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Sorting Cut Roses with Color Image Processing and Neural Network

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Abstract: Quality sorting of cut flowers is very essential to increase the value of products. There are many factors that determine the quality of cut flowers such as length, thickness, and straightness of stem, and color and maturity of bud. Among these factors, the straightness of stem and the maturity of bud are generally considered to be more difficult to evaluate. A prototype grading and sorting machine for cut flowers was developed and tested for a rose variety. The machine consisted of a chain-drive feed mechanism, a pneumatic discharge system, and a grading system utilizing color image processing and neural network. Artificial neural network algorithm was utilized to grade cut roses based on the straightness of stem and maturity of bud. Test results showed 89% agreement with human expert for the straightness of stem and 90% agreement for the maturity of bud. Average processing time for evaluating straightness of the stem and maturity of the bud were 1.01 and 0.44 second, respectively. Application of neural network eliminated difficulties in determining criteria of each grade category while maintaining similar level of classification error.
Keywords: Cut rose, Grading, Sorting system, Color image processing, Neural network

Introduction

The area and amount of cut-flower production have continuously increased in Korea. As of 1997, the production area of cut flowers totaled 2,559 ha including the area of greenhouse cultivation. Cut flowers shared 47.9% of the total value of flower production in 1997. With the expansion of cut-flower industry, mechanization needs for sorting and packaging operations have been well recognized by the growers due to the lack of adequate machinery and the intensity of labor. A survey study of the mechanization status of cut flower production indicated that harvesting and sorting operations took 28.2% and 19.0% of total labor in cut-flower production, respectively (Bae and Koo, 1999).

Shipping standards of cut flowers are determined by quality and size. The quality is described based on color and shape of the bud, width and straightness of the stem, and the balance among bud, leaves, and stem. Length of the stem represents the size of the flower and is a key factor for the price. Some species of flowers such as carnation and chrysanthemums are relatively easy to sort since there exist little variation in length, straightness of the stem, and bud maturity for a batch of produce. Therefore, simple electro-mechanical sorters based on the stem length are sufficient for those. However, in case of roses, variations among flowers are so large that the sorting operation is more difficult and time consuming. Therefore, in sorting cut roses, many quality factors should be considered and complex sorting machine is 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 using color image processing (Bae and Koo, 1996). In grading cut roses using color image, 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). Steinmetz et al. (1994) developed color image processing algorithms to grade cut roses. Their results showed classification error of 17% to 18% and 15% to 21% for stem straightness and bud maturity, respectively. One limitation of their research was that each cut rose was evaluated in a static position yielding maximum curvature of stem, which cannot be achieved in on-line processing. Bae and Koo (1999) also reported a prototype sorting machine and image processing algorithms for grading cut roses. Their research indicated classification errors of 8.6% for stem straightness and 1.5% to 13.5% for bud maturity depending on varieties. However, their methods are lacking the rigidity in determining criteria among different grades for the stem straightness and the bud maturity.

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Objectives of this study were 1) determining feature vectors and structure of neural network for judging the stem straightness and the bud maturity and 2) evaluating the performance of the developed system.

Materials and Methods

1. Prototype Sorting Machine

The prototype machine consisted of a feeding mechanism (Fig. 1) and an image inspection chamber (Fig. 2). These two units were built with separate frames to isolate mechanical vibration caused by the chain-drive mechanism. The feeding mechanism included a power transmission system with a variable speed dc motor, a chain-drive feed mechanism, and pneumatic cylinders to discharge graded roses. Each rose was positioned on a black-painted support plate in such a way that the bud was seated 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 board was attached to the side of each support plate to identify the location of the plate in an image.

Three tungsten halogen lamps (20 W each) and two fluorescence lamps (10 W each) were placed in the image inspection chamber to provide 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 reflection-type photo sensor was utilized to provide the image acquisition signal 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.

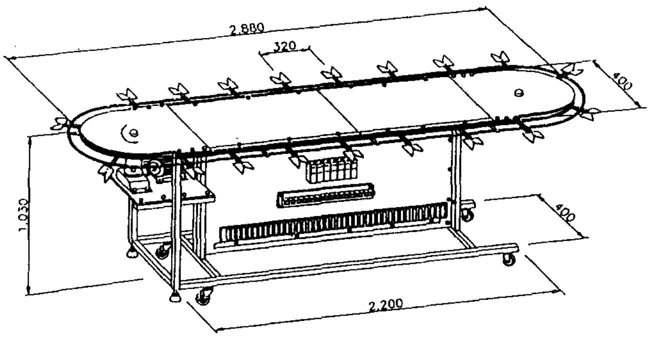


Fig. 1 Schematic figure of the prototype sorter.

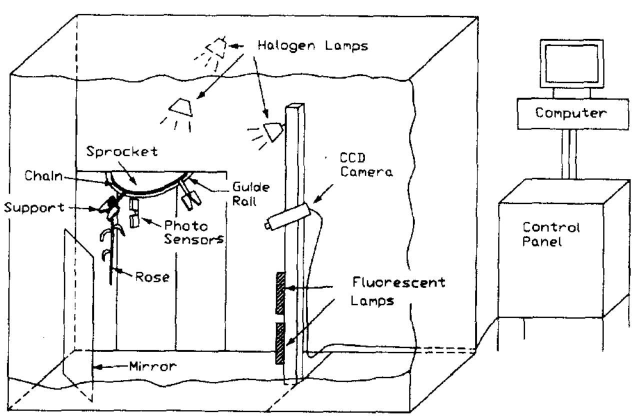


Fig. 2 Schematic figure of the image inspection chamber.

Images were acquired using a color CCD camera (Sony, XC-711) mounted with 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 coincide 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 and to activate the discharge cylinders. The analysis and control software was developed using MS C/C++ 7.0.

2. Determination of Stem Straightness

Fig. 3 illustrates four different types of stem images. Fig. 3(a) shows straight stem in both direct and mirror images. Either 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.

Three slopes were computed from each image of the stem to determine the feature vector for stem straightness (Fig. 4): slope1 – the slope of the line connecting the beginning and the end of a stem to the horizontal line, slope2 – the slope of the first stem segment to the horizontal line, and slope3 – the slope of the last segment to the horizontal line. In computing 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 with respect to the horizontal line. The deviations of the first and last segments from the line connecting the beginning and the end points of the stem, as indicated by α and β in the Fig. 4, were computed by using three slopes.

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

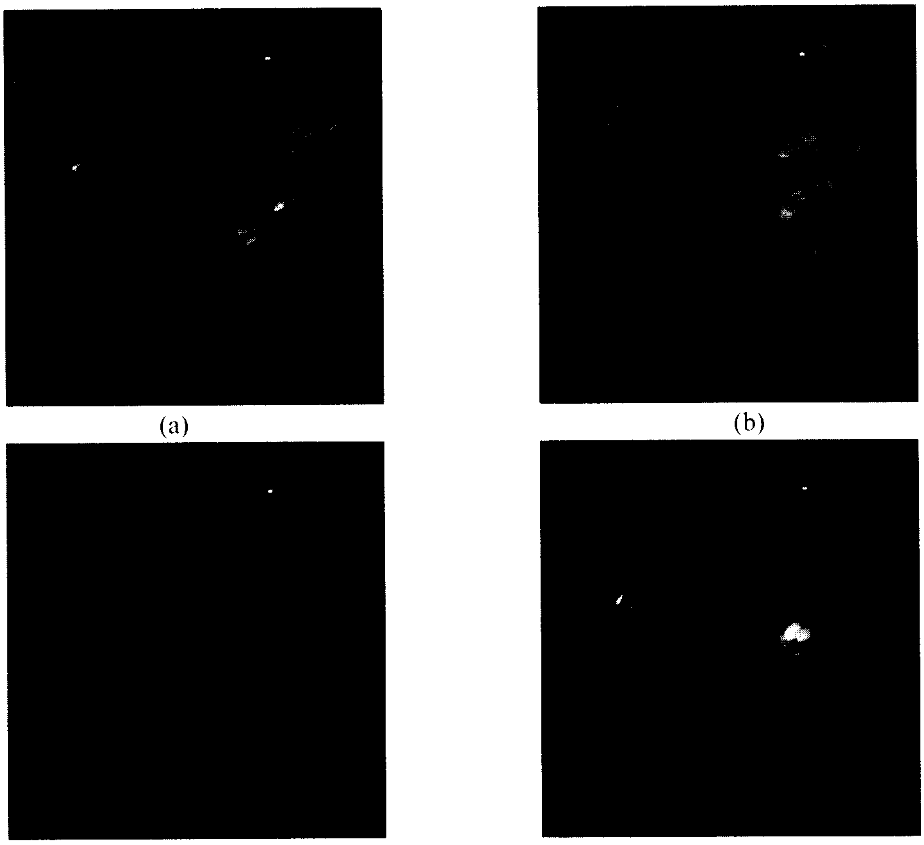


Fig. 3 Examples representing patterns of stem curvature.

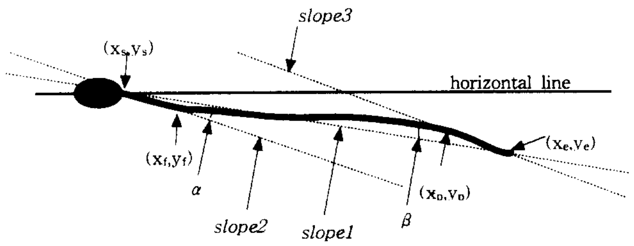


Fig. 4 Illustration of the slopes utilized in evaluating the stem straightness.

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

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

3. Determination of Bud Maturity

Three categories were assigned to designate the stage of the bud maturity: immature, mature, or over-ripen. Fig. 5 illustrates images of rose buds for each category. The second category ("mature") was considered to be adequate to pick by the growers.

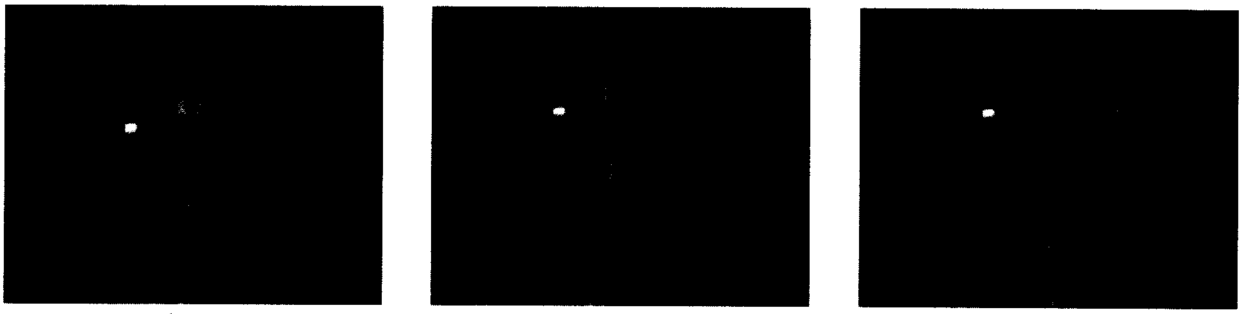
The first step in determining the bud maturity was finding the top of a bud. A predetermined area of 6× 30 pixels, identified relative to the center location of the white marker on each support plate, was searched for the top of the bud based on the R value to eliminate the effect of sepals (Fig. 6). The elements of the feature vector for bud maturity 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.

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) immature (b) mature (c) over ripen

Fig. 5 Sample bud images of different maturity stages.

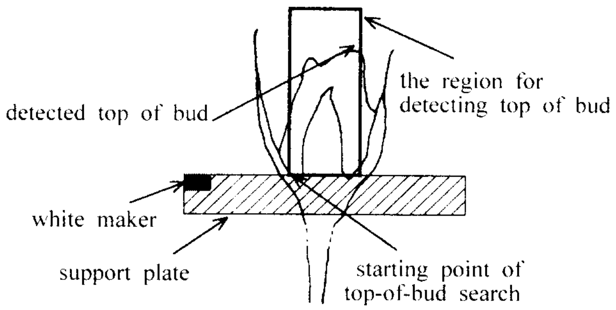


Fig. 6 Illustration of search region for the top of bud.

a predetermined threshold,

N_T = total number of pixels in the search area, and

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 composed of:

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

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

$$Input[i] = \frac{\max - slope[i]}{\max} \tag{5}$$

$(i=1,2,3,4)$

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

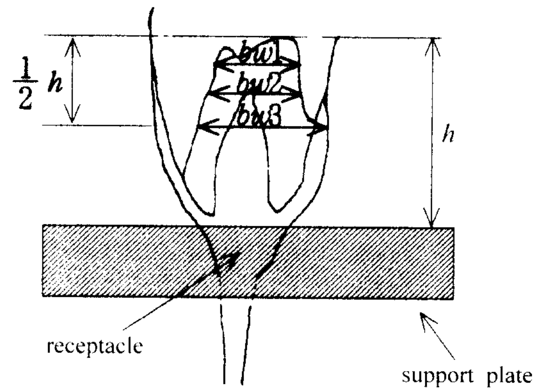


Fig. 7 Illustration of height and widths utilized in evaluating the maturity of buds.

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, Korea. 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 by using a mechanical remover. 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:

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

$(i=1,2,3)$

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

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

$(i=2,3,4)$

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

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

1. 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. The details of the analysis can be found in the work of Seo (2000). 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.

2. 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).

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).

The test results for stem straightness and bud maturity were comparable to the results by Bae and Koo (1999), which indicated a classification error of 8.6% for stem straightness and 1.5 to 13.5% for bud maturity depending on varieties. Considering the elimination of the difficulties in determining criteria among different grades for stem straightness and bud maturity, the application of neural network was considered to be very effective in developing algorithms for cut-flower quality evaluation.

Conclusions

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

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

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

1. Feature vector for judging the stem straightness was composed of five elements. Four of them were slopes of a stem computed 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 the width of the 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 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 grade results agreed with those of a human expert.

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

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

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