# GRADING CUT ROSES BY COLOR IMAGE PROCESSING AND NEURAL NETWORK

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## ABSTRACT

Sorting cut roses according to quality is very essential to increase the value of the product. Many factors are involved in determining the grade of cut roses: length, thickness, and straightness of stem, color and maturity of bud, and extra. Among these factors, the stem straightness and bud maturity are considered to be difficult to set proper classification criteria. In this study, a prototype machine and an analysis procedure were developed to grade cut roses according to stem straightness and bud maturity by utilizing color image processing and neural network. The test results indicated 15.8% classification error for stem straightness and 10.0% for bud maturity.

Key words: cut flower, rose, grade, color image processing, neural network

## INTRODUCTION

The area and amount of cut-flower production have been continuously increasing in Korea. As of 1997 the production area for cut flowers totaled 2,559 ha including the area of protected cultivation. Cut flowers shared 47.9% of the total value of flower production in the same year. With the increase of cut-flower production, the needs to mechanize sorting and packaging operations have been recognized by the growers. A survey study to cut-flower producers indicated that harvesting and sorting operations took 28.2% and 19.0% of total labor for cut-flower production, respectively (Bae and Koo, 1999).

The shipping standards for cut flowers are determined by quality and size of the produce. The quality is described based on color and shape of bud, width and straightness of stem, and the balance among bud, leaves, and stem. The length of stem determines the size. Some species of flowers such as carnation and chrysanthemums are relatively easier to sort since there exist small variations in the length and straightness of stem and size of bud in a batch of produce. Therefore, simple electro-mechanical sorters based on stem length are sufficient. However, in case of roses, the variations among individual flowers are so large that the sorting operation is more difficult and time consuming. Therefore, in sorting cut roses, many quality factors and complex sorting machines are required. Color image processing has been considered to be a feasible and adequate tool for sorting cut roses (Steinmetz et al., 1994; Bae and Koo, 1999). There also exist some commercial sorters for cut roses utilizing color image processing (Bae and Koo, 1996). In grading cut roses by color image processing, it is difficult to set criteria among different grade categories for some quality factors such as bud maturity and stem straightness since these are not easy to evaluate. Neural network has been widely adapted to solve such difficulties (Ikeda and Sawada, 1993; Lee et al, 1995; Ghazanfari et al., 1996).

The objectives of this study were 1) the determination of feature vectors and structure of neural network for judging stem straightness and bud maturity and 2) the evaluation of the performance of the developed system.

## MATERIALS AND METHODS

### Prototype sorting machine

The prototype machine was consisted of a delivery mechanism (Fig. 1) and an image inspection chamber (Fig. 2). These two were constructed in separate frames to isolate mechanical vibration originating from the chain-drive mechanism. The delivery mechanism includes a variable speed dc motor power transmission system, a chain-drive feed mechanism, and pneumatic cylinders to discharge graded roses. Each rose is positioned by a black-painted support plate in such a way that the bud is hung through the opening in the plate. The support plates were separated by a distance of 320 mm each and transported horizontally by the chain-drive system. A small piece of white acrylic plate was attached on one side of each support plate for easy identification of the location of the plate in an image.

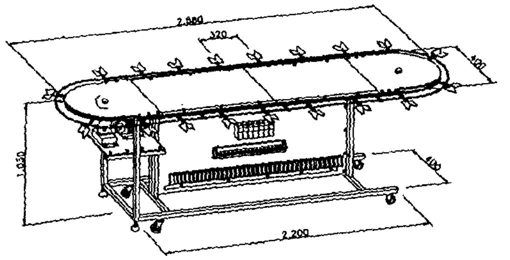



Fig. 1 Schematics of the sorter.

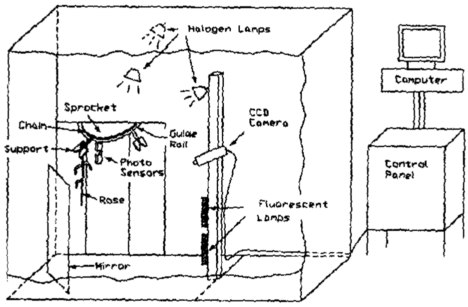



Fig. 2. Schematics of the image chamber.

Three tungsten halogen lamps (20 W each) and two fluorescence lamps (10 W each) were placed in the image inspection chamber and provided diffuse illumination. Also a reflection mirror of 250×900 mm in size was placed in the chamber such that the stem is viewed in two different directions. A refection-type photo sensor was utilized to provide timing signal for image acquisition by detecting the arrival of a support plate to a predetermined position. Another photo sensor was utilized to detect the existence of a rose on the arriving support plate.

Images were acquired by using a color CCD camera (Sony, XC-711) mounting an 8-mm focal length lens and a color frame grabber (Oculus-TCX, Coreco). The camera was fixed in a rotated position such that the horizontal axis of the image coincided with the stem axis. The captured images were analyzed by using a 100 MHz Pentium PC. A digital I/O board was utilized to read signals from the photo sensors. The analysis program was written in MS C/C++ 7.0.

### Determination of stem straightness

Fig. 3 illustrates four different types of stem images. The stem looks straight in both direct and mirror images in Fig. 3(a), one of the two images looks straight in Figs. 3(b) and 3(c), and the stem looks crooked in both images in Fig. 3(d). To determine the straightness of stem, it was necessary to trace the stems in both direct and mirror images. However, the operation of identifying the whole stems in the two images were time consuming since parts of them were covered with the image of leaves. Through careful observation of rose stems it was recognized that in many cases the crooked stems were bent in the first and/or last segments. Therefore, it was decided to utilize only the first and last segments of a stem in evaluating the straightness to reduce processing time.

(a) (b) (c) (d)

Fig. 3.Sample images representing patterns of stem curvature.

Three slopes were calculated from the image of a stem to determine feature vector for stem straightness (Fig. 4): slope1–slope of the line connecting the beginning and end of a stem to the horizontal line, slope2–slope of the first stem segment to the horizontal line, and slope3–slope of the last segment to the horizontal line. In calculating slope2 and slope3, at least five points on each stem segment were identified and least-squares linear regression equations were obtained to determine the slopes to the horizontal line. From the three slopes the deviations of the first and last segments to the line connecting the beginning and end of stem, as indicated by $\alpha$ and $\beta$ in the Fig. 4, were calculated.

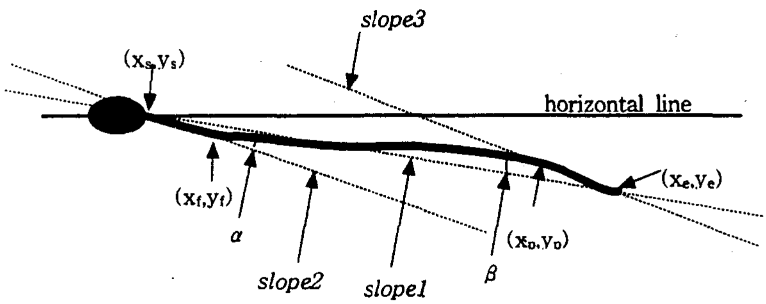



Fig. 4 Illustration of slopes utilized in evaluating the stem straightness.

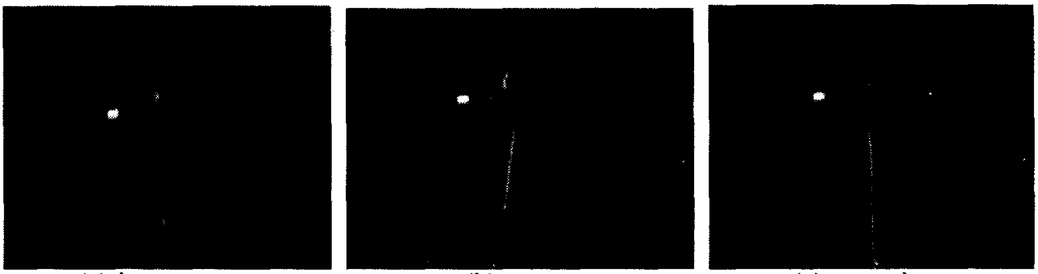
The feature vector, S, for the stem straightness was then determined from the direct and mirror images:

$$S = \begin{bmatrix} slope(f_d) \\ slope(e_d) \\ slope(f_m) \\ slope(e_m) \end{bmatrix} \tag{1}$$

where f and l indicate first and last segments of a stem, and d and m for direct and mirror images, respectively.

**Determination of bud maturity**

One of the three categories was assigned to designate bud maturity: immature, mature, and over-ripen. Fig. 5 illustrates images of rose buds for the three maturity categories. The second category ("mature") is considered adequate to pick by the growers.



(a) immature (b) mature (c) over ripen

Fig. 5. Sample bud images of different maturity stages.

The first step in determining the bud maturity was finding the top of a bud. A predetermined area of 6×30 pixels, identified relative to the center location of the white marker on each support plate, was searched for the top of the bud based on the R value to eliminate the effect of sepals (Fig. 6). The elements of the feature vector for bud maturity were consisted of width and area attributes. The width attributes were determined as indicated in Fig. 7. The symbols bw1, bw2, and bw3 were the widths of a bud at the vertical location of 1/6, 2/6, and 3/6 from the top of the bud. A rectangular search region was selected to evaluate the color attributes of a bud whose vertical region covered the top half of the bud height and horizontal region covered the largest of bw1, bw2, and bw3.

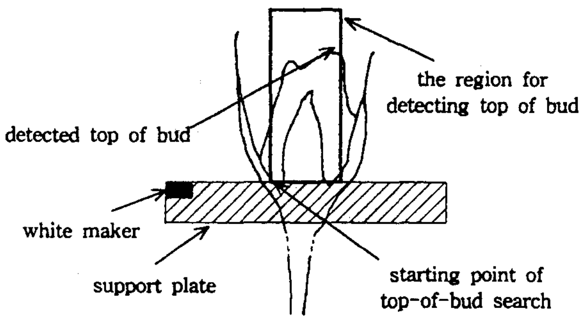



Fig. 6 Illustration of search region for the top of a bud.

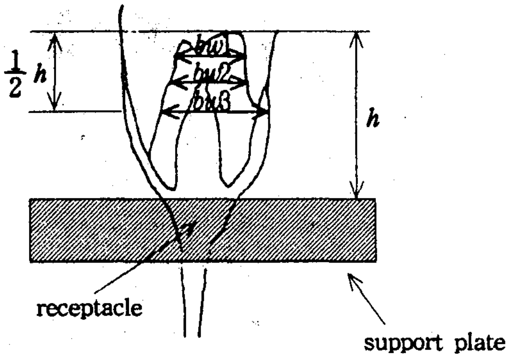



Fig. 7 Illustration of height and width utilized in evaluating the maturity of rose buds.

The elements of the feature vector based on area attributes were determined by considering the R and G values of pixels in the search area:

$$Area1 = \frac{N_{R>G}}{N_T} \tag{2}$$

$$Area2 = \frac{N_{R>G}}{N_R} \tag{3}$$

where $N_{R>G}$ = number of pixels in the search area having R value greater than G value and a predetermined threshold

$N_T$ = total number of pixels in the search area

$N_R$ = number of pixels in the search area having R value greater than a predetermined threshold

Therefore, the feature vector for the bud maturity was determined:

$$M = \begin{bmatrix} bw1 \\ bw2 \\ bw3 \\ Area1 \\ Area2 \end{bmatrix} \tag{4}$$

**Artificial Neural Network**

**Stem straightness.** The neural network classifier was composed of an input layer with five processing units, a hidden layer with 5, 10, 15, and 20 processing units, and an output layer with two processing units. The number of hidden layer units was later determined by observing the mean square error (MSE).

The input data were normalized in the range of 0 to 1 by using the feature vector such that

$$Input[i] = \frac{\max - slope[i]}{\max} \tag{5}$$
$$(i = 1,2,3,4)$$

$$Input[5] = \frac{\sum_{i=1}^{4} Input[i]}{4} \tag{6}$$

The max value in equation (5) was set to 0.577 (tan30°). The roses utilized in this research were collected from a grower at Yeosu. Immediately after picking, the roses were graded by the grower for bud maturity and stem straightness and brought to the laboratory for training and evaluating the neural network. The leaves and thorns in the bottom 10 cm region of stem were removed before the test. The variety of the rose was Sandra. Fourteen straight roses and 26 crooked roses were utilized in training the neural network for stem straightness. The parameters of learning rate and momentum were set to 0.2.

**Bud maturity.** The neural network classifier was composed of an input layer with five processing units, a hidden layer with 5, 10, 15, and 20 processing units, and an output layer with three processing units. The number of hidden layer units was determined later by observing MSE. The input values were normalized by using the feature vector:

$$w[i] = \frac{dw[i]}{30} \tag{7}$$

$$(i = 1,2,3)$$

$$Input[1] = \frac{Area1 + Area2 + w1}{3} \tag{8}$$

$$Input[i] = \frac{Area2 + w[i-1]}{2} \tag{9}$$

$$(i = 2,3,4)$$

$$Input[5] = \frac{\sum_{i=1}^{4} Input[i]}{4} \tag{10}$$

Fourteen immature, twelve mature, and fifteen over-ripen roses were utilized in training the neural network for bud maturity. The parameters of learning rate and momentum were again set to 0.2.

## RESULTS AND DISCUSSION

### Results of Training

**Stem straightness.** After observing MSE for different number of hidden layer units and number of repetitions, 10 units and 5,000 repetitions were selected. In this case the MSE reached 0.002895. When the 40 rose samples of training set were tested with the trained neural network, 35 rose samples (87.5%) were classified as desired. The inconsistency in the result might be attributed to the change in orientation when the roses were placed on the support plates and thus resulting in different input values. The accuracy of the grower in evaluating the stem straightness might also have affected the result.

**Bud maturity.** After observing MSE for different number of hidden layer units and number of repetitions, 10 units and 2,500 repetitions were selected. In this case the MSE reached 0.003135. When the 41 rose samples of training set were tested with the trained neural network, 37 rose samples (90.2%) were classified as desired.

**Test Results**

**Stem straightness.** A set of 76 roses was utilized to test the effectiveness of the neural network. Thirty-eight of these were classified as straight and the rest 38 as crooked by the grower. The image analysis and neural network resulted in an overall classification error of 15.8% (Table 1).

Table 1. Comparison of the results of classification by neural network and by grower (stem straightness)

| True class (grower) | Assigned class (neural network) | | Total | Error (%) |
|---|---|---|---|---|
| | Straight | Crooked | | |
| Straight | 29 | 9 | 38 | 23.6 |
| Crooked | 3 | 35 | 38 | 7.8 |

**Bud maturity.** A set of 90 roses was utilized to evaluate the effectiveness of the neural network for bud maturity. Thirty roses each were selected for immature, mature, and over-ripen categories. The test results indicated an overall classification error of 10.0% between the grades assigned by the neural network and by the grower (Table 2).

Table 2. Comparison of the results of classification by neural network and by grower (bud maturity)

| True class | Assigned class | | | Total | Error (%) |
|---|---|---|---|---|---|
| | Immature | Mature | Over ripen | | |
| Immature | 26 | 4 | 0 | 30 | 13.3 |
| Mature | 0 | 28 | 2 | 30 | 6.6 |
| Over ripen | 0 | 3 | 27 | 30 | 10 |

## CONCLUSIONS

A prototype sorter was developed to inspect cut roses. The sorter was consisted of a chain-drive rose delivery system and an image inspection chamber. The stem straightness and bud maturity were analyzed by neural network. The results of the study are summarized as followings:

1. The feature vector for judging the stem straightness was composed of five elements. Four of them were slopes of a stem calculated from both direct and mirror images, and the other one was the average of the four slopes. A structure of 5-10-2 was selected for the neural network.

2. The feature vector for judging the maturity of bud was composed of five elements. Three of them were related to width of bud, and the other two were related to area and

color of bud. The structure of the artificial neural network for the evaluation of bud maturity was 5-10-3.

3. The learned artificial neural network was applied to grade 76 cut roses for stem straightness. Eighty-four percent of the grade results agreed with those of a human expert.

4. The trained neural network was applied to grade 90 cut roses for bud maturity. Ninety percent of the grade results agreed with those of a human expert.

5. The average processing time for stem straightness and bud maturity were 1.01 and 0.44 second, respectively.

6. The application of neural network eliminated the difficulties in setting criteria for grade categories for stem straightness and bud maturity while maintaining similar level of classification error.

## ACKNOWLEDGEMENTS

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