Project Report

on

Detection and Counting of On-Tree Citrus Fruit for Crop Yield Estimation

By

Mukesh Singh Patel

2008390100036

Supervisor Name

Abhishek Bajpai

Assistant Professor

Department of Computer Science and Engineering

Rajkiya Engineering College, Kannauj

Uttar Pradesh-209732

1 Abstract

Machine Learning is the vision of science in the recent year. It provides many critical prediction on learning.This paper study a better machine learning vision for estimating number of citrus fruits. The objective of this study is to design and develop image detection algorithm for accurate estimation of fruits count. Manually counting the fruits of yield estimation for marketing and other manageable purpose is time consuming which requires more human resources resulting in their cost.Many different approaches put forward for this challenge to overcome the production, yet separation of fruits from their background is not so efficient. So, this Machine Vision algorithm specifically focus on detecting and counting immature green citrus fruits using outdoor colour images.
We use K-means segmentation for recognition of fruits. This is unsupervised based learning algorithm which helps in segmenting the images more accurately. There are different method of image segmentation but this paper uses most popular method i.e. K-Means Clustering Algorithm. This algorithm involves converting an image into a collection of region of pixel that are represented by a mask or a label image.Further, these image are segmented into leaf,stem and fruits and is processed important segments of the image.This algorithm is tested on a data set containing trees images with an accuracy of 87.3 percent.
But the work can be more enhanced and can further used for calculating ripe fruits from trees. Still there can be more work on image enhancement and shadow reduction to gain more optimal result.

2 Introduction

Citrus comprises of many species of economic importance. Few species are commercially cultivated which include grapes fruit, lemons, limes, sweet oranges and mandarins. So its estimation is typically carried out a few weeks earlier to frontage to estimate the resources requirement. This require a lots of human efforts,labour, cost and time. Cost and time reduces profit at large scale. To overcome the challenges precisely and low cost estimation this machine learning model is developed. In this scenario, the various task involved in the pre-harvest; using the example of precision algorithm techniques in the harvest and post harvest activities is improved. Image processing can help in the improving decision making process for irrigation, fruit sorting and yield estimation.
Citrus fruits have different properties that can be used for detection purposes. The most natural properties that is being used in model is colour. Colour itself provide enough information; greenish in unripe in most fruits, yellow reddish yellow or ripen fruits. Although, image processing have also many complexes depending upon the image.One complexity is of occlusion; between green fruits and leaves, fruits and step and other depending on the climatic condition; Cloud and sun lights directly affect a image giving undesired colour, shadow and more. Many studies have been reported to automatically detect immature green fruit in

images. These studies usually fall into two categories based on the imaging systems used. One category is those studies using infrared (IR), multi spectral, and hyper-spectral imaging.Some of them described applications of thermal imaging for detecting objects or plant parts in a low contrast background because thermal imaging utilizes different thermal characteristics of observed objects compared with the use of visual cameras. For IR images, Sapina (2001) computed six texture features based on co-occurrence matrix, which is the second order statistics method characterizing spatial interrelationships of grey tones. The texture images showed good results of variance and correlation for all tested images, which were helpful to identify warm objects and background in low contrast images.

Stajnko et al. (2004) developed an algorithm to estimate number and diameter of apple fruits in an orchard by thermal imaging during a growing season. The coefficients of determination, R2, were used to show the relationship between the manual measurement and estimated results. They reported that the R2 between the manually counted number of fruit and the number estimated was ranged from 0.83 to 0.88, and the R2 between the manually measured fruit" diameter and the estimated diameter was ranged from 0.68 to 0.70 based on their algorithm. Some researchers have explored the feasibility of detecting fruits utilizing multi-spectral or hyper-spectral information. Annamalai and Lee (2004) conducted spectral analysis for immature green citrus fruits and leaves using a spectrophotometer in a laboratory. They found two important wavelengths, 815 and 1190nm, which were significant for fruit identification. Kane and Lee (2007) used a monochrome near-infrared camera with interchangeable optical band pass filters to capture images of green citrus fruit in Florida.

The images were processed using indices and morphological operations. The results showed an R2 of 0.74 between the predicted number of citrus pixels and number of pixels Precision Agric 123 manually masked. Okamoto and Lee (2009) developed a hyperspectral image processing method to detect green citrus fruit in individual trees from hyperspectral images captured in 369–1042 nm. The detection success rates were 70–85percent, depending on the citrus varieties.

3 Related Work

Despite these challenges involved in image processing has been used with good result for counting. In the past variety of techniques have been used across diverse fruits. Jun Lee, Won Suk Lee, Hao Gan, Xiuven Hu[1] used LBP features and hierarchical contour analysis. He proposed for two stage for detection and counting the number of citrus fruits in the image of tree canopy. The first stage was identifying potential candidate objects which include k points detection and classification . The second stage was hierarchical colour analysis (HCA). The positive prediction by the classifier was considered as candidate.

Han Li, Won Suk Lee, Ku Wang uses First Normalized Cross Correlation (FNCC) [2] using natural outdoor colour images. He divided the method into

Figure 1:

Figure 2: : Citrus tree images captured under two different sunlight conditions.

five steps. Firstly FNCC was applied to obtain potential fruit positrons by calculating error correlation between an input image ad template fruit image. In the second stage he filter out false positives through colour analysis. In the third stage he followed colour and shape feature were combined for detection potential fruits positions utilizing circular Hough transform(CHT). In fourth stage he combine multiple defections from step 2 and 3 and in final step he removed false positives using texture and determine final number of fruit.

Alexandria Engineering Journal [9] uses methodology pipeline to automate the pineapple crow detection and counting from RGB images. He stares by collecting data at the plantation, pre-processing image feature extraction ANN classification, feature selection using ANOVA algorithm and yield counting.

Chenglin Wang, Won Suk Lee [10] proposed algorithm including three stages: prepossessing, training and testing for detection and counting immature green citrus fruit from tree. The processing stage was composed of image size conversion and enhancement and normalization of illumination which was the crucial part of the algorithm and was used to remove noise as much as possible. He also used wavelet transformation-based algorithm for illumination normalization of the images.

Hannan et al. [14] used red chromaticity coefficients for enhancement of images. This contributed to the improved segmentation of his images containing variable bright orange trees. They used the shape analysis technique to detect overlapping oranges and with 4 percent false positives he achieved a 90 percent detection rate. Yet another enumeration scheme for citrus was proposed by Chinchuluun et al.[15]. They used Bayesian classification in addition to morphological manipulations and watershed segmentation for citrus segmentation and detection. They reported a correlation value of of 0.89 between manual and automated fruit counting.

Billingsley [16] presented an imaging system for counting macadamia nuts on harvest rollers. I used RGB color feature to separate the nuts and leaves from the roller.To separate the nuts from the leaves, they used a modified version of the circular Hough transform. oysters, etc. [17] used color histograms and shape analysis to detect and count his fruits of orange color on tree images. They were able to achieve his recognition accuracy of 76.5%.

4 Proposed Methodology

4.1 Image Preprocessing

Images generally contain a lot of redundant information that is not needed for a particular application. Images can be noisy and prone to errors in edge detection and segmentation tasks. Therefore, it is often necessary to perform some kind of noise reduction and image enhancement before doing any meaningful image processing. Image denoising is a classic and important task in the field of computer vision, with broad applications in image restoration, super-resolution, optical flow, etc. The goal of image denoising is to recreate the noiseless image

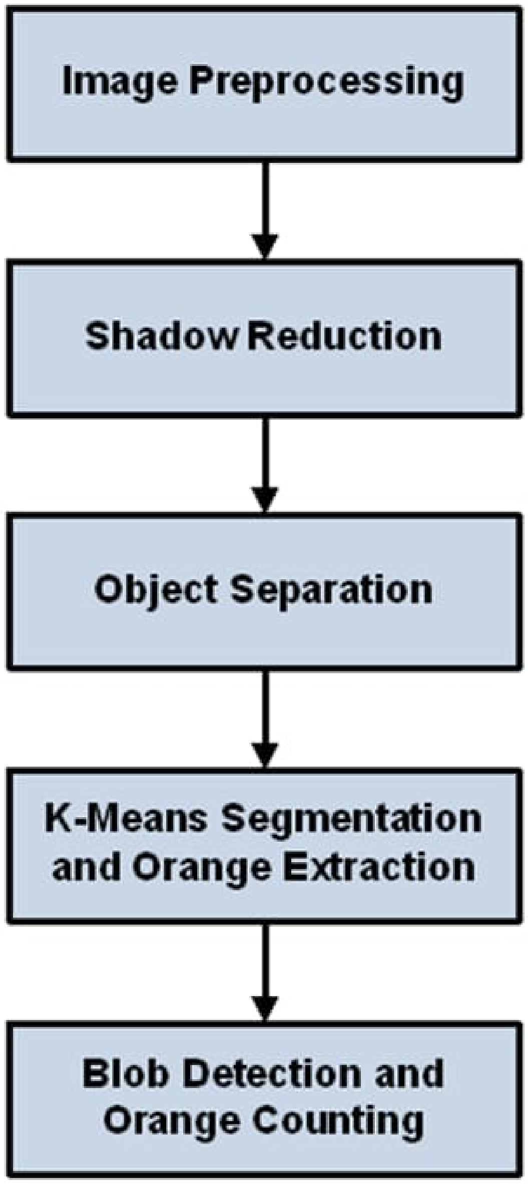

Figure 3: An overview of the proposed technique

x from the noisy observations y by subtracting the noise map from the noisy observations.
This article uses the Jiayi-Ma[15] gain algorithm to solve the problem of noise reduction from a special perspective. It has been widely used in the field of traditional image noise reduction. In recent years, several gain-based methods have been proposed to improve the ability of existing algorithms to remove noise while preserving image content. The "twice" technique is very early research. The boost process can be described as follows.

$$x^n = x^n - 1 + f(y - x^n - 1) \tag{1}$$

where f(●) represents the denoising operator and xˆ n is the nth iteration of the denoised image. Based on the "twicing" technique, Bregman iteration utilizes an iterative regularization method, in which the residual noise is added back to the observed signal based on the concept of the Bregman distance . The boosting process of Bregman iteration can be written as:

$$\hat{xn} = f(x^n - 1 + 1/(n-1)\sum_{i=1}^{n} -1(y - x^i))(2)$$

The technique proposed here uses the k-means segmentation algorithm on orange tree images. First, several preprocessing steps are performed, including noise reduction and image enhancement. Next, minimize the effects of shadows in the image. Next, we use blob detection and size calculation to extract the oranges, after which we estimate the final yield. Figure 3 provides an overview of the proposed technique by listing the various steps of the 4244 in sequence. Details of these steps are provided in the following subsections.

4.2 Shadow Reduction

Lighting conditions play a very important role in the performance of many computer vision algorithms. In particular, shadows in images cause problems in detection, segmentation, and tracking algorithms, making it impossible to achieve desired results. Unique objects can be combined by shadows, which can obscure object recognition systems. Minimizing shadows is an important task when shooting outdoors. Adjust the brightness of the image to minimize shadows. First, convert the RGB image to an L*a*b image. where L is the luminance layer and a and b represent opposite color dimensions. Then increase the brightness of the image to reduce the effect of shadows on the image. Finally, after replacing the lightness plane with the processed data, convert the image to the RGB color space.

4.3 Object Separation

One of the biggest challenges in counting oranges is orange overlap. Because of the overlap, multiple fruits may be counted as one, adversely affecting fruit number and yield estimates. To overcome this challenge and separate overlapping fruits, we convolve the images with a variance mask. After convolution, each pixel of the output RGB image contains adjacent variances of the R, G, and B channels [20]. Then convert the image to gray-scale by averaging the three color channels. Finally, a threshold is applied to the image. These steps not only separate overlapping fruit, but also help reduce unwanted edges, such as those found in leaves and grass.Figure 5 shows the image after the Object Separation step has been applied. is shown.

4.4 K means Segmentation

Image segmentation is the most important part of the overall yield estimation process. The k-means clustering algorithm is used for the orange segmentation. K-means clustering is an unsupervised classification technique that deals with finding patterns in a collection of unlabeled data [21]. The k-means algorithm aims to minimize the squared error function by iteratively reorganizing clusters. The iterations continue times until the cluster means does not exceed a certain cutoff value. The K-Means algorithm is popular due to its simplicity and relatively low computational complexity. It is suitable for the scenario as it is easy to choose the number of clusters (K). An image of an orange tree usually consists of areas representing oranges, leaves, branches, and the sky. So for K, choose 4 which corresponds to these 4 regions. After clustering , we apply threshold to extract the oranges from the tree images. Each object in the image is segmented using a specific RGB value.

4.5 Blob Detection and Lemon counting

Fruits are often visually fragmented due to obstructions created by leaves. more likely to occur. To remove these small pieces of fruit, I converted the image to binary and applied an erosion operation.

5 Result

Experiments were performed by obtaining automated citrus counts using the proposed scheme and comparing the resulting to the ground truth. Experimental results show that the correct recognition rate for is 87.3%.
In addition to detection rate, we used linear regression to model the relationship between the automated results and the ground truth. Figures 7, 8, and 9 show the graphed results of manual and automatic lemon counts for data sets Khanpur, NARC 1, and NARC 2, respectively. The figure also shows the coefficient of determination for regression equation and R2. As can be seen, neither the precision in Table I nor the coefficients of determination in Figures 7, 8, and 9 differ significantly between different data sets.

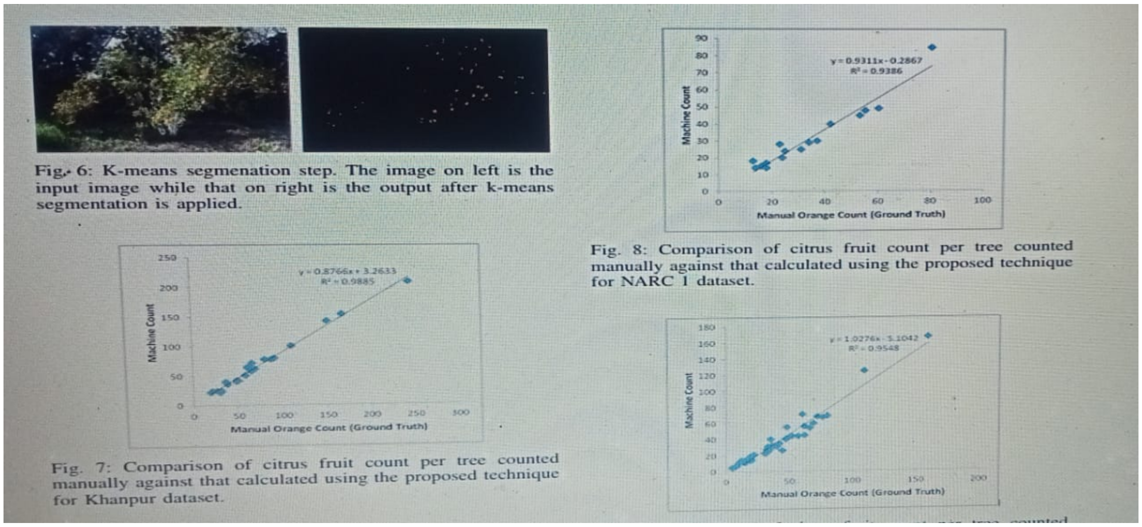

Figure 4:

Dataset	No of Images	No of Fruits	Machine Count	Accuracy (Khanpur
23	1662	1532	92.2	
NARC	1	16	543	501
92.3				
NARC	2	44	1796	1621
90.3				
Overall	83	4001	3654	91.30percent

Table 1: Caption

6 Conclusion

In this article, we introduced segmentation, recognition, and yield measurement techniques for citrus fruits.The proposed approach gives very good results with changing light conditions, foliage occlusion and overlap images of fruits taken from different distances from lemon trees. Experiments on three different datasets showed an accuracy of 91.3 percent with an R^2 value as high as 0.99. In the future, we aim to collect larger datasets for further experiments. Also, instead of manually capturing the citrus tree image, we plan to use a camera-mounted robot for image capture.

7 Reference

1. Zeeshan Malik, Sheikh Ziauddin, Ahmad R. Shahid, and Asad Safi "Counting of On-Tree Citrus Fruit for Crop Yield Estimation", Department of Computer Science, COMSATS Institute of Information Technology, Park

Road, Islamabad

2. R hinchuluun, W. Lee, R. Ehsani et al., “Machine vision system for determining citrus count and size on a canopy shake and catch harvester,” Applied Engineering in Agriculture, vol. 25, no. 4, pp. 451–458, 2009.

3. R. Chinchuluun, W. Lee, R. Ehsani et al., “Machine vision system for determining citrus count and size on a canopy shake and catch harvester,” Applied Engineering in Agriculture, vol. 25, no. 4, pp. 451–458, 2009.

4. J. Billingsley, “More machine vision applications in the NCEA,” in Mechatronics and Machine Vision in Practice. Springer, 2008, pp.333–343. Y. Cakir, M. Kirci, E. O. Gunes, and B.B. Ustundag, “Detection of oranges in outdoor conditions,” in Agro-Geoinformatics (Agro Geoinformatics), 2013 Second International Conference on. IEEE, 2013, pp. 500–503.

5. Y. Cakir, M. Kirci, E. O. Gunes, and B. B. Ustundag, “Detection of oranges in outdoor conditions,” in Agro-Geoinformatics (Agro Geoinformatics), 2013 Second International Conference on. IEEE, 2013, pp. 500–503.

6. Y. Cakir, M. Kirci, E. O. Gunes, and B. B. Ustundag, “Detection of oranges in outdoor conditions,” in Agro-Geoinformatics (Agro Geoinformatics), 2013 Second International Conference on. IEEE, 2013, pp. 500–503.

7. P. Perona and J. Malik, “Scale-space and edge detection using an isotropic diffusion,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 12, no. 7, pp. 629–639, 1990.

8. D. Stajnko, J. Rakun, M. Blanke et al., “Modelling apple fruit yield using image analysis for fruit colour, shape and texture.” European journal of horticultural science, vol. 74, no. 6, pp. 260–267, 2009.

9. R. Zhou, L. Damerow, Y. Sun, and M. M. Blanke, “Using colour features of cv. 'gala' apple fruits in an orchard in image processing to predict yield,” Precision Agriculture, vol. 13, no. 5, pp. 568–580, 2012.

10. M. Regunathan and W. S. Lee, “Citrus fruit identification and size determination using machine vision and ultrasonic sensors,” in ASABE Annual International Meeting, 2005.

11. Annamalai, P., Lee, W. S. (2004). Identification of green citrus fruits using spectral characteristics. ASAE Paper No. FL04-1001. St. Joseph: ASAE.

12. Bansal, R Lee, W S. Satish, (2013). Green citrus detection using fast Fourier transform (FFT) leakage. Precision Agriculture, 14(1), 59–70. Brill, M. H. (2014). Definition of chromaticity coordinates. Color Research Application, 39(3), 317–318.

13. Duda, R. O. Hart, P. E. (1972). Use of the Hough transform to detect lies and curves in pictures. Communications of the ACM, 15(1), 11–15. Duda, R. O., Hart, P. E., Stork, D. G. (2001). Chapter 4: Nonparametric techniques. In R. O. Duda, P.

14. E. Hart, D. G. Stork (Eds.), Pattern classification (pp. 182–186). Wiley: New York.

15. Gong, A. Yu, J, He, Y, Qiu, Z. (2013). Citrus yield estimation based on images processed by an android mobile phone. Biosystems Engineering, 115(2), 162–170.