

# Real-time monitoring of optimum timing for harvesting fresh tea leaves based on machine vision

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**Abstract:** The harvesting time of fresh tea leaves has a significant impact on product yield and quality. The aim of this study was to propose a method for real-time monitoring of the optimum harvesting time for picking fresh tea leaves based on machine vision. Firstly, the shapes of fresh tea leaves were distinguished from RGB images of the tea-tree canopy after graying with the improved B-G algorithm, filtering with a median filter algorithm, binary processing with the Otsu algorithm, and noise reduction and edge smoothing using *open* and *close* operations. Then the leaf characteristics, such as leaf area index, average length, and leaf identification index, were calculated. Based on these, the Bayesian discriminant principle and method were used to construct a discriminant model for fresh tea-leaf collection status. When this method was applied to a RGB tea-tree canopy image acquired at 45° shooting angle, the fresh tea-leaf recognition rate was 90.3%, and the accuracy for fresh tea-leaf harvesting status was 98% by cross validation. Hence, this method provides the basic conditions for future tea-plantation operation and management using information technology, automation, and intelligent systems.

**Keywords:** agricultural machinery, fresh tea leaves, machine vision, intelligent recognition, real-time monitoring

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## 1 Introduction

In recent years, much research has focused on the mechanization and automation of tea production and the application of intelligent systems based on machine vision. An RGB model has been used to detect tea quality by monitoring color changes in the tea-drying process<sup>[1]</sup>. An artificial neural network algorithm was used to detect the liquor color change in the HSI color space during fermentation of black tea<sup>[2]</sup>. A hyperspectral imaging technique was used in an attempt to classify green tea with band selection by principal component analysis, characteristic variable extraction by texture analysis and classification model

construction using a support vector machine<sup>[3,4]</sup>. Correlations of the quality and shape factors of tea leaves were analyzed using a computer image analysis system, and tea quality identification has been automated using an improved neural network algorithm<sup>[5-6]</sup>. An online identification technology with a speed 20-30 times that of manual methods was developed to sort tea leaves and tea stalks based on their differences in color, shape, and weight<sup>[7]</sup>. Many other methods for recognition and detection of tea buds were studied, such as *k*-means clustering and texture classification<sup>[8-12]</sup>.

The tea plant originated in China, and China remains the largest tea producer and the second largest exporter country. The tea plant is a very important economic crop in China<sup>[13,14]</sup>. With advancing urbanization and a decreasing labor force year by year, the labor costs of tea production have increased significantly, which has seriously restricted development of the tea industry. Hence, how to reduce labor costs and enhance quality in the tea-production process and in tea-garden management are important issues.

The harvesting time of fresh tea leaves has a significant impact on yield and product quality. With reference to previous research on computer vision<sup>[15-18]</sup>, this study aims to develop a real-time monitoring system to determine the optimum harvesting time for fresh tea leaves. For this purpose, the shapes of fresh tea leaves were distinguished from RGB images of the tea-tree canopy, then the leaf characteristics were calculated, lastly, the Bayesian discriminant principle and method were used to construct a discriminant model for fresh tea-leaf collection status.

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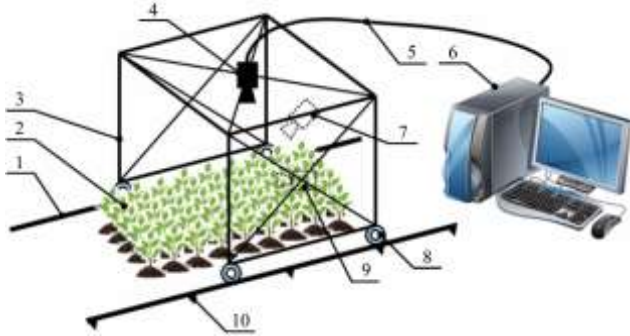
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## 2 Materials and methods

### 2.1 Image acquisition and processing equipment

A specialized test device was used for image acquisition, consisting of ten main parts (Figure 1). On April 8, 2014, images of the canopy of living Purple Rose tea trees were shot at the ChangAn tea garden in Changsha, covering a field area of 180 mm×135 mm, and saved in 640×480 pixels JPG format.

The LabVIEW 2014, IMAQ Vision, and Vision Assistant 2013 software packages were used for image processing, on a Lenovo X220 computer with a 2.30 GHz CPU (Intel i5-2410M) and Windows 7 OS (64-bit).



1. Guide rail 2. Living tea trees 3. Rack 4. Camera with focal length 2.8-12 mm 5. USB cable 6. Computer 7. Camera with 45° shooting angle 8. Guide wheel 9. Camera with 0° shooting angle 10. Rack positioner

Figure 1 Schematic diagram of tea-garden experimental apparatus

### 2.2 Image segmentation

Images of the canopy of living Purple Rose tea trees were mainly made up of fresh leaves and background material (jannums and branches), as shown in Figure 2a. A large number of trials demonstrated that the G-B operation ( $G(x,y) - B(x,y)$ ) on these images was not optimal for separating the fresh leaves from the background. To enhance the images of fresh leaves and inhibit the background, an improved G-B operation was chosen for gray image processing. The algorithm is shown as Equation (1), and the processing results are shown in Figure 1b:

$$C(x,y) = \begin{cases} 0 & A(x,y) \leq B(x,y) \\ A(x,y) & A(x,y) > B(x,y) \end{cases} \quad (1)$$

where,  $A(x,y) = G(x,y) - B(x,y)$  is the G-B color factor;  $G(x,y)$  and  $B(x,y)$  are the green and blue values of the color image at  $(x,y)$ ; and  $C(x,y)$  is the grey value of the grayscale image at  $(x,y)$ .

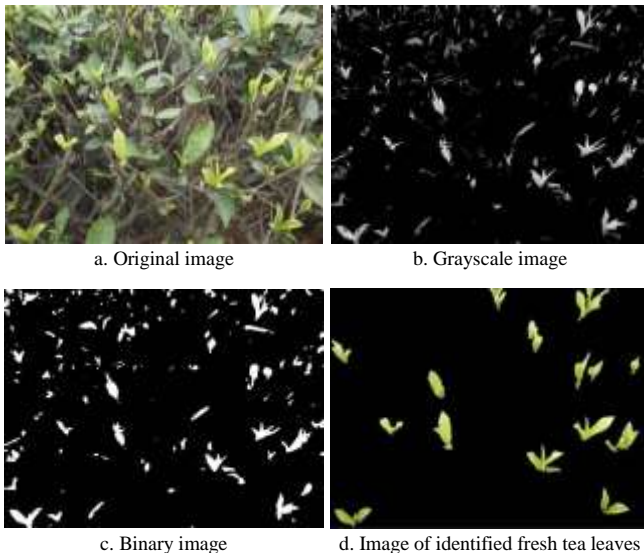


Figure 2 Image segmentation

After filtering by a median filter with a 5×5-template, the grayscale images were converted to binary images using the Otsu method.

The between-cluster variance method, also called the Otsu algorithm is derived from the principles of probability and statistics and the least-squares method and is based on the gray histogram of an image<sup>[19-21]</sup>. The basic idea is to divide the image into target and background based on the gray level of each pixel. The larger the difference between target and background, the greater is the value of the Otsu statistic, and the smaller is the difference, the lesser the Otsu statistic. The Otsu measures efficiently and adaptively calculates thresholds for target and background in gray image segmentation. Hence, Otsu is an appropriate method for segmenting canopy images of living tea trees with irregular geometric features and color differences between fresh leaves and background.

In this study, the Otsu method was used to calculate the optimal threshold. Then Equation (2) was used to divide the canopy images into two parts (fresh leaves and background). The processing results are shown in Figure 2c:

$$BN(x,y) = \begin{cases} 255 & C(x,y) \geq T \\ 0 & C(x,y) < T \end{cases} \quad (2)$$

where, the background is  $BN=0$  (black) and  $B=255$  for fresh tea leaves or noise (white).

*Open* and *close*-operators were used to remove small amounts of noise from the binary canopy image, to separate fresh tea leaves from the noise attached to them, and to keep the morphological characteristics of fresh tea leaves. The *open-close* operation is a fundamental operation in mathematical morphology based on erosion and dilation. The *open* operator for erosion processing after dilation processing is defined by Equation (3), which can separate target images from noise, eliminate small amounts of noise that are smaller than the structural elements, and smooth the image outlines. The *close* operator for dilation processing after erosion processing is defined by Equation (4), which can connect the target image with adjacent pixels, fill small holes and narrow gaps, and smooth the target image edges<sup>[22]</sup>:

$$BN \oslash BS = (BN \otimes BS) \ominus BS \quad (3)$$

$$BN \oslash BS = (BN \otimes BS) \ominus BS \quad (4)$$

where, BS represents structural elements; BN represents the image collection;  $\otimes$  is the dilation process; and  $\ominus$  is the erosion process.

### 2.3 Recognition method for fresh tea leaves

The coverage area and length were extracted as geometric characteristics of fresh tea leaves in the canopy image to identify fresh tea leaves and to calculate the geometric characteristics of the living tea-tree canopy (Figure 3).

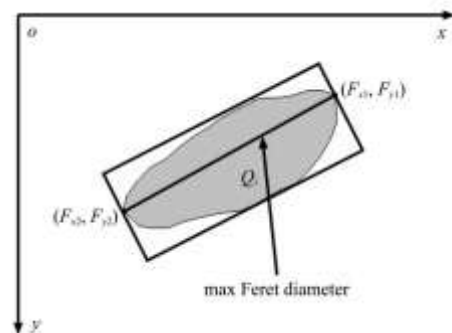


Figure 3 Schematic diagram of geometric characteristic quantity

The *coverage area* (CA) is the area covered by object  $Q_i$  in an image and is calculated by counting the number of image pixels as

in Equation (5):

$$CA(Q_i) = \sum_{(x,y) \in Q_i} 1 \tag{5}$$

where, the coverage length (CL) is the max Feret diameter of object  $Q_i$ , as calculated by Equation (6):

$$CL(Q_i) = \max_{(x,y) \in Q_i} \sqrt{(F_{y2} - F_{y1})^2 + (F_{x2} - F_{x1})^2} \tag{6}$$

Based on morphological characteristics, fresh tea leaves in the binary canopy image of the living tea tree were distinguished from noise using Equation (7):

$$TL(Q_i) = \begin{cases} 1 & CA(Q_i) \geq CA_h, CL(Q_i) \geq CL_h \\ 0 & \text{Other} \end{cases} \tag{7}$$

For Purple Rose tea, empirical values were  $CA_h = 25$  and  $CL_h = 10$ . The recognition results for fresh tea leaves are shown in Figure 1d.

The fresh-leaf recognition rate (FLRR), or the number of fresh tea leaves identified divided by the number of fresh tea leaves in the living tea-tree canopy image, was used to evaluate this recognition method.

**2.4 Discriminant method for fresh tea-leaf growth status**

According to the growth characteristics of fresh tea leaves, such as the fresh tea-leaf area index, the fresh tea-leaf average length, and the fresh tea-leaf identification index, a discriminant model for fresh tea-leaf development status was proposed based on the Bayesian posterior probability criterion.

**2.4.1 Calculation of fresh tea-leaf growth characteristics**

The fresh tea-leaf area index (FLAI, denoted by  $\alpha$ ) or the total area of all fresh tea leaves in the living tea-tree canopy image divided by the coverage area of the image, was defined to describe the percent coverage of fresh tea leaves in the living tea-tree canopy, as calculated by Equation (8):

$$\alpha = \sum_{i=1}^N \frac{AR_i}{AR_t} \times 100\% \tag{8}$$

where,  $AR_i$  is the coverage area of fresh tea leaf  $i$ ;  $AR_t$  is the area of the canopy image; and  $N$  is the number of fresh tea leaves identified.

The fresh tea-leaf average length (FLAL, denoted by  $\beta$ ) is the average length of all fresh tea leaves in the living tea-tree canopy image and is calculated by Equation (9):

$$\beta = \sum_{i=1}^N CL_i / N \tag{9}$$

where,  $CL_i$  is the coverage length of fresh tea leaf  $i$ .

The fresh tea-leaf identification index (FLII, denoted by  $\gamma$ ) is the number of fresh tea leaves identified in the living tea-tree canopy image divided by the coverage area of the image and is calculated using Equation (10):

$$\gamma = N / AR_t \tag{10}$$

**2.4.2 Bayes posterior probability criterion<sup>[26]</sup>**

If  $G_1, G_2, \dots, G_k$  are  $k$  normal populations, the mean and the covariance matrix are  $\mu_r$  and  $\Sigma_r$  respectively, where  $r = 1, 2, \dots, k$ , and  $\Sigma_1 = \Sigma_2 = \dots = \Sigma_k$ , then for sample  $X=x$ , the Bayesian posterior probability function is given by Equation (11):

$$g_r(x) = \mu_r \sum_r^{-1} x - \frac{1}{2} \mu_r \sum_r^{-1} \mu_r + \ln q_r \tag{11}$$

where, the Bayes posterior probability criterion is  $X \in G_r$ , where  $G_r(X) = \max_{1 \leq r \leq k} g_r(X)$ .

**3 Results and discussion**

**3.1 Evaluation of the fresh tea-leaf recognition method**

Three types of canopy images were collected at three shooting angles: 0°, 45°, and 90°. The recognition results for these three types of canopy image showed that the average processing time was less than 1.5 s, which satisfies the requirement of real-time processing. The FLRRs of the canopy images shot at 45° and 90° angles were higher than for those shot at a 0° angle, and the FLAIs were lower than at a 0° angle. Moreover, the FLRR at a 45° angle was 90.3%, which was higher than at a 90° angle; the FLAI was 4.7% higher than at a 90° angle (Table 1).

**Table 1 Comparison of recognition effects**

Shooting angle	FLAL/%	FLRR/%	Processing time/s
0°	13.5	83.5	1.19
45°	4.7	90.3	1.21
90°	2.6	88.5	1.18

As shown in Figure 4, for the canopy images shot at 0°, the fresh-leaf outlines are clearer, but the coverage rate is higher, which seriously affects fresh tea-leaf image collection and decreases segmentation accuracy. On the other hand, for canopy images shot at 90°, the coverage rate is lower and the fresh-leaf outlines are unclear, which seriously affects discrimination of fresh tea-leaf growth status. Hence, canopy images were shot at a 45° angle in practice.



**Figure 4** Canopy images of living tea trees at three shooting angles

Contrast to only 90° shooting angle used<sup>[23]</sup>, three shooting angles: 0°, 45°, and 90° were used in image collection in this study and the results suggested 45° was the best among the tree shooting angles. However, which is the best shooting angle of all shooting angle is under discovered.

**3.2 Evaluation of the growth status discriminant method**

Sixty canopy images were collected at a 45° shooting angle,

and the growth status of the collection was appraised by nine tea experts. Each leaf was categorized into one of three classes: Not Suitable, Suitable, and Optimum. After applying graying, filtering, segmenting, and *open-close* operators on canopy images, fresh tea leaves were identified, growth characteristics were calculated, and development status was discriminated by the Bayesian posterior probability criterion. Fivefold cross validation

was performed to assess the classification results of the discriminant model, using 50 canopy images for the training sample and the other 10 for pending approval samples. The Bayesian discriminant function was computed using the SPSS statistical analysis software, as shown in Equations (12)-(14):

$$g_1(X) = -3.43X_1 + 3.57X_2 + 0.12X_3 - 50.82 \quad (12)$$

$$g_2(X) = -3.77X_1 + 4.10X_2 + 0.16X_3 - 75.92 \quad (13)$$

$$g_3(X) = -2.72X_1 + 4.27X_2 + 0.13X_3 - 78.60 \quad (14)$$

where, the independent variables  $X_1$ ,  $X_2$ ,  $X_3$  correspond to FLAI, FLII, and FLAL respectively. The growth status is Not Suitable when  $g_1(X) = \max_{1 \leq r \leq 3} g_r(X)$ , Suitable when  $g_2(X) = \max_{1 \leq r \leq 3} g_r(X)$ , and Optimum when  $g_3(X) = \max_{1 \leq r \leq 3} g_r(X)$ .

The results showed that the discriminant accuracy for 50 training samples was 100% and the discriminant accuracy of 10 pending-approval samples was 90% (Table 2). The discriminant accuracy of this is study higher than the reference<sup>[23,24]</sup>, however it is lower than the reference<sup>[25]</sup>.

**Table 2 Discriminant results for fresh tea-leaf growth**

No.	FLAI/%	FLAL/mm	FLII/ (number m <sup>-2</sup> )	Actual category	Predicted category
1	9.84	23.66	493.83	2	2
2	14.9	39.63	329.21	3	3
3	12.63	19.13	740.74	2	2
4	15.65	30.42	452.67	3	3
5	14.8	25.44	617.28	3	3
6	16.44	27.21	740.74	3	2**
7	21.37	34.04	411.52	3	3
8	11.56	25.04	493.83	3	3
9	15.06	31.12	452.67	3	3
10	16.3	34.48	452.67	3	3

Note: \*\* corresponds to wrongly discriminated samples

## 4 Conclusions

This research has proposed a method based on machine vision for real-time monitoring to determine the optimum harvesting time for fresh tea leaves. The proposal is intended for large-scale application to reduce the required rural labor force. The results indicate a discriminant accuracy of 90%, which provides the basic conditions for future tea plantation operation and management using information technology, automation, and intelligent systems.

However, the system proposed here is still insufficient. Although live tea-leaf images are collected in the natural environment, image exposure variations can reduce recognition and discriminant accuracy. The improved G-B operator needs further optimization to improve its adaptability to natural environments.

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