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Location Recognition and Quality Evaluation of Bundle of Dried Tobacco Leaves Via Color Computer Vision

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Abstract

Locations of tobacco leaves are critical to quality grading. In Korea, the state of the leaf locations is divided into four categories such as high, middle, low and inside ones. Grades of tobacco leaves are mainly classified into 5 grades manually according to the attached locations, visual appearances including color and texture. Leaves taken from high and low locations receive a low grade, under grade 3. Generally, leaves from the inside and medium locations get a high grade. In this paper, recognition of leaf location and grading using the color machine vision was performed aiming to develop a real time tobacco leave grading system combined with a portable NIR spectrum analysis system. The RGB color information was converted into HSI image format and all the samples were investigated using the bundle of tobacco leaves. A well-known general error back propagation neural network was utilized for the quality grading and location recognition.

Key words: automatic recognition, leaf location, BP neural network, quality evaluation, color computer vision

Introduction

Quality evaluation of tobacco has been done mainly based on chemical composition as an off-line basis. Quality measurement based on chemical compositions such as moisture content, nicotine, nitrogen, and so on requires cautious sample preparation and several complex and time consuming process. Because of the lack of real time processing in quality grading, grading of tobacco leaves, the grading has been done manually via visual inspection as a sample basis by human experts. Moreover, a bundle of tobacco leaves is randomly selected from a box and graded manually. In order to automate the human grading process while realizing real-time performance, nondestructive automatic measurement methods such as computer vision and NIR are known to be good approaches.

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Cho (1994a) investigated feasible wavelengths in the range of NIR for a concise quality grading. Sets of efficient wavelengths were recommended to evaluate a certain chemical composition. However, it still required a cautious preparation of sample tobacco leaves. Cho (1994b) tried to evaluate tobacco leaf grades using a computer vision and neural network. Texture descriptor and RGB color information were utilized as network input variables. However, grading test was performed with an individual leaf and leaf should have been prepared good enough for the proper data acquisition. A portable color measurement device using RGB photodiode (color sensor) was developed and grading performance was tested by inputting output sensor signals to a back propagation neural network (Lee *et al.*, 1995).

Main goal of this research was to develop a real time robust tobacco grading system via sensory fusion of computer vision and NIR spectrum. In grading tobacco leaves, size and location of tobacco leaves should be recognized first via computer vision, and then the information obtained from spectrum analysis and color computer vision was used for final grading. This paper was focused on measurement and evaluation of the location recognition and preliminary grading experiment of tobacco leaves using a color computer vision.

Materials and Methods

Materials

Sample tobacco leaves were collected from the Chungbuk province of Korea. In Korea, categories of tobacco leaf grades are divided into 5. As shown in Table 1, primarily 4 different leaf locations are major factor for grading. Leaf positions in grading are divided into 4 categories such as U(upper), I(inside), M(mid), and L (lower). In general, leaves located at the upper and lower part of plant have mid and low quality levels of G3, G4, G5 and leaves located at the inside and middle of plant have good and mid quality levels of G1, G2, and G3.

Here, Gi represents grade category and as value i increases, quality of leaves degrades. In this paper, quality evaluation of tobacco leaves was performed as a bundle basis considering practical application using color computer vision system. Frame grabber (Bandit, Coreco Co., Canada) and color CCD camera (TM-7, Pulnix Co.) were used to capture the image. Chamber was built to block the ambient light and high frequency 3-wavelength fluorescent lamp was used. All measurements were done with a bundle of tobacco leaves.

Table 1. Tobacco leaf grade according to leaf locations of the plant

Index		Tobacco Grade				
		G1	G2	G3	G4	G5
Leaf Location	Upper			◆	◆	◆
	Inner	◆	◆	◆		
	Mid	◆	◆	◆		
	Lower			◆	◆	◆

Recognition of Leaf Position

The size of a unit pixel and average intensity value of an image captured from a white paper were measured for compensation, shape property and size were computed using real variable chain coding algorithm (Lee, 1995). C_x and C_y, Coordinates of the centroid of leaf image were computed using following formula.

$$C_x = \frac{1}{n}\sum_{i=0}^{n-1} x_i, \quad C_y = \frac{1}{n}\sum_{i=0}^{n-1} y_i$$

Acquired image format was 24 bit true RGB color information. RGB Color information was converted to hue (H), saturation (S) and intensity (Y) to imitate humans color recognition using following formula.

$$Y=0.3R+0.59G+0.11B$$

$$C_1=R-Y=0.7R-0.59G-0.11B$$

$$C_2=B-Y=-0.3R-0.59G+0.89B$$

$$H=\tan^{-1}(C_1/C_2),\ S=(C_1^2+C_2^2)^{0.5}$$

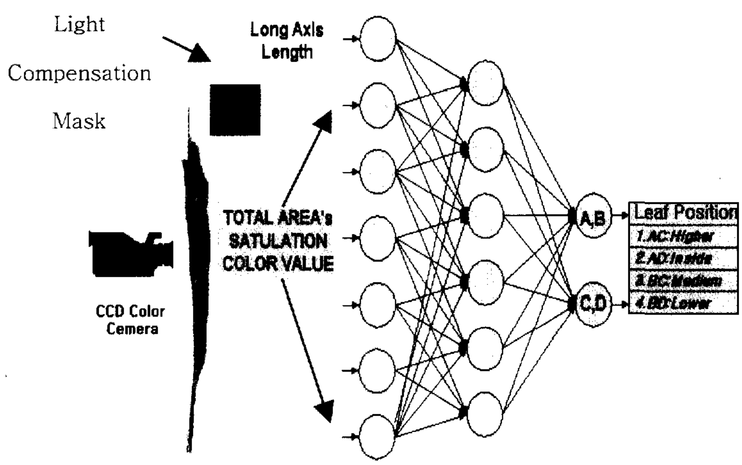

Fig. 1 Structure of the network for leaf position recognition.

Threshold was done with boundary Y value obtained from the window extension method (Lee, 1995). In training, geometric and color information of a bundle of leaves was input to the network. Color information was converted to hue, saturation and intensity values prior to input to the network. Variation of illumination was investigated by averaging 10 measured intensity values. It showed that maximum error was not over the range ±2.4%. And while capturing each image of samples, the intensity of the previously specified small reference mask (7×7) was measured for compensation with an assumption of linearity over the image according to the input light variation.

Recognition of leaf location was done with back propagation (BP) neural network and clustering was done based on the Euclidean distance metric between patterns and cluster centers. BP network requires desirable target values (supervisory learning) but clustering self organization method doesnt need it. The maximum number of cluster could be created as many as number of input patterns. Input pattern and learned weights are stored in memory. For the recognition of leaf location, input data was prepared as 4 categories according to the harvested leaf location.

Quality Evaluation

Quality evaluation procedure was also done with BP network and a clustering method. All pairs of training data were selected according to their grades instead of leaf locations. The category of grade 3(G3) contains all locations of leaves. Target grades were determined from the human grading expert. In the case of BP network training, raw information of image was used as input data such as average color values of specified small square area. However, feature information such as texture descriptors, size, color and shape criteria was extracted for clustering method.

Texture descriptors were adopted to analyze the relationship between grade and texture state. These values were only used for clustering method and were not adopted into the BP network model. In the case of BP network model, raw image information was directly used to the network input similar to the process of the previous leaf location recognition. Masks used for texture analysis were shown in Fig. 2 and information according to each mask was obtained to select the best result. Texture descriptor was defined as shown in Table 2 and detailed algorithm should refer to the reference (Haralick, 1979). Here, MP means maximum color distribution state over the surface and EDM has a characteristics such that total values decrease in proportion to the increase of each element and Inverse EDM has an opposite result. If the difference for the element of C matrix is small, entropy will be large and uniformity value reveals with opposite result. The basic "A" matrix consist of (0,0), (0,1), (1,0), and (1,0). Covariance matrix C was calculated from "A" matrix divided by the total scanning number of interest regions.

(a) mask 1	(b) mask 2	(c) mask 3	(d) mask 4
ⓟ → ⓔ	ⓟ → ⓔ	ⓟ	ⓟ → ⓔ
↓		↓	↓ ↘
ⓖ		ⓖ	ⓖ ⓗ

Fig. 2 Mask descriptor for texture analysis.

Table. 2 Definition of various texture descriptor (Haralick, 1979)

Descriptor	Definition
Maximum probability(MP)	$\mathrm{Max}\,(C_{ij})$
Kth order element difference moment(EDM)	$\sum_i \sum_j (i-j)^k C_{ij}$
Kth order inverse EDM	$\dfrac{\sum_i \sum_j C_{ij}}{(i-j)^k}$
Entropy	$-\sum_i \sum_j C_{ij} \log C_{ij}$
Uniformity	$-\sum_i \sum_j (C_{ij})^2$

Results and Discussion

Color and Texture

Color information of tobacco leaves was measured with RGB values and transformed to HSI(hue, saturation, and intensity) values. HSI values are known to be similar to human vision rather than RGB. According to

Table 3. Correlation coefficient, average length and color on the saturation value

	U3	U4	U5	I1	I2	I3	M1	M2	M3	L3	L4	L5
U3'	1											
U4'	–0.02	1										
U5'	–0.01	0.14	1									
I1'	–0.23	0.29	0.21	1								
I2'	–0.48	0.17	0.46	0.08	1							
I3'	0.13	0.35	–0.06	–0.48	–0.15	1						
M1'	0.01	–0.06	–0.33	–0.40	–0.30	–0.13	1					
M2'	0.00	0.10	0.45	0.38	–0.28	–0.01	–0.09	1				
M3'	–0.27	–0.14	–0.06	–0.44	0.04	0.18	0.10	–0.02	1			
L3'	–0.53	–0.09	–0.01	0.40	0.61	–0.16	–0.69	–0.23	–0.13	1		
L4'	–0.30	0.12	0.41	0.65	0.33	-0.15	–0.59	0.17	0.08	0.50	1	
L5'	0.47	–0.55	0.03	–0.14	–0.46	–0.26	–0.08	–0.01	0.32	–0.32	0.07	1
Length (mm)	430.9	409.6	436.4	528.7	534.8	507.3	488.0	471.1	384.1	345.8	332.0	330.3
Saturation	82.1	94.3	114.5	81.7	97.4	89.5	77.9	82.3	88.1	77.1	66.9	79.2

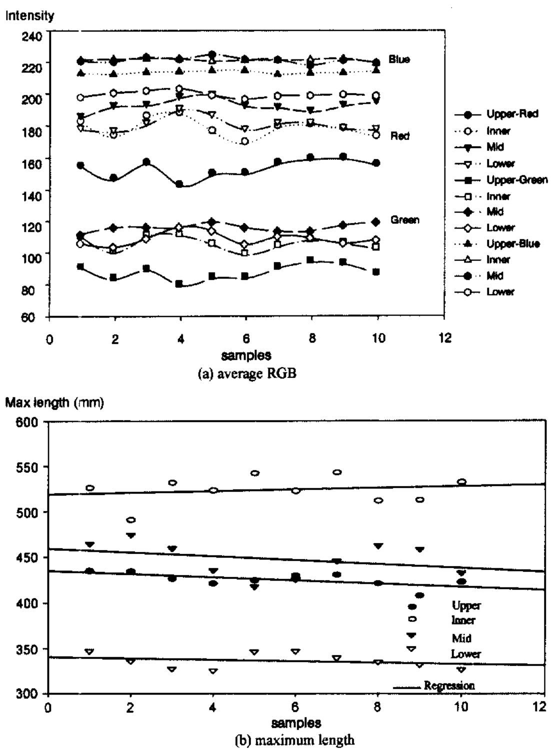

Fig. 3 Average RGB color and maximum length of leaves at various locations.

the leaf location, RGB values had a different intensity range and color of each leaf also revealed same characteristics as shown in Fig. 3 In Fig. 3(a), values of RGB showed different ranges with respect to leaf locations and each average value was different according to leaf locations. From Fig. 3(b) maximum length of leaves are relatively different from various leaf locations.

Table. 4 Correlation coefficient for attached leaves position on the saturation value

	U (Upper)	I (Inner)	M (Mid)	L (Lower)
U(Upper)	1			
I(Inner)	0.26	1		
M(Mid)	–0.02	–0.28	1	
L(Lower)	0.07	0.30	–0.12	1
Length(mm)	425.7	523.6	447.7	336.0
Saturation	97.0	89.5	82.8	72.4

The correlation analysis was performed with saturation value for each location and grade. I2 had some correlation with L3 and L4 and I2 with L3. However, I3 had independent relation. Table 3 shows an average length along the maximum axis and saturation values with correlation coefficient values. From this result, it could be seen that clustering leaves to different grades by color information only is almost impossible. However, average saturation values obtained from various leaf locations without considering leaf grades gave possibility of differentiating location relationship as shown in Table 4.

All texture values from mask operation were obtained. Lengths of tobacco leaves were measured for each grade and average values were computed for the attached locations of leaves. Image processing was done by previously mentioned method and the searching region of texture analysis (Haralick, 1979) was determined by

(a) original (b) binary image (c) detected edge (d) max/min axis length

Fig. 4 Image processing overview for feature and texture analysis.

Table. 5. Texture value from descriptors

Position & Mask		C_{11}	C_{12}	C_{21}	C_{22}	Max C	EDM	Entropy	Uniformity
U(Upper)	Mk1	0.73	0.014	0.018	0.246	0.73	0.033	0.393	0.604
	Mk2	0.662	0.044	0.052	0.241	0.662	0.097	0.313	0.522
	Mk3	0.675	0.036	0.035	0.253	0.675	0.074	0.307	0.538
	Mk4	0.74	0.014	0.017	0.249	0.74	0.031	0.257	0.616
I(Inner)	Mk1	0.65	0.03	0.037	0.283	0.65	0.063	0.451	0.545
	Mk2	0.63	0.074	0.076	0.224	0.63	0.149	0.35	0.511
	Mk3	0.638	0.071	0.067	0.231	0.635	0.138	0.334	0.491
	Mk4	0.713	0.025	0.043	0.219	0.713	0.058	0.265	0.603
M(Mid	Mk1	0.681	0.021	0.019	0.279	0.681	0.041	0.432	0.568
	Mk2	0.62	0.049	0.055	0.277	0.62	0.101	0.335	0.488
	Mk3	0.631	0.044	0.044	0.28	0.631	0.088	0.332	0.498
	Mk4	0.699	0.019	0.018	0.268	0.699	0.037	0.279	0.584
L(Lower)	Mk1	0.827	0.02	0.015	0.137	0.827	0.031	0.278	0.732
	Mk2	0.758	0.054	0.048	0.141	0.758	0.097	0.259	0.629
	Mk3	0.781	0.035	0.034	0.15	0.781	0.068	0.242	0.667
	Mk4	0.857	0.01	0.012	0.12	0.857	0.028	0.186	0.745

Note: Mki represents the ith mask used to obtain the texture descriptor.

central and boundary coordinates as Fig. 4(d). Texture descriptors were computed using formula of Table 2 for each path mask. Values of texture descriptors were denoted in Table 5.

Location Recognition

Samples were collected 50 each per grade for total 12 grades and total number of samples was 600. Experiment for recognizing leaf location was performed first using the BP neural network with 10 samples per grade. Each location had 30 training data set. Input data set was composed of 122 nodes consisting of 121 average values and the length of maximum axis. Each node was determined by previous texture scanning methods and quarter region consisted of 40 sequential average saturation value blocks. Before measuring the saturation value, total pixel number of each quarter region was computed from the previous texture analysis. Therefore, small quarter region was scanned in a manner that 1/4 region divided by number 40.

Initial input condition of BP was set such that learning rate was 0.6, momentum coefficient was 0.4, and number of units for hidden layer and output layer were 10 and 2 respectively as shown in Fig. 1. Total iteration epoch was set to 10,000 and normalized system error was set to be 0.005. Training was not converged to predefined values such as 0.0141, but it showed successful results for the trained sample data set. To verify generalization effect of the BP network, untrained samples were tested with previously trained weight values of network. For each leaf location, 45 untrained samples (15 samples per grade) were used to verify the learning effect. Results of verification were shown in Table 6. Total recognition rate was around 68.3%, and recognition rates for upper, inner, medium and lower cases were 64.4%, 75.6%, 73.3% and 60.0%, respectively.

Table 6. Verification results of 15 samples per each grade

Input	Upper			Inner			Mid			Lower		
Output	U1	U2	U3	I1	I2	I3	M1	M2	M3	L3	L4	L5
Upper	10	11	8	3	2	3	1	1	2	2	1	2
Inner	3	4	5	11	11	12	2	1	4	4	3	5
Mid	–	–	2	–	–	–	12	13	8	–	1	–
Lower	2	–	2	1	2	–	–	–	1	9	10	8

Table 7. Quality evaluation results from the BP network.

Input	Upper			Inner			Mid			Lower		
Output	U3	U4	U5	I1	I2	I3	M1	M2	M3	L3	L4	L5
G1	–(–)	3(2)	–(–)	15(16)	1(2)	1(2)	14(15)	5(3)	–(–)	4(–)	1(–)	1(–)
G2	1(3)	–(1)	4(2)	–(–)	14(16)	–(–)	4(4)	12(14)	4(4)	4(4)	5(1)	–(–)
G3	14(14)	1(2)	1(2)	1(2)	–(–)	14(14)	2(1)	–(3)	15(15)	12(16)	3(4)	4(2)
G4	1(3)	16(15)	3(2)	4(2)	–(1)	4(4)	–(–)	3(–)	1(1)	–(1)	11(14)	–(2)
G5	4(–)	–(–)	12(14)	–(–)	5(1)	1(–)	–(–)	–(–)	–(–)	–(–)	–(–)	15(16)

(#): number of samples which should belong to the grade category, (–): no samples.

Quality Evaluation

Quality evaluation was also performed with BP network and the input data set was same as previous leaf location recognition experiments. Learning rate was set to be 0.8 and momentum coefficient was set to be 0.4. Number of units in hidden layer and output layer were 15 and 3 respectively. Training samples was selected 10 number per each 12 class. Training results showed a successful normalized system error at 0.0197.

Another learning method was adapted using the texture descriptor parameter and maximum length of leaf. The training sets were prepared such as maximum length, max C, C matrix (C_{11}~C_{22}), EDM, entropy and uniformity. It was also trained with learning rate 0.7, momentum coefficient 0.3, 7 hidden layer units and 3 output units. Training results also gave successful results for given input data sets having a 0.094 converged system error. And it was verified with untrained 240 samples.

Verification results of the first methods which used color information of total area showed in Table 7 and its recognition performance was 68.3% for 240 verification samples, and 74.5% for the second input methods which consisted of small number of descriptors. From these results, it could be seen that feature based input and output training revealed better performance.

Conclusions

Leaf location of tobacco plant in harvesting is important to decide its grade. Color computer vision showed a feasibility of the system integration with NIR spectrum analysis by recognizing leaf location and quality. The proposed algorithm was developed via Microsoft visual c++6.0. Performance of leaf location with a bundle of dried tobacco leaves showed as around 68.3% of success rate. In quality evaluation, raw image and feature vectors were used as input variables of BP neural network. Test results with untrained samples showed recognition rates of 68.3% and 74.5%, respectively.

Though results did not show good performance of recognizing leaf location, the proposed scheme showed a feasibility of system integration with another additive sensor such as spectrophotometer for automatic grading. Further research will be done with portable I/O bus type spectrum analyzer and verify the network performance for more sample tobacco leaves.

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