POSITION RECOGNITION AND QUALITY EVALUATION OF TOBACCO LEAVES VIA COLOR COMPUTER VISION

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ABSTRACT

The position of tobacco leaves is affluence to the quality. To evaluate its quality, sample leaves was collected according to the position of attachment. In Korea, the position was divided into four classes such as high, middle, low and inside positioned leaves. Until now, the grade of standard sample was determined by human expert from korea ginseng and tobacco company. Many research were done by the chemical and spectrum analysis using NIR and computer vision. The grade of tobacco leaves mainly classified into 5 grades according to the attached position and its chemical composition. In high and low positioned leaves shows a low level grade under grade 3. Generally, inside and medium positioned leaf has a high level grade.

This is the basic research to develop a real time tobacco leaves grading system combined with portable NIR spectrum analysis system. However, this research just deals with position recognition and grading using the color machine vision. The RGB color information was converted to HSI image format and the sample was all investigated using the bundle of tobacco leaves. Quality grade and position recognition was performed through well known general error back propagation neural network. Finally, the relationship about attached leaf position and its grade was analyzed.

Keyword : Automatic Pattern Recognition, Position Recognition, Back Propagation

INTRODUCTION

Until now, the chemical composition based quality evaluation method of tobacco is known for major factors, and also chemical analysis of tobacco compound was investigated through worldwide researcher. However, the measurement method for basic composition such as moisture content, nicotine, nitrogen and leaves color always requires several complex processing. In order to improve the above process and realize the real-time analysis, it is necessarily needs to establish automatic measurement techniques that is a nondestructive manner such as computer vision and NIR. In domestic cases, some researcher was performed through the nondestructive measurement manner(Cho,"1994") that was investigated on the capability for adaptation of NIR analysis system by the nondestructive technique, and it was reported as rapid computation rate and capability as a portable measurement device. Another research was performed on the recognition simulation of tobacco grade using computer vision and neural network ,and the network training was tested using texture descriptor and RGB color information(Cho,"1994"). Portable color measurement device using RGB photo-diode(color sensor) was developed and decide the grade from the output sensor signal by the back propagation neural network(Lee,"1995").

The main goal of this research was focused on the sensor fusion technique contains of computer vision and portable I/O type spectrometer. In order to do it, the size and position recognition of leaves must evaluate via machine vision, and then combination of both measuring system will be developed. This paper just performed about the measurement and evaluation of the position recognition and preliminary experiment for tobacco leaves grading using the color computer vision.

MATERIALS AND METHODS

Materials

The sample tobacco leaves was collected from the Chungbuk province of Korea. In Korea, the grade of tobacco was divided into 5 classes and each grades decided according to the attached 4 leaf positions as shown in Table 1. Attached tobacco leaves were divided into upper, inside, medium, and lower positioned tobacco leaves. In general, upper and lower poisoned leaf have a bad quality level for G3,G4,G5, and the inside and medium position has a good quality level for G1,G2,G3. Korea Tobacco and Ginseng Corporation(KTGC) purchased all harvested tobacco leaves, and grade was determined by KTGC. Therefore, the standard classification rule is important for farmer. In this paper, prototype system of tobacco quality evaluation was developed based on the color computer vision system. The frame grabber was used Bandit(Coreco Co, Canada)model, and camera was used Pulnix Co. TM-7 color CCD. Chamber for outside light interception and higher frequency illuminator was adapted. All measurement method was performed with a bunch of tobaccos leaves to avoid of sampling error.

Table1. Tobacco leaves grade according its attached position

Index		Tobacco Grade				
		G1	G2	G3	G4	G5
Attached Leaf Position	Higher			◆	◆	◆
	Inside	◆	◆	◆		
	Medium	◆	◆	◆		
	Lower			◆	◆	◆

Leaves Position Recognition

The unit pixel size and standard average intensity values were measured for compensation, the shape property and size were calculated through the regional property and real variable chain coding algorithm (Lee,"1995"). Area is the sum of binary pixel number represent for object after threshold procedure. The major feature from the binary tobacco image was measured by chain coding. The centroid coordinate C_x, C_y was represented as below formula.

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

Acquired image format is 24bit true RGB color information. RGB Color information was all converted to hue (H), saturation (S) and intensity (Y) because of the approximation for human vision.

$$Y=0.3R+0.59G+0.11G$$
$$C_1=R-Y=0.7R-0.59G-0.11B$$
$$C_2=B-Y=-0.3R-0.59G+0.89B$$
$$Hue=\tan^{-1}(C_1/C_2), \quad Saturation=(C_1^2+C_2^2)^{0.5}$$

C_1 is a R-Y and C_2 is B-Y differential values. Threshold procedure was calculated from the Y value through window extension method (Lee,"1995"). In the training, geometrical and color information was assigned into the network. Each input element units of color information was already converted to hue, saturation and intensity values. The variation of illumination was investigated with 10times average intensity values. This result shows that maximum error is not over the range ±2.4%. From the result, one assumption was necessary that all variation of input light has linear characteristics. And, intensity measurement for compensation was performed to all samples using the one small reference mask (7×7).

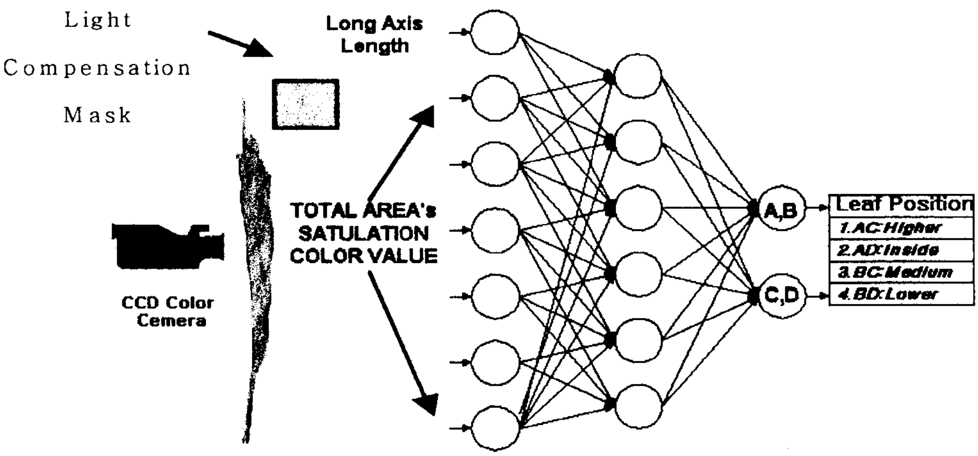


Fig. 1 Structure of the network for leaf position recognition

The attached leaves position recognition was performed with back propagation(BP) and clustering uses the euclidean distance metric for determining distance between patterns and cluster centers. The main difference of this network is whether it has a target value or not. BP must assign the desirable target value(supervisory learning),but clustering self organization method don't necessary of 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 leaf position recognition, all input data was prepared as 4 categories according to the harvested leaf position.

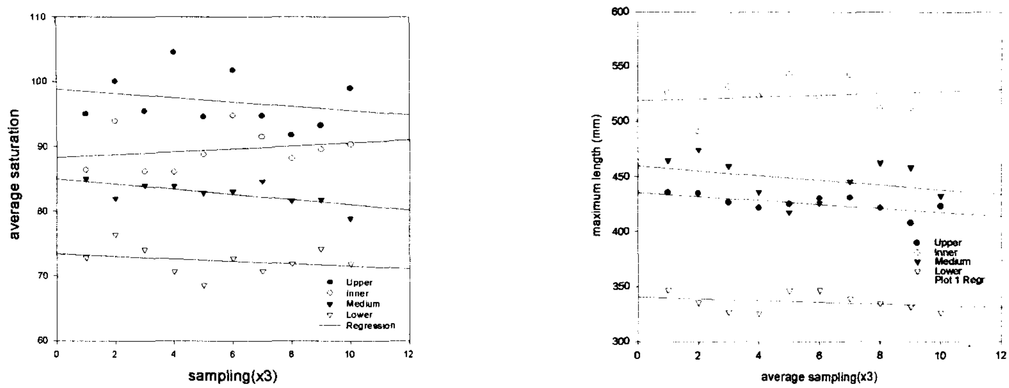
Quality Evaluation

Quality evaluation procedure was also performed with back propagation (BP) and clustering method. During the preparation, all training data pairs were selected by its grade not in a leaves position. In the case of grade 3 was contained of all 4 leaves positions. The grade of this simulation was determined from the expert of tobacco research . In the case of BP training, the input data was used raw image information such as averaging color values of structured small square area. However, it was used extracted feature information such as texture descriptor, size, color and shape criteria for clustering method.

The texture parameter was adapted to analysis of relationship between grade and texture state. This value only used to recognize clustering method and do not adapted into the BP model. In case of BP model, raw image information was directly used to the network input as same as previous leaves position recognition. This texture analysis mask as shown in Fig. 2 and each mask information was all measured for selection of the best results. The texture descriptor was defined as follow and detailed algorithm should refer to reference (Haralick,"1979"). In here, MP means maximum color distribution state over the surface, EDM has a characteristics such that total values decrease in proportion to each element is increase and Inverse EDM has a opposite results. If the difference for the element of C matrix is small, entropy will be a large values and uniformity value reveals with opposite results. The basic "A" matrix consist of (0,0),(0,1),(1,0) and (1,0). Covariance matrix C was calculated from that "A" matrix divides by the total scanning number of interest regions.

Table. 2 Texture descriptor parameter definition(Haralick,"1979")

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



(c) Average saturation for leaves position (d) Average of max. length for leaves position

Fig. 3 Average RGB color, saturation and maximum length for leaves position

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

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

	Upper	Inner	Medium	Lower
Upper	1			
Inner	0.26	1		
Medium	-0.02	-0.28	1	
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

And also, texture value from mask operation was all measured for each tobacco leaves. The length of tobacco leaves were all measured for each grade and calculated its average value for attached position of leaves. Image processing was done by previous mentioned methods and the searching region of texture analysis (Haralick,"1979") was determined by central and boundary coordinates as Fig. 4-(d). The scanning region was divided into 4 areas based on this information and were calculated for each quarter regions using the descriptors using formula of table 2. The result from descriptor was denoted in table 5 and figure 5.

(a)original (b) binary (c)Edge detection (d)max/min axis length

Fig. 4 Image processing overview for feature and texture analysis

Table. 5. Texture value from the descriptors.

Position &	Mask	C11	C12	C21	C22	Max C	EDM	Entr	Unif.
Upper	M1	0.73	0.014	0.018	0.246	0.73	0.033	0.393	0.604
	M2	0.662	0.044	0.052	0.241	0.662	0.097	0.313	0.522
	M3	0.675	0.036	0.035	0.253	0.675	0.074	0.307	0.538
	M4	0.74	0.014	0.017	0.249	0.74	0.031	0.257	0.616
Inner	M1	0.65	0.03	0.037	0.283	0.65	0.063	0.451	0.545
	M2	0.63	0.074	0.076	0.224	0.63	0.149	0.35	0.511
	M3	0.638	0.071	0.067	0.231	0.635	0.138	0.334	0.491
	M4	0.713	0.025	0.043	0.219	0.713	0.058	0.265	0.603
Medium	M1	0.681	0.021	0.019	0.279	0.681	0.041	0.432	0.568
	M2	0.62	0.049	0.055	0.277	0.62	0.101	0.335	0.488
	M3	0.631	0.044	0.044	0.28	0.631	0.088	0.332	0.498
	M4	0.699	0.019	0.018	0.268	0.699	0.037	0.279	0.584
Lower	M1	0.827	0.02	0.015	0.137	0.827	0.031	0.278	0.732
	M2	0.758	0.054	0.048	0.141	0.758	0.097	0.259	0.629
	M3	0.781	0.035	0.034	0.15	0.781	0.068	0.242	0.667
	M4	0.857	0.01	0.012	0.12	0.857	0.028	0.186	0.745

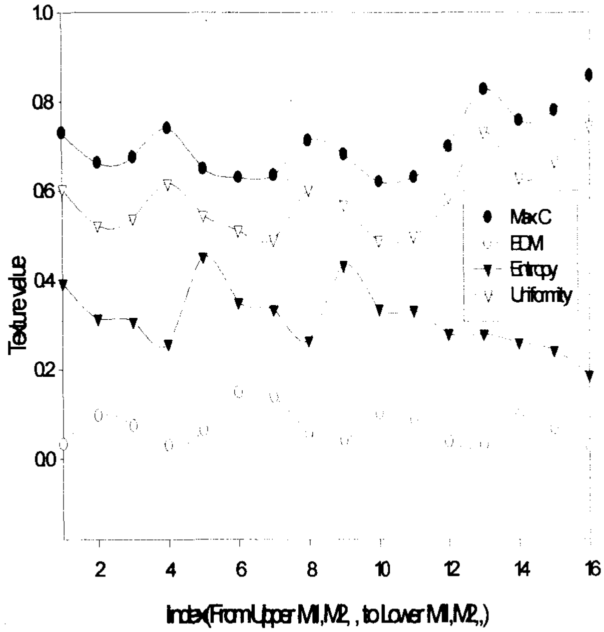


Fig. 5 Average texture descriptors value

Position Recognition

The sample was collected 50 for each 12 grade and total sum is 600. The simulation for attached leaves position recognition was performed firstly using the back propagation neural network(BP) for 10 sample per grade, therefore each position has 30 training data set. The input data set was made 121 nodes consisting of 121 average values and the length of maximum axis. Each node was determined by previous texture scanning methods and quarter region consist of 40 sequential average saturation value block. Before measurement of saturation value, the total pixel number of each quarter region was calculated previous texture analysis. Therefore, small quarter region was scanned in a manner that 1/4 region divide by number 40.

The initial input condition of BP was determined that learning rate is 0.6, momentum is 0.4, hidden layer unit is 10 and output layer unit is 2 as shown in Fig. 1. Total iteration epoch was set to 10000 and normalized system error was set to 0.005. The training was not converged predefined values such as 0.0141, but it was showed successful result for trained data set. To verify generalization effect of BP network, untrained sample was tested with already saved weight value of network. For a each harvested position, 45 untrained sample was used to verify the learning effect that is consist of 15 samples per grade. The verification results are shown in table 6. The total recognition rate was showed in 68.3% , and upper, inner, medium and lower cases has a each 64.4%, 75.6%, 73.3% and 60.0%.

Table 6. Verification result of 15 samples per each grade

Input / Output	Upper			Inner			Medium			Lower		
	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
Medium	-	-	2	-	-	-	12	13	8	-	1	-
Lower	2	-	2	1	2	-	-	-	1	9	10	8

Quality Evaluation

Quality evaluation was also performed with BP network and the input data set was same as previous position recognition methods. The learning rate was 0.8, momentum was 0.4, hidden layer unit was 15 and output layer unit was set to 3. Training sample was selected 10 number of each 12 class. The training result shows 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 set was 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 0.3, hidden layer 7 and output unit 3. The training result also gives a successful for a given input data sets having a 0.094 converged system error. And it was verified with untrained same 240 samples.

The verification results of first methods which uses a total area's color information were showed in table 7 and its recognition performance was 68.3% for total 240 verification samples, and 74.5 % for a second input methods which was consist of small number of descriptors. From the results, small number of feature based results revealed for more good relatively.

Table 7. Quality evaluation results from BP network.

Input / Output	Upper			Inner			Medium			Lower		
	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)

CONCLUSIONS

Tobacco leaves position is important to decide its grade and development of real time automatic quality measurement system. This paper was just perform with color computef vision and showed a capability for system integration NIR spectrum analysis according to its position recognition performance. This software was developed via Microsoft visual c++6.0. The position recognition performance was showed as 68.3. From the quality evaluation method, two input set was verified with untrained samples and gives a recognition rate 68.3% and 74.5.

Despite of this result was brought somewhat improper recognition rate, this leaves position recognition result gives a probability for the system integration for automatic grading with another addictive sensor fusion such as spectrophotometer. Further research will perform with portable I/O bus type spectrum analyzer and verify the network performance for more sample tobacco leaves.

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