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A computer Vision Algorithm for TangerineYield Estimation

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Abstract

The specific objective of this paper is to develop a computer vision algorithm to detect and count tangerine flowers in an image for estimate tangerine crops. The algorithm consists of image acquisition, Gaussian filter to remove noise, white color detection, counting of tangerine flowers. A Gaussian filter was used to reduce noise and illumination adjustment as much as possible for better clarity. It is observed that the developed method gives better valid output for tangerine flower detection in natural outdoor lighting, with different lighting condition without any alternative lighting source to control the luminance. The simulation result reveals that the method is reliable, feasible and efficient compared to other existing methods.

Keywords: *Tangerine flower, yield estimation, color detection, counting algorithm*

1. Introduction

Research is still being carried out through different computer vision algorithms in diversified fields in order to perform an automated agricultural task which has many real time potential applications. Currently, many researchers are carrying out research in fruit and vegetable recognition system to perform automated harvesting including educational purpose to enhance learning to increase more productivity with respect to less cost. In specific, previous research papers employed many computer vision strategies to recognize four basic features to characterize the object such as intensity, color, shape and texture. Patel *et al.*, [1] presented automatic segmentation and yield calculation of fruit based on shape analysis. Gracia *et al.*, [2] presented the theoretical background and the real implementation of an automated computer system to introduce machine vision in flower, fruit and vegetable processing for recollection, cutting, packaging, classification, or fumigation tasks. Fu *et al.*, [3] developed a new approach that combines a thresholding method and an artificial neural network (ANN) classifier to extract leaf veins. Stajnko *et al.*, [4] presented modeling of apple fruit development and growth by application of image analysis. Zulham *et al.*, [5] presented an automated grading system for Jatropha curcas by using a color histogram. Stajnko *et al.*, [6] developed and tested a new method for estimating the number of apple fruits and measuring their diameter in the orchard. A thermal camera captured images of apple trees five times during the vegetation period. Lü Qiang *et al.*, [7] studied application of the cluster barycentre (CB), edge barycentre (EB), circular Hough transform (CHT) and least square circle fitting (LSCF) to extract the features of fruit. The results indicated that the first two

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methods cannot accurately determine the circle in the presence of partial occlusion. The objects extracted by the CHT method include false targets in addition to longer time and larger memory required. The LSCF method, on the other hand, can accurately extract the features in a real-time mode. Jimėnez *et al.*, [8] described a laser-based computer vision system used for automatic fruit recognition. Manuel *et al.*, [9] proposed a system for the detection and location, in the natural environment, of bunches of grapes in color images. Morimoto *et al.*, [10] developed a new technique to evaluate the fruit shape quantitatively using attractor, fractal dimension and neural networks. Palaniappan Annamalai [12] presented a machine vision algorithm to identify and count the number of citrus fruits in an image and finally to estimate the yield of citrus fruits in a tree. Nilsback [13] investigated the problem of flower classification from images. She developed an iterative segmentation scheme which is able to segment a flower given only a general color model for flowers and no information about the flower in a particular image. For classification, she investigated how combining different features, which are carefully honed to describe different aspects, can improve performance, and used the geometric model introduced for the segmentation to develop a affine invariant geometric layout features. Chai [14] designed and built a system which automatically classifies an image of a flower for hundreds of flower species. Also, Jimėnez *et al.*, [15] used CCD cameras to capture the images and use local or shape-based analysis to detect the fruit.

Among precision technologies, yield estimation is one of the important first steps for precision crop management. It allows growers to know where a site-specific management would be needed to increase yield, fruit quality and profit. To a tangerine grower, who deals with thousands of trees in many blocks, site specific management or precision agriculture provides ability to apply technology and manage inputs as close as required within a given area. This management of field variability could improve fruit yield, quality, and income and limit negative impacts on the sensitive environments. Yield with other associated field characteristics would tremendously help growers more intimately know their groves and evaluate the entire tangerine grove graphically and thus prepare them to make important and efficient decisions. The use computer vision has many real time potential applications for automated agricultural tasks, but not in tangerine flower recognition. Tangerine yield estimation using computer vision can be classified into two categories: 1) Yield estimation by detecting tangerine flowers. 2) Yield estimation by counting number of tangerine from orchards. Hence, one can count can count the tangerine tree flowers and control yield of the tangerine every year by manually. In order to overcome the existing problems a new method has been introduced and executed to obtain better solution.

The paper is arranged as follows. Section 2 discusses about the objectives and newly proposed methodology. Results and discussion is presented in Section 3. Finally, conclusion and future work is given in Section 4.

2. Objectives and Methodology

The system consists of four major components such as image acquisition, image preprocessing, image recognition, and output image in order to perform color detection and counting tangerine flowers. The system architecture overview is shown in Figure 1.

The ultimate objective is to develop an image analysis system capable of determining tangerine flowers in natural tangerine tree with the following requirements:

1. The system should be able to recognize tangerine tree flowers accurately.
2. Images should be acquired on May, when flowers of tangerine tree are blooming.

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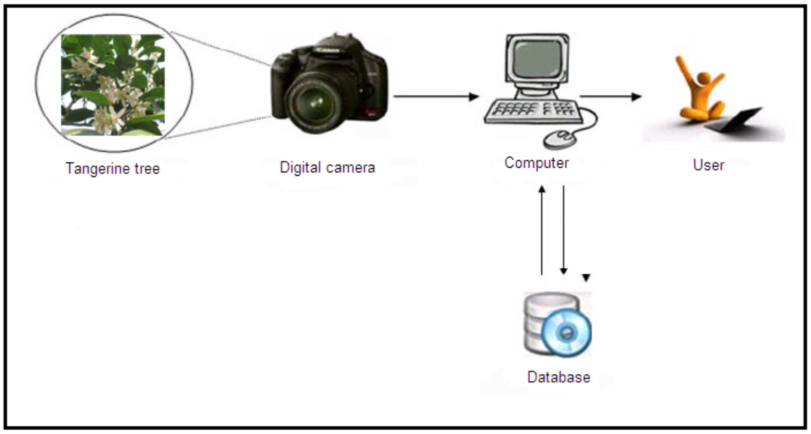

Figure 1. System Overview Architecture

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During image acquisition, brightness, contrast, shutter speed, and aperture of the camera were kept constant most of the time during imaging. Under backlighting conditions, the image has to be captured in a controlled environment. The controlled environment is a situation where the end user controls the picture background, the distance between a camera and an object, and a light source [11].

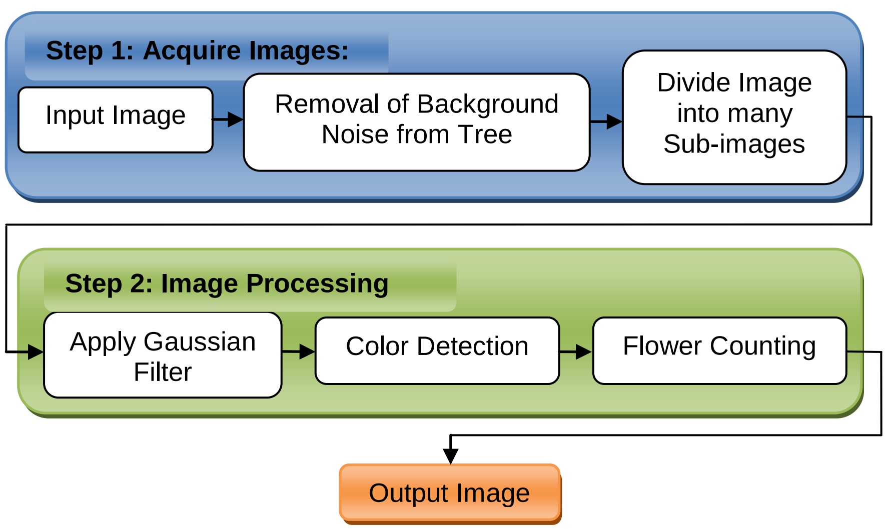


Figure 2. Flow Diagram for Tangerine Tree Flower Processing

A detailed schematic representation of a proposed method is presented in Figure 2 as a flow diagram process [16] which in turn gives better idea on the methodology to be incorporated to obtain better output with respect to existing models/methods.

For developing a tangerine flower recognition algorithm, images were taken in the tangerine tree field, which is in Jeju Island. A total of 21 sample tree images were taken on May during tangerine flower blooming season. The tangerine tree images were taken in natural outdoor lighting condition. Each tree picture was taken from four sides. The tree images were noisy and different lighting conditions. Flowers in some images were under the shadow of the leaves and branches. Also, there were too many flowers in the one tree for counting. So the input image was first removed noise, divided many sections (from ten into thirty five) before image processing steps [16]. Figure 3 shows the input / original RGB image of a tangerine tree with background noise and figure 4 illustrates the ground noises are removed manually *i.e.*, output RGB image of a tangerine tree without blurred noise.

Figure 3. Original RGB Image of Tangerine Tree with Background Noise

Figure 4. Output RGB Image of Tangerine Tree without Background Noise

Image processing was carried out using 28 calibration images and tested on the 172 images. Also, the preprocessing of the input image was performed first. A Gaussian Filter was used to reduce the noise as much as possible. In order to use an optimal Gaussian filter, Gaussian 1x1, 2x2, 3x3 filters carried out.

Input image of tangerine flower is presented in Figure 5, which is divided into sections.

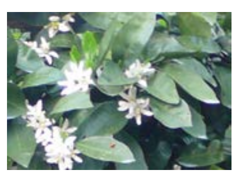


Figure 5. Input Sub Image of Tangerine Tree Flower

One of the most fundamental aspects of an image is the colors. Based on the principle, the end user can use colors to differentiate between different objects from others. Further, it is possible to isolate the white color pixels from the image and find out the number of white flowers. In this paper we isolated white color pixels of the image and counted a number of white color pixels and also, counted a number of white color pixels of the one flower [16]. However, flower counting was performed by dividing a total number of white color pixels of the image to a total number of white color pixels of the one tangerine flower as following

$$N_{\text{tangerine flowers}} = \frac{N_{\text{total tangerine flower pixels}}}{N_{\text{one tangerine flower pixels}}} \quad (1)$$

where

$N_{\text{tangerine flowers}}$ – a total number of tangerine flowers of the input sub image.

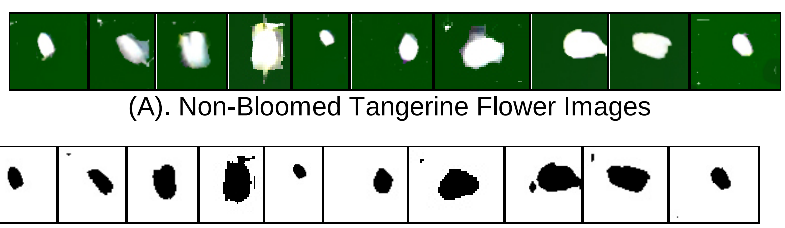
$N_{\text{total tangerine flower pixels}}$ – a total number of white color pixels of the sub image.

$N_{\text{one tangerine flower pixels}}$ – a total number of white color pixels of the one tangerine flower.

Input picture was included with different kinds of flowers, like small, bloomed and mixed (small and bloomed). Accordingly, white color pixels of the one flower were calculated by using 10 images for two kinds of flower images: small and bloomed. In order to perform optimal counting of flowers, flower counting algorithm was employed as follows [16]:

- Input image was checked by manually and was classified for three types: small (s), bloomed (b), mixed (m)
- White color pixels of the one small type tangerine flowers were calculated by 253 pixels
- White color pixels of the one bloomed type tangerine flowers were calculated by 601 pixels
- Almost all mixed type tangerine flower images were included 50% small, and 50% bloomed tangerine flowers. Then mixed input image tangerine flowers were counted by 50% white color pixels of the one small type tangerine flowers and 50% white color pixels of the one bloomed type tangerine flowers and tested on the 28 calibration images.

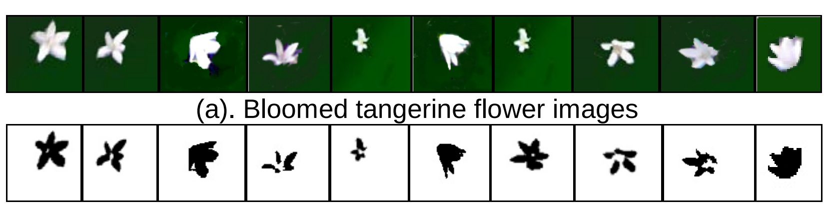
Here, calibration refers to calculating the small tangerine flowers, but not bloomed (see Figure 6), and computing the bloomed tangerine flowers (see Figure 7). The pre-processing of input image was performed initially [11].



(A). Non-Bloomed Tangerine Flower Images

(b). Resultant of Non-bloomed Image of Tangerine Flowers

Figure 6. Calibration of Images (Non-bloomed)



(a). Bloomed tangerine flower images

(b). Resultant of Bloomed Image of Tangerine Flowers

Figure 7. Calibration of Images (Bloomed)

In order to evaluate the performance of the algorithm, flowers were counted by the flower counting algorithm should have been compared with the actual number of flowers. The flowers were counted manually from an input image by two different persons for three times. The percentage error of images was defined as percentage error between the number of flowers counted by the machine vision algorithm, and the average number of flowers counted by manually as follows [16].

$$\mathrm{Error}_{\mathrm{image}}(\%) = \frac{\mathrm{MV}-\mathrm{MC}}{\mathrm{MC}} \times 100 \tag{2}$$

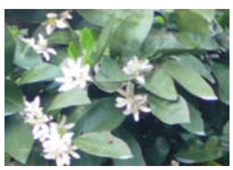
where

MV - number of flowers counted by the machine vision algorithm

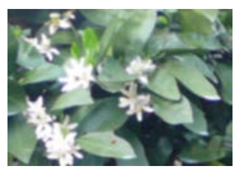
MC – average number of flowers counted manually.

3. Results and Discussion

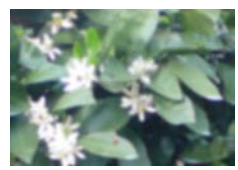
In order to use an optimal Gaussian filter, Gaussian 1x1, 2x2, 3x3 filters carried out, and compared for 25 calibration images. Result images Gaussian 1x1, Gaussian 2x2, and Gaussian 3x3 filters are as shown in Figure 8. In table 1 presented compared results of Gaussian 1x1, 2x2, 3x3 filters.



a). Gaussian 1x1 Filter



a). Gaussian 2x2 Filter



a). Gaussian 3x3 Filter

Figure 8. Blurred image using Gaussian Filters

Table 1. Comparison Result of Gaussian Filters

Type of Gaussian filters	Number of Gaussian filters the closest to the average value of observations	Percentage
G0 (No Gaussian filter)	3	13%
G1	6	25%
G2	**12**	**50%**
G3	3	13%
Total	**24**	**100%**

From Table 1 we can see Gaussian 2x2 filter is very close (50%) to the value of observations. Then we used Gaussian 2x2 filter for this research.

As a result, total of 200 images of tangerine flowers was detected by this algorithm. White flowers of tangerine tree were presented in the resultant image by black color.

In specific, color detection algorithm was performed and the output image of tangerine flowers is presented in Figure 9 for better understanding.

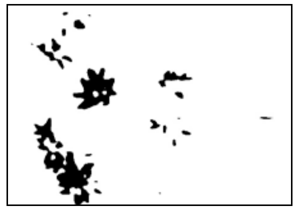


Figure 9. Output Image using Color Detection Algorithm

A regression analysis is performed between the number of flowers counted by flower recognition algorithm and the number of flowers counted by human observation for 200 images as shown in Figure 10. Regression analysis value was R^2=0.94.

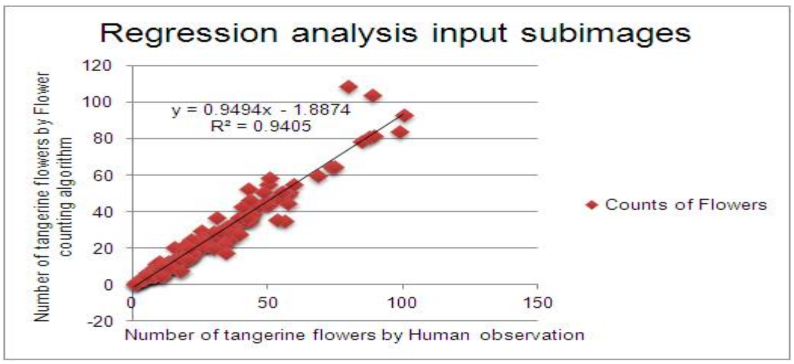


Figure 10. Regression Analysis between the Number of Flowers Counted by Flower Recognition Algorithm and the Number of Flowers Counted by Human Observation

The white color pixels of the one small and bloomed type flowers were calculated to the 10 images and tested 28 calibration images. The white color pixels of the one small type flowers were calculated by 253 pixels. The percentage error was as low as 4% and as high as 27% for all images. The mean of absolute error was determined to be 27%. The white color pixels of the one bloomed type flowers were calculated by 601 pixels. The percentage error was as low as 1% and as high as 63% for all images. The mean of absolute error was determined to be 30%.

Patel *et al.*, [1] presented automatic segmentation and yield calculation of fruit based on shape analysis. They applied Guassian Low Pass Filter, converted RGB to L*a*b space, selected the range of “a” for coarse detection, extracted the fruit regions by adding the input image with the binary mask, used morphological operations for remove noise, generated a binary image, labeled the pixels, applied Sobel Edge Detection, for each labeled region edge points are used for fitting of appropriate circle. A total of 100 images of different fruit were collected from internet. The percentage error was as low as 0%, and as high as 72%. The mean absolute error was determined to be 31.4% for all validation images.

A machine vision algorithm to identify and count the number of citrus fruits in an image and finally to estimate the yield of citrus fruits in a tree was discussed by Palaniappan Annamalai [12]. They Converted RGB to HIS, binarizated of color image in hue-saturation color plane, pre-processing (threshold using area, dilation, erosion, extracted features of fruits) to remove noise and to fill gaps, and, finally, counting the number of fruits. The fruit counting algorithm was applied to the 329 images. The percentage error was as low as 0%, as high as 100%. The mean absolute error was determined to be 29.33% for all validation images. The value for the regression analysis (R2) was 0.79.

It is noticed from above discussion that Patel *et al.*, [1], and Palaniappan Annamalai [12] methods gives less significant results. Therefore, in order to yield better results we introduced our machine vision method, there by percentage error was as low 0% and as high as 55% for all input images. The mean of absolute error was determined to be 17% for all input images. The main reason for this error was due to the fact that there were many and, small flowers or were in a shaded place and clear to the human eye. The algorithm would have treated them as noise or would not recognize well and left them while counting the flowers. Also, when conducting the tangerine flower counting-based yield estimation, computer vision systems face three challenges due to the characteristics of orchard environments.

Challenge 1: Variance in natural illumination, which makes any pixel-level data based method difficult to tune and work reliably.

Challenge 2: Tangerine flower occlusion by foliage, branches, and other flowers.

Challenge 3: Multiple detections of the same tangerine flower in sequential images, possibly causing over counting.

4. Conclusions and Future Work

In this present paper, a new algorithm for tangerine flower recognition using machine vision for tangerine yield estimation system is proposed since manual operations are found to be uncomfortable. The use of machine vision to analyze images has many potential applications for automated agricultural tasks but sometimes, variability of agricultural objects makes very troublesome to employ the existing algorithms to the agricultural domain. In order to yield better results in early time the developed algorithm is composed of white color detection, and white color pixels counting. It is important to point out that the introduced method gives better output of tangerine tree flower detection in natural outdoor lighting, in different lighting condition and found to be efficient and effective. Future work is to develop yield prediction model for estimation yield information of the tangerine grove and mobile system for counting tangerine fruit, and its related applications.

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