바이오시스템공학 (*J. of Biosystems Eng.*)
Vol. 32, No. 4, pp. 256~262 (2007)

기계시각을 이용한 상추의 엽색 및 건강상태 판정

이종환

Determination of Leaf Color and Health State of Lettuce using Machine Vision

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Abstract

Image processing systems have been used to measure the plant parameters such as size, shape and structure of plants. There are yet some limited applications for evaluating plant colors due to illumination conditions. This study was focused to present adaptive methods to analyze plant leaf color regardless of illumination conditions. Color patches attached on the calibration bars were selected to represent leaf colors of lettuces and to test a possibility of health monitoring of lettuces. Repeatability of assigning leaf colors to color patches was investigated by two-tailed t-test for paired comparison. It resulted that there were no differences of assignment histogram between two images of one lettuce that were acquired at different light conditions. It supported that use of the calibration bars proposed for leaf color analysis provided color constancy, which was one of the most important issues in a video color analysis. A health discrimination equation was developed to classify lettuces into one of two classes, SOUND group and POOR group, using the machine vision. The classification accuracy of the developed health discrimination equation was 80.8%, compared to farmers' decision. This study could provide a feasible method to develop a standard color chart for evaluating leaf colors of plants and plant health monitoring system using the machine vision.

Keywords : Machine vision, Leaf color, Health state analysis, Color calibration, Lettuce

1. INTRODUCTION

Color and shape of plant are the main parameters used as indicator of plant health. Practically, farmers have judged nutrient stresses and water stress from changes of color and structure of plants. Machine vision and image processing system is very useful to detect changes of color and shape of plants. Nevertheless, powerful and adaptive monitoring systems of plant health using machine vision are not presented yet.

Several researchers attempted to apply image processing to studies of plant shape and structures (Meyer & Davison, 1987; Hatou et al., 1995; Lee et al., 1996; Singh et al., 1996a; Kim & Ryu, 1998). Meyer and Davison discussed the use of image processing for measuring plant growth such as leaf area, stem diameter and leaf and petiole angles. They also discussed lighting problems when trying to measure canopy areas. In generally, assessment of plant growth states has been carried out using color camera (Singh et al., 1996b), light interference filters (Franz et al., 1991; Shimizu & Yamazaki, 1996; Adamsen et al., 1999) and tunable filter (Thai et al., 1998). Adamsen et al. measured wheat senescence with a digital camera, a hand-held radiometer, and a SPAD chlorophyll meter. The green to red, G/R for each pixel in an image from a digital camera was responded well to both chlorophyll content in the leaves as well as the

The article was submitted for publication in June 2007, reviewed and approved for publication by the editorial board of KSAM in August 2007.
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number of leaves present.

In a while, Hetzroni and Miles (1992) applied the color image processing techniques to assess disorders in plants. They discussed the overview of a health assessment system and specific details on classification using artificial neural networks. In Korea, there were some researches for estimating fresh/dry weights of lettuces by projected area of plant canopy (Lee et al., 1996; Kim & Ryu, 1998). There are few papers related to color analysis for obtaining indices of plant health and quantitative estimation of plant diseases. The reason may be mainly due to difficulties of color constancy when an image processing system is operated under various light sources or illuminations. Color constancy has two features such as spectral normalization and spatial decomposition. Spectral normalization refers to the ability to correct for temporal changes in the spectral content of the scene. Spatial decomposition, on the other hand, refers to the ability to ignore changes in the illuminant across the scene.

This study was conducted as the primary research to assess the growth state and health of plants in greenhouse by machine vision. Particularly, it was focused to present method for analyzing plant color regardless of illumination conditions. This study suggested the calibration bar with color patches and discussed its feasibility in assessing the plant health.

2. MATERIALS AND METHODS

A. Plant samples

The test samples were lettuces growing in greenhouse. Lettuces were transplanted with distances between each plants by 20 cm × 20 cm. Days after seedling (DAS) of plant samples for this research were 7, 10, 13, 17, 19 and 22 day. At each DAS, images for 6~12 plants were captured and stored with TIFF image format in the host computer.

The experienced farmer had selected 26 plants among 78 lettuces and classified them into two groups according to health state based on leaf color, plant shape and canopy, etc. Lettuces in 1st group (SOUND group) looked healthy rather than ones in 2nd group (POOR group).

Table 1 Specifications of machine vision system for plant growth monitoring

Item		Specifications
Input device	RGB camera	XC-711 (Sony, Japan), Wide-angle lens: 6.4mm, Operating modes: Automatic Iris, Automatic Gain Control and No White Balance
Image processor	Frame grabber	FlashPoint (Integral Technologies Inc., USA)
	Image signal	RGB, S-VHS, NTSC, RS-170
Host computer	Computer	Pentium III-600MHz, RAM 128M
	Image storage	1.3GB MO Disc interfacing with IEEE-1394 card

B. Machine vision system

The machine vision system for monitoring health of plant consisted of RGB color camera with a wide-angle lens, frame grabber, image signal multiplex, magnet-optical disk storage and host computer, as shown in Table 1. A wide-angle lens should be used because space in the greenhouse between camera and plants was within 1 m.

C. Calibration procedure

Although plant growth states are not different, each images of the same plant tends to have very different color characteristics if images are taken at different time. Also, images captured at the different distance and angle between camera and object have different image formations. Hence, the plant health monitoring system using machine vision needs to calibrate pixel intensity and geometric distance between pixels.

The calibration bars, which consisted of the standard reference bar and the complementary reference bar, were presented as shown in Fig. 1. The standard reference bar had 50 color patches that were selected by visual inspection

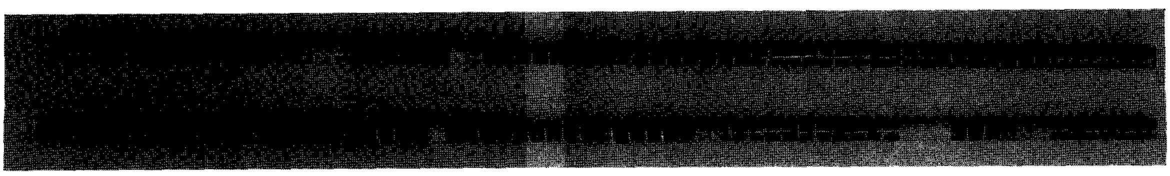


Fig. 1 The calibration bars used in this study (Upper: the complementary reference bar, Lower: the standard reference bar).

to represent leaf colors of lettuces and whose numbers ranged 1 to 50. The complementary reference bar had 50 color patches that made L, a and b values distribute as broadly as possible and whose numbers ranged 51 to 100. Color patches made by the color guide of Dainippon Ink and Chemicals, Inc., Japan.

The calibration bars had set parallel to plant rows and above plants by 25 cm. Distance between a couple of calibration bars was 40 cm. Images of the calibration bars were captured with every set of plant sample images.

After finding both end sides of each calibration bars interactively, edges of every color patches were extracted each by each using a profile of longitudinal line through both end sides. The longitudinal profile had the strong derivatives just at the lateral boundary between neighbored color patches. Center of each color patches located at middle positions of two neighbored lateral edges. Then, horizontal and vertical lengths per pixel were calculated by using real values of distance and mean values of tangential distances between lateral edges in image. Representative color values of each color patches were determined by calculating mean values of R, G and B in middle regions of each color patches and saved into database.

D. Classification of plant color values into color patches

Assignment procedure of color values of plants to color patches of the calibration bars was as follows. Because B frame among R, G and B channels was best for segmenting plant pixels from background pixels, plant image was segmented using histogram of B frame. Then, lettuce areas were defined using already known positions of each plant and the calibration bars. All pixel values in plant area were read and saved to the data file.

By method of the maximum likelihood classification, every pixel values were classified into one color patch among one hundred color patches. It meant that a very large data set of real color values was no more necessary and only a small data set of the assignment histogram was enough to process plant color analysis.

If the grouping distance by the maximum likelihood classification exceeded the critical value defined in this study, plant color values became to be assigned as the 101^{st} color patches. But such a case was very rare.

E. Health evaluation of lettuce by histogram of leaf colors on color patches

In general, the farmer evaluates a health of plant by leaf color, plant shape, nutrient state, disease symptom and growth rate, etc. As Fig. 2 shows, the experienced farmer selected twenty-six plants that could be classified with confidence as one of SOUND group or POOR group according to the appearance of plant. Samples of SOUND group and POOR group were 13 plants, respectively. It was investigated the possibility of the machine vision system in evaluating health of lettuces by assignment of plant color values to the color patches of the calibration bars.

Images for twenty-six plants (13 plants $\times$ 2 groups) were taken twice under white sunlight. Acquisition interval between two captures of the plant was 10~30 minutes to get temporal change of illumination.

This study developed the health discrimination equation of lettuce by SAS package software with fifty-two images that were two images of each twenty-six plants. Images at

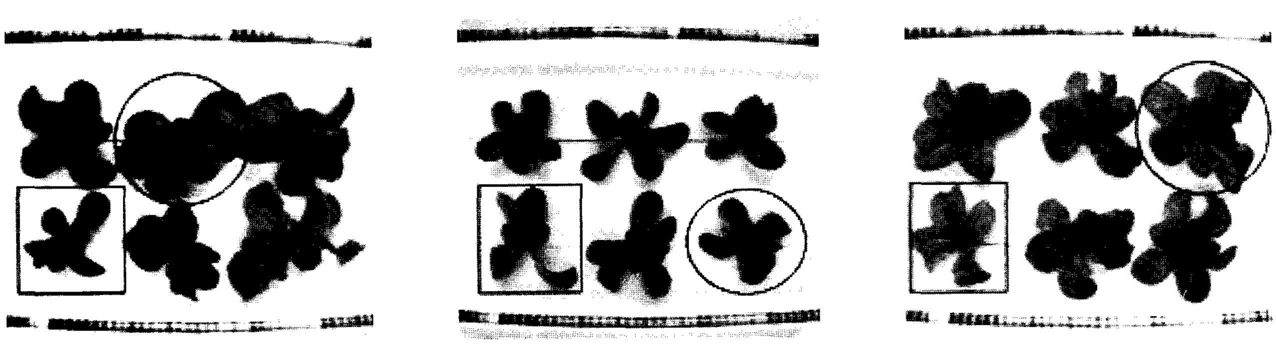


Fig. 2 Example images of lettuces classified into one of SOUND class (in circle) and POOR class (in rectangle).

the first capture were used for developing the health discrimination equation. Images at the second capture, on the other hand, were used for evaluating the developed equation.

3. RESULTS AND DISCUSSION

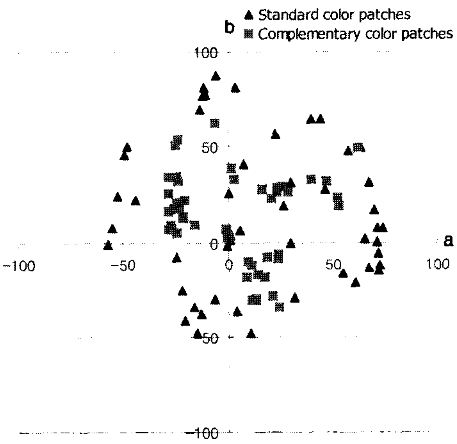
A. Lab Characteristics of the Calibration Bars

L, a and *b* values of the color patches on two reference bars were measured using the colorimeter (CR-100, Minolta, Japan). Fig. 3 shows the distributions of *L*, a and *b* values for the standard color patches (Patches' number: 1~50) and the complementary color patches (Patches' number: 51~100). It implies that the complementary color bar contributes to make *L*, a and *b* values distributed broadly.

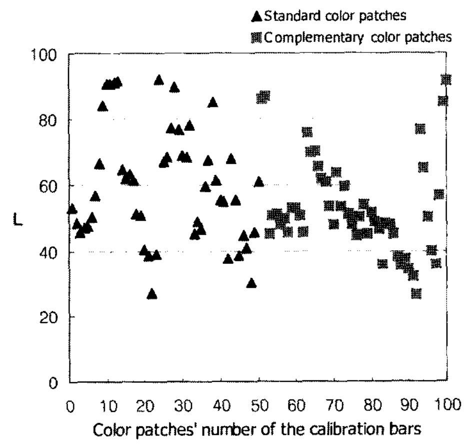
B. Constancy of color analysis by using the calibration bars

Color constancy problem is one of the most important issues on color analysis using machine vision. This study proposed the calibration bars used to analyze plant colors by the machine vision system regardless of variation of illumination.

Paired comparison t-test using MS-Excel was conducted to investigate the difference between assignment histogram of color patches of two images of the same plants that captured at different light conditions. Table 2 shows the result of the paired comparison t-test at 5% probability level for repeatability of lettuce color analysis using the calibration bars. There were no significant differences be-



(a) *a* and *b* values



(b) *L* values

Fig. 3 Distribution of *L*, a and *b* values for the calibration bars proposed in this study.

Table 2 Results of the paired comparison t-test for repeatability of lettuce color analysis using the calibration bars

Name of samples	t-values for samples	P (T<=t) in two-tailed	Name of samples	t-values for samples	P (T<=t) in two-tailed
Plant 1	-0.0396	0.9687	Plant 14	-0.0015	0.9989
Plant 2	0.0000	1.0000	Plant 15	-0.0522	0.9587
Plant 3	0.0000	1.0000	Plant 16	0.0000	1.0000
Plant 4	0.0000	1.0000	Plant 17	0.0000	1.0000
Plant 5	0.0000	1.0000	Plant 18	0.0000	1.0000
Plant 6	0.0000	1.0000	Plant 19	0.0000	1.0000
Plant 7	0.0000	1.0000	Plant 20	0.0000	1.0000
Plant 8	0.0000	1.0000	Plant 21	0.0000	1.0000
Plant 9	0.0013	0.9990	Plant 22	-0.0020	0.9984
Plant 10	0.0040	0.9968	Plant 23	0.0000	1.0000
Plant 11	0.0000	1.0000	Plant 24	0.0000	1.0000
Plant 12	-0.5704	0.5731	Plant 25	-0.5695	0.5737
Plant 13	0.0000	1.0000	Plant 26	-0.5695	0.5737

Degree of freedom is 27 for each samples and t-values for H_a is 2.0518 tween the assignment histogram of one hundred color patches of the pair images of 23 plants among 26 plants except Plant 12, Plant 25 and Plant 26 that seemed to have excessive difference in light conditions. This good repeatability implied that the use of the calibration bars proposed in this study for leaf color analysis provided the color constancy, which is one of the most important issues in a video color analysis. It supported that the machine vision system with the calibration bars could be used for analyzing colors of lettuces in a greenhouse.

Table 4 Results for classification of the health into two groups according to leaf color of lettuces

		By the machine vision	
		SOUND class	POOR class
By farmer	SOUND class	10 plants	3 plants
	POOR class	2 plants	11 plants
Classification accuracy: 21/26 = 80.8%			

C. Health evaluation by color distribution of lettuce images

When every pixel of images for 26 plants was assigned to number of one patch among one hundred color patches in the calibration bars, seventy-two color patches were never assigned in this experiment. Fig. 4 shows the assignment histogram of color patches for examples of a SOUND class plant and a POOR class plant. In Fig. 4, labels of x-axis represent numbers of the assigned color patches, respectively.

This study used the assignment histogram of 28 color patches for developing the health discrimination equation by

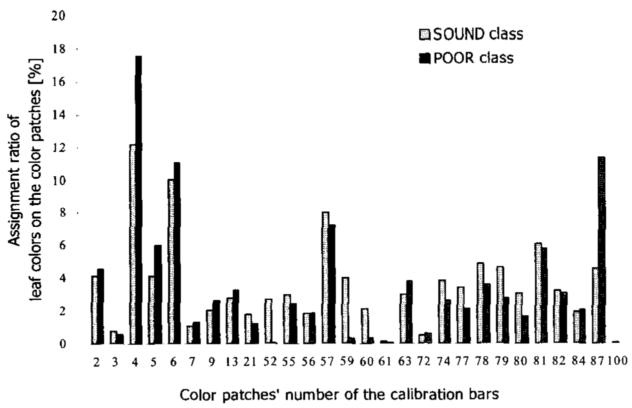


Fig. 4 Example of assignment histogram for each color patches on the calibration bars.

SAS software because twenty-eight ones among 100 color patches were selected as plant colors once or more times while 72 color patches were never assigned in the assignment histogram.

By PROC STEPDISC (Backward) of SAS, sixteen color patches among 28 color patches were selected as the independent variables of the health discrimination equation at the significant level of p = 0.15. It was obvious that using the calibration bars could provide a feasible method for color reduction in plant color analysis using a machine vision system.

Color values (L, a and b) of the selected color patches were not always related to only optical properties of lettuce plants, because the color patches were not based on spectroscopic characteristics of plants but selected by visual inspection. Background and shades on plant images could also exert influence on selection of color patches for the machine vision system.

Among the selected sixteen color patches, 6 patches were from the standard reference bar that consisted of color patches selected by visual inspection to represent leaf color of lettuces while 10 color patches were from the complementary reference bar. It implied that using only visual inspection is not desirable for developing the standard color chart for evaluating leaf colors of plants.

After selecting sixteen variables, PROC DISCRIM of SAS was applied to obtain coefficients of the discrimination equation. Coefficient values (A_n) in Table 3 obtained from 26 plant images at the first capture.

Twenty-six plant images taken at the second capture were used for evaluating the developed health discrimination equation. The results of the classification are summarized in Table 4. The machine vision system of this study could classify the health state of lettuces with accuracy of 80.8%, 21 plants among 26 plants, based on the classification by the experienced farmer. Considering that the farmer might not decide the plant health state by various factors besides plant color properties, this result was satisfactory to analyze the plant health state by using the machine vision system and the calibration bars.

Table 3 Discrimination equations developed by PROC DISCRIM of SAS for classifying lettuces into one of SOUND class or POOR class

Discrimination equation: $Y = \Sigma A_n X_n + A_0$		
X_n*	A_n for SOUND class	A_n for POOR class
X_3	0.60814	0.52913
X_5	0.39841	0.34813
X_7	0.72489	0.62939
X_9	0.3555	0.30536
X_{13}	1.25337	1.05624
X_{21}	0.02131	0.14567
X_{52}	-1.83167	-1.03420
X_{55}	4.3675	3.76029
X_{56}	0.52187	0.32088
X_{59}	6.15758	5.35600
X_{77}	4.59953	3.88604
X_{78}	-6.61485	-5.98236
X_{80}	0.69985	0.94728
X_{81}	0.94693	0.54060
X_{82}	-0.40029	-0.78997
X_{84}	1.61805	1.31773
A_0	-22.47554	-16.66667

*Subscript, n means color patches' number of the calibration bars.

4. CONCLUSIONS

Using image processing and machine vision has been useful to analyze the response of plants to changes in environment and nutrient factors, and to measure plant parameters such as size, shape and structure of plants, etc. But there are yet some limits on plant color analysis because illumination conditions might be changeable and color values of plant images are diverse. In assessing the growth pattern of plants and measuring the changes of plant color, the most important issues are calibration procedure for a color sensor and the color constancy problem of a machine vision system. Hence, this study focused on the adaptive methods to analyze plant colors regardless of illumination conditions.

A couple of the calibration bars were provided to test the possibility of health monitoring of lettuces based on leaf color by using a machine vision. One hundred of the color patches were selected and attached on the calibration bars to represent leaf colors of lettuces, and to make L, a and b values distributed as broadly as possible.

Two-tailed t-test for the paired comparison was conducted to investigate the repeatability in assigning leaf colors of lettuce samples to color patches of the calibration bars. It resulted that there were no significant differences statistically between two images of the same plant captured at different light conditions. It means that the machine vision system with the calibration bars was adaptive to assess colors of lettuces even under changeable illumination conditions.

In order to classify lettuces using the machine vision into one of two classes, SOUND group and POOR group, the health discrimination equation was developed and verified using SAS software. Sixteen color patches were selected for the health discrimination equation. It was obvious that using the calibration bars could provide a feasible method for color reduction in plant color analysis. The classification accuracy of the developed equation was 80.8%, compared to the farmer's decision. It was concluded that the machine vision system with the calibration bars provides a promising method for analyzing the leaf color and determining the health state of lettuces.

It was expected that this research made some contributions toward developing the standard color chart of plants and the machine vision monitoring system of plant growth in greenhouse.

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