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A Novel Red Apple Detection Algorithm Based on AdaBoost Learning

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** Short Paper*

***Abstract*:** This study proposes an algorithm for recognizing apple trees in images and detecting apples to measure the number of apples on the trees. The proposed algorithm explores whether there are apple trees or not based on the number of image block-unit edges, and then it detects apple areas. In order to extract colors appropriate for apple areas, the CIE L*a*b* color space is used. In order to extract apple characteristics strong against illumination changes, modified census transform (MCT) is used. Then, using the AdaBoost learning algorithm, characteristics data on the apples are learned and generated. With the generated data, the detection of apple areas is made. The proposed algorithm has a higher detection rate than existing pixel-based image processing algorithms and minimizes false detection.

***Keywords*:** Crop yield estimation, Image segmentation, Apple tree detection, Apple detection, Object detection

1. Introduction

Generally, a crop disaster evaluation procedure entails a sample survey that measures the yield before and after a natural disaster through visual inspection and manual work to judge the size of the crops and the disaster damage. This consumes a lot of time and money, and it is possible to compromise fairness depending on the accuracy of the inspector. However, developments in image processing and machine vision technologies have been proposed as a solution to these problems. Most existing studies on fruit detection have determined the area with the pixel-based image processing method and counted the number of detected areas [1-3].

This study analyzes the shape of the apple tree to detect its existence and recognize the apple tree in the first stage. Then, apples on the trees are detected using learned apple data through AdaBoost Learning as an edge-based pre-process. Various detection errors occur when detecting apples on a tree. Examples of errors in apple detection include detecting other objects with similar colors to the fruit, errors due to reflection or the shade of the apples, and not detecting fruit hidden behind objects like leaves. This method extracts colors suitable to an apple area using the CIE L*a*b color space to minimize detection errors with colors similar to an apple.

In addition, this study utilizes modified census transform (MCT), which reduces the influence from illumination changes by extracting structural information about the apple region. Also, in the post-processing stage, outliers are eliminated by using normal distribution characteristics, which finally reduce the fault detection area of the apple.

2. Related Work

Existing studies that detected and measured the fruit area with an image processing technique generally utilized external or structural information of the pixel itself. They proposed a method that implemented labeling and boundary detection after removing the background of the input image and extracting the area of the fruit, finally counting and calculating the amount of fruit. Wang et al. [2] used the HSV color space to extract the pixel area of the red of the apple and labelled nearby pixels. Patel et al. [5] implemented a noise reduction algorithm on the extracted area based on color to detect the orange color

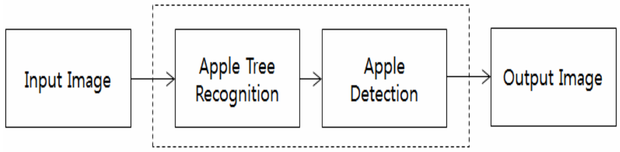


Fig. 1. Entire system block diagram.

and judged circular forms as the fruit through boundary detection. Other studies have shown common detection errors including missing the fruit area owing to the light source, missing fruit hidden by other fruit or by a leaf, and counting as fruit items that have colors similar to the fruit.

3. The Proposed Scheme

This paper proposes a system that dramatically reduces the fault detection rate while minimizing the effect from the existing light source by introducing AdaBoost Learning and MCT algorithms. The proposed apple detection system consists of apple tree recognition and apple area detection modules. The pre-process, or apple tree recognition module, analyzes the external shape of the tree on the input image based on the edge to judge the existence of the apple tree, and then goes to the apple area detection stage.

The block diagram for the entire system is shown in Fig. 1.

3.1 Apple Tree Recognition

Most of existing apple detection systems generated false detection results in performing the detection process, even though the input image was not an apple tree. An unfocused camera image also generates the same results. This paper segments the input image into blocks as a pre-process of the system to solve such recognition errors. And then, the number of edges in each block is extracted to judge whether the block is included in the tree candidate area. The apple area contains a smaller number of edges than that of the tree area, causing empty space in the tree area, and the empty space is filled. Finally, the tree block candidate is judged as a tree if the block meets a certain rate. The study tested hundreds of apple tree images to analyze the edge information on the tree shape and finally extract them to more precisely apply the tree shape information to the algorithm.

Th_1 is the parameter indicating the number of pixels on the edge for each block area, and Th_2 is the parameter indicating the number of blocks corresponding to the tree block in each block area. Th_1 and Th_2 had values of 50 and 120, respectively, on an experimental basis. The edge extraction resulting images from the tree shape pre-process and the proposed algorithm are as follows.

3.2 CIE LAB Color Space Analysis

It is important to clearly separate the apple region from the background to precisely detect the apples in the image. Therefore, this study compared and analyzed various color

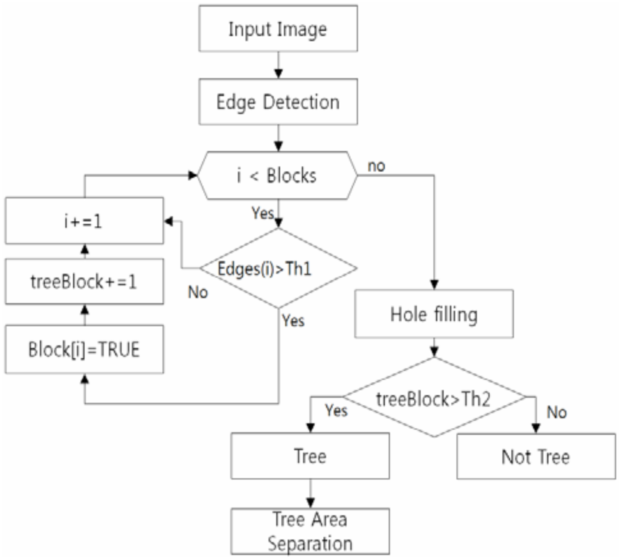


Fig. 2. Apple tree region extraction algorithm.

(a) Input image (b) Apple tree region extraction

Fig. 3. An example of the apple tree region extraction result.

space models (RGB, HSI, CIE L*a*b) to find out the proper color range of the apple. The CIE L*a*b space [11], similar to the human visualization model, showed the most remarkable separation of the apple from the background. Therefore, this study used the L*, a* and b* color space to define the range of the red apple area. The color range in the defined condition and the extracted apple area are as follows.

$$
\begin{aligned}
&0 \le L^* \le 100 \\
&15 \le a^* \le 80 \qquad (1) \\
&0 \le b^* \le 60
\end{aligned}
$$

The three coordinates of CIE L*a*b* represent the lightness of the color (L* = 0 yields black and L* = 100 indicates diffuse white), its position between red/magenta

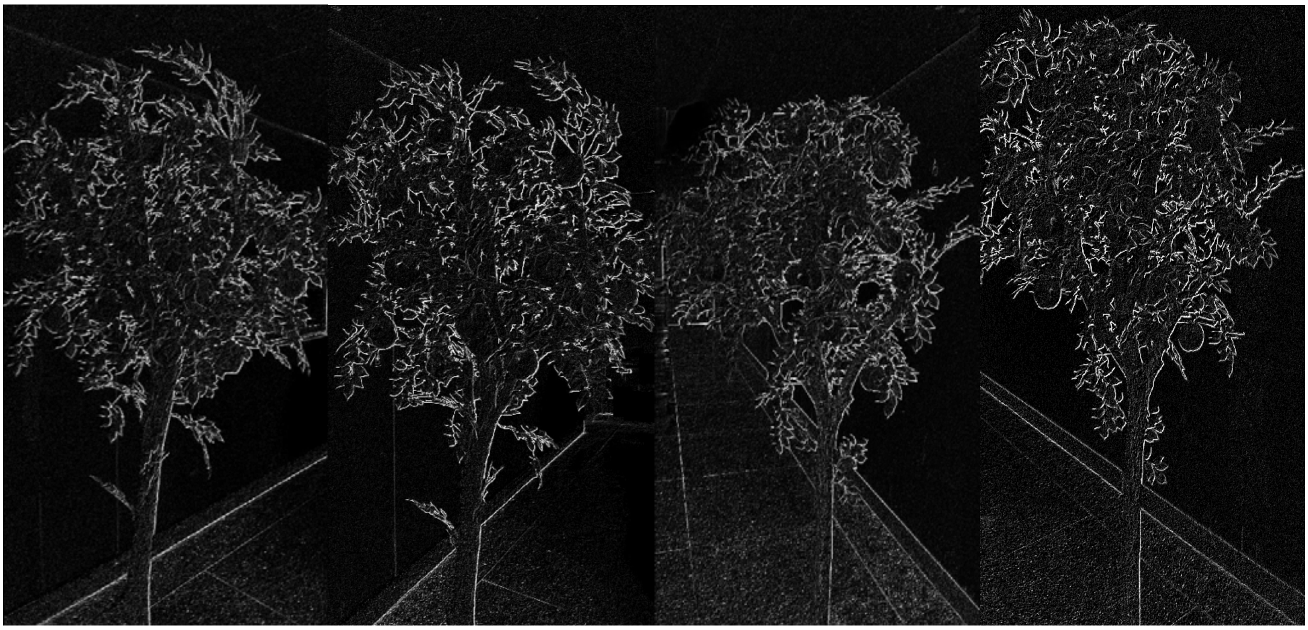


Fig. 4. Apple tree shape analysis examples.

(a) Input image (b) Apple color area extraction

Fig. 5. Apple area extraction from the CIE L*a*b* color space.

and green (a*, negative values indicate green, while positive values indicate magenta) and its position between yellow and blue (b*, negative values indicate blue and positive values indicate yellow).

Figures with various color space models (RGB, HSI, CIE L*a*b) used to find the proper color range of the apple and background area are shown in Fig. 6.

3.3 MCT

The MCT of the apple area extracted from the input image may minimize the effect from the light source and only extract texture information in the apple area to minimize fault detection due to reflection from the light source or items hidden by shade on the apple area. The MCT calculates the average brightness based on a 3×3 mask, and then compares and calculates the brightness to nearby pixels.

Eq. (2) and the MCT calculation process are as follows. X = (x, y) means the location of each pixel in the image, and the image brightness corresponding to each position is defined as I(X). The 3×3 window, of which X is the center, is W(X); N′ is a set of pixels in W(X), and Y represents nine pixels each in the window. In addition, $\overline{I}(X)$ is the average value of pixels in the window, and I(Y) is the brightness value of each pixel in the window. As a comparison function, ζ() becomes 1 if $\overline{I}(X) < I(Y)$, otherwise, it is 0. As a set operator, ⊗ connects binary patterns of function, and then nine binary patterns are connected through the operations. MCT was applied for apple and non-apple areas in a 20 × 20 window.

The extracted features effectively distinguish apple and non-apple areas through the AdaBoost learning algorithm proposed by Viola and Jones [12].

$$\Gamma(X) = \bigotimes_{Y \in N'} \zeta(\overline{I}(X), I(Y)) \tag{2}$$

3.4 Removal of Fault Detection Area

There may exist areas with faulty detection of the apples due to colors and patterns similar to the apple area during apple area detection. The study calculated the average (μ) and standard deviation (σ) of the areas of the apple area detected during apple image extraction to eliminate such errors. The apple area detected from the normal distribution feature was distributed within a range of 3σ standard deviation (μ -3σ, μ +3σ) for 99.7%. Therefore, the study judged the red object rather than the

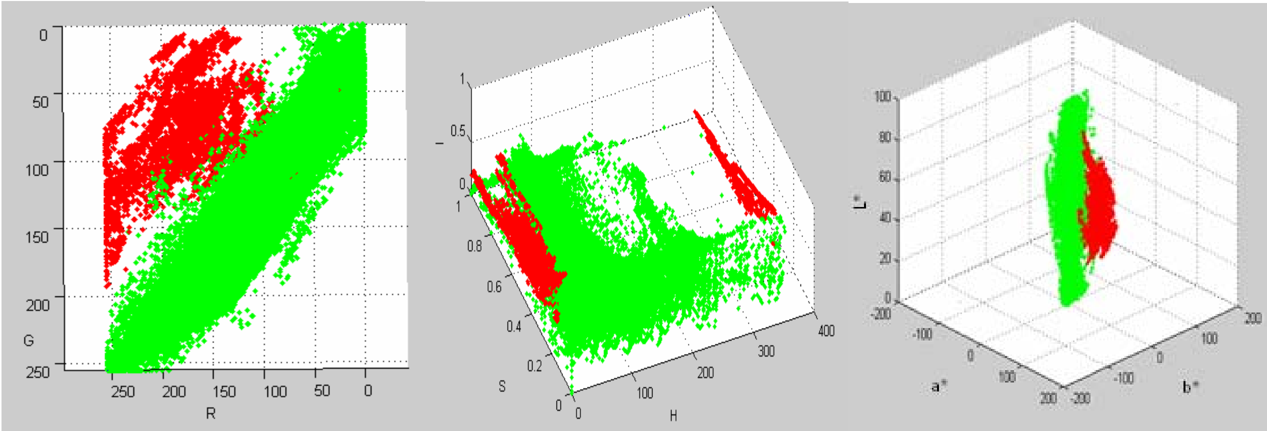


Fig. 6. Apple and background areas in the RGB, HSI and CIE L*a*b* color spaces (red: apple region, green: background).

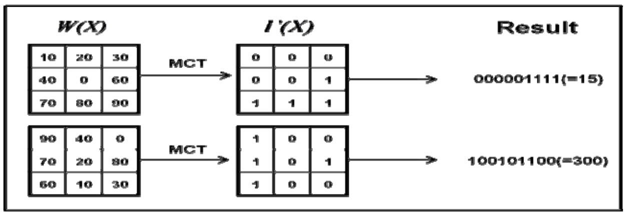
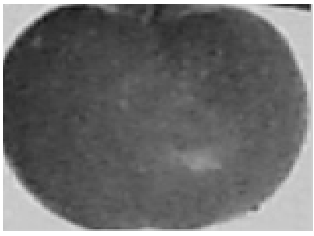
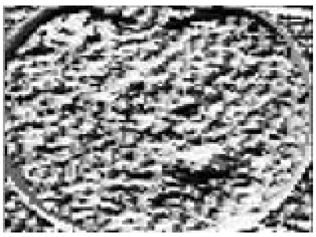


Fig. 7. MCT calculation process.


(a) Experiment image 1


(b) Experiment image 2


(c) MCT conversion image of (a)

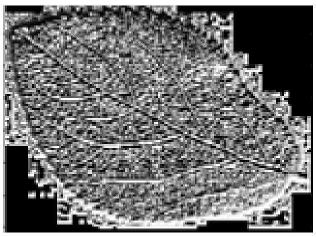

(d) MCT conversion image of (b)

Fig. 8. MCT of two images with different objects.

apple within the 3σ range as faulty and eliminated it from the detection area.

4. Performance Evaluation

Apple detection was verified with about 30 apple images under environments with various apple sizes, colors and light sources.

A comparison of the proposed apple detection study against the study by Yeon et al. [1] shows that the proposed method recorded a 3.5% higher detection rate and faulty detection was dramatically decreased. Furthermore, we have compared the coefficient of determination values of existing detection systems. The proposed method shows the best results, as shown in Table 2. Fig. 10 shows the output of our apple detection system for color images.

Table 1. Processing time and accuracy of the proposed method.

Image index	Pieces of fruits	Proposed	
		Detection rate (%)	False detection
1	15	86.70	2
2	15	80.00	3
3	16	68.80	5
4	17	70.60	5
5	18	77.80	4
6	16	68.80	5
7	16	87.50	2
8	15	80.00	3
9	15	86.70	2
10	15	80.00	1
Average (30)	**502**	**80.68**	**18**

Module name	Image size	Processing timing	Cumulative timing
Image resize	864 x 648	·	·
Apple tree recognition	384 x 288	0.370 sec	0.370 sec
Apple detection	384 x 288	0.440 sec	0.810 sec

Table 2. Comparison of detection performance.

Algorithm	Proposed method	Yeon et al. [1]	Linker et al. [3]	Chinhhuluun and Lee [6]	Aggelopoulou et al. [8]
Coefficient of determination (R^2 value)	0.8402	0.7621	0.8006	0.8300	0.7225

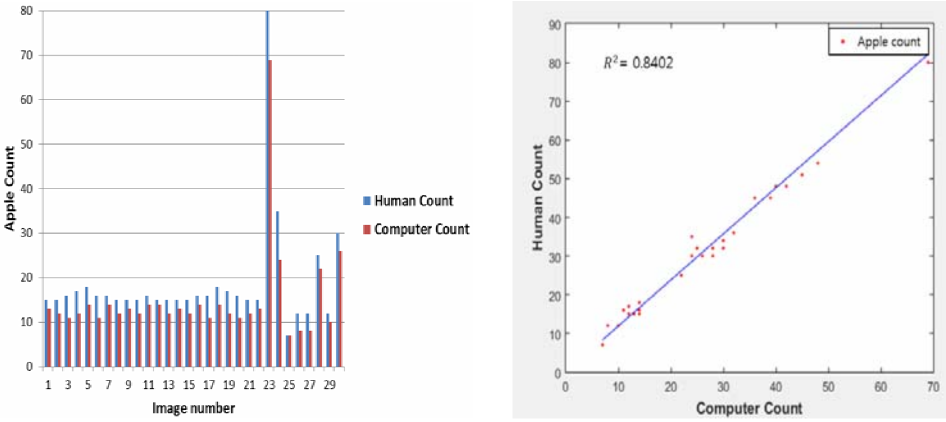


Fig. 9. Comparison between ground truth and the proposed method.

Fig. 10. Results of apple area detection.

5. Conclusion

The analysis of existing apple detection methods shows that a lot of the faulty detection was due to the color, the light source, and shades being similar to the apple.

This paper recognizes the apple tree first and extracts proper colors for the apple area through various color space analyses as a pre-process to solving various problems in apple detection. In addition, the study applied MCT to minimize problems in reflection and shade, and conducts an AdaBoost machine learning process on the applied features to learn the shape information (pattern) corresponding to the apple. The study developed an apple detection algorithm that dramatically decreases faulty detection and improves the detection rate, compared to existing studies, and verified that it operates in real time.

Acknowledgement

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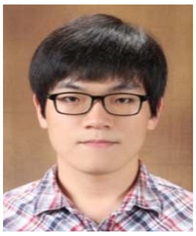

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