other two methods.

5 Results and Validation

All the steps including pre-processing, segmentation and counting were programmed and run on the validation image set. The equations (7) and (8) show the error definitions used for validation. The percentage error per image defined in equation (7) enables tracking how the error varies from image to image and thereby to go back and examine the reason from each image. However, this definition has the disadvantage of giving a larger error even when the program has miscounted only 1 or 2 fruit, if the the total fruit count is small. For example, if the true fruit count of the image is 2 and the program has counted only 1, then the percentage error will be 50%. The average percentage error in equation (8) averages the error over all the images to compare the different methods used for counting.

Percentage error per image,

$$PEperI = \left[\frac{|PC - TC}{TC}\right] * 100 \quad (7)$$

Average percentage error,

$$AvgPE = \frac{1}{N}\sum\left[\frac{|PC - TC|}{TC}\right] * 100 \quad (8)$$

Where N is the number of images, PC is program count and TC is True count.

The percentage error indicates how many error counts per hundred kiwifruit, either by under-estimation or by over-estimation. The resulting error values, calculated using equation (8), for each method are shown in Table 3.

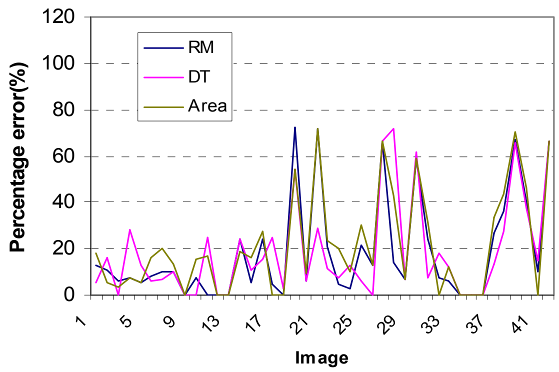
Table 3. Average Percentage Error of Counting Methods

Variety	Average percentage error		
	RM	DT	Area
Gold	10.28	7.09	17.62
Green	31.28	24.88	37.78

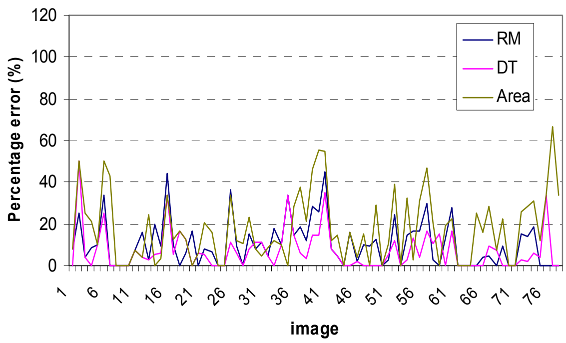
In orchards the kiwifruit are counted as the fruit count per bay. Typical fruit count per bay is around 700 to 1200. Therefore if we define the error count per bay without considering the error count per image, then our results show a more representative error.

6 Discussion and Future Work

The result shows the potential for developing an automated counting technique for the application of kiwifruit counting. However the methods are yet to be tested on different image sets taken on different days taken at night with artificial light. The pre-processing, data extraction and analysis methods require human intervention and decisions. Therefore, automation or calibration of the technique will be difficult.



(a)

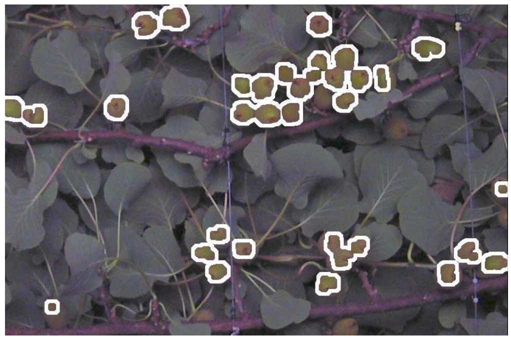


(b)

Figure 6. Variation of percentage error per image - Images are chosen in an arbitrary order (a) Green kiwifruit images (b) Gold kiwifruit images

Even though the average results gave a good impression, when each image's result is carefully considered as shown in Figure 6, several cases with large differences between manual count and program count were found in all methods. It was clear from the results that all methods on green kiwifruit have given a comparatively large error. The cause for large error can be the thicker calix in the centre of green kiwifruit, which makes the segmentation difficult. Another reason for large errors in some of the images of both gold and green fruit is the supporting wood bars in the orchard appear in the image which is shown in Figure 7(b). A separate algorithm could be used to mask this area. Careful examinations on the process show two main reasons for the errors in counting both gold and green kiwifruit

The first reason is the poor segmentation. It sometimes misclassifies similar coloured parts of leaves and branches as kiwifruit and results an over-segmentation. Similarly, under-segmentation happens when similar coloured kiwifruit are misclassified as leaves or branches. This is shown in Figure 7. In Figure 7(a), several kiwifruit have not been recognized as fruit while one leaf region is classified as a fruit. In Figure 7(b), there are several unrecognized fruit, whereas some parts of the wooden bar have been misclassified as fruit.



(a)

(b)

Figure 7. Poor segmentation

The second reason is the errors in counting techniques. This is mainly due to the occluded fruit and bunches of fruit. Distance transform method is underestimating fruit count, when many fruit are connected as one object as shown in Figure 8(a). On the other hand the regional maximum method overestimates fruit count due to too many local maximums and this situation is shown in Figure 8(b). Sometimes one kiwifruit object contains many local maximums while another object does not show any local maximum. Then when both under-estimation and over-estimation occur in an image the error can be neutralized. The accuracy of the area method depends on the size of the kiwifruit. If the size of the kiwifruit appears to be comparatively big or small either due to the distance to the camera or different size of the fruit, then the error from the area method will be high.

(a)

(b)

Figure 8. Erroneous counting

Further research will be carried out to develop a more robust automated counting system, focusing on the accuracy of the count. Currently, Random field based Maximum a poseterori (MAP) technique for segmentation and watershed method based techniques for automated counting will be considered. A robust segmentation technique which uses more features than colour components, and a scale invariant counting technique with special attention to deal with occluded and connected objects will be the main objectives of the next stage of research.

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