MACHINE VISION BASED QUALITY EVALUATION OF CHRYSANTHEMUM CUT FLOWER

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Abstract: Cut flower evaluation has been usually conducted by human sense and its criteria are uncertain and subjective. In this paper, machine vision based quality evaluation was done using neural networks to quantify the ambiguous criteria. As input parameters of neural networks, cut flower length, stem diameter, leaf area, and etc. were selected, while human evaluation score was used for an output parameter. The neural networks were trained by KNT method. From the results, it was observed that output value satisfactorily agreed the human evaluation score. The error was less than the human error resulted from the human double check procedure.

Keywords : Intelligence, Quality, Evaluation, Kalman filters, Neural networks

1. INTRODUCTION

Chrysanthemum is one of the most typical cut flowers in Japan, which has been associated with Japanese people as the national flower. The cut flower is evaluated by human criteria at market and Fig. 1 shows examples of cut flowers and their evaluated scores at the bottom right corner in the images. In the figure, top left flower was given best score and bottom right flower was the worst score. However, the criteria of evaluation are different depending on season and district so that it may be difficult for human to assign appropriate scores which always satisfy everyone anytime and anywhere. It is, therefore, desired to objectively evaluate cut flower based on its quality and to subjectively evaluate it depending on season and district sometimes.

Recently, machine vision techniques are widely spread and are also applied to many kinds of biological objects. It has been well known that neural networks can tell a relation between multi-inputs and multi-outputs, even if it is a very complicated system. In addition, the neural networks also can learn from its training data including human subjective judgement. It implies that it is possible to construct a flexible system which is adaptable to season's and district's requirements by changing the training data, if neural networks are used.

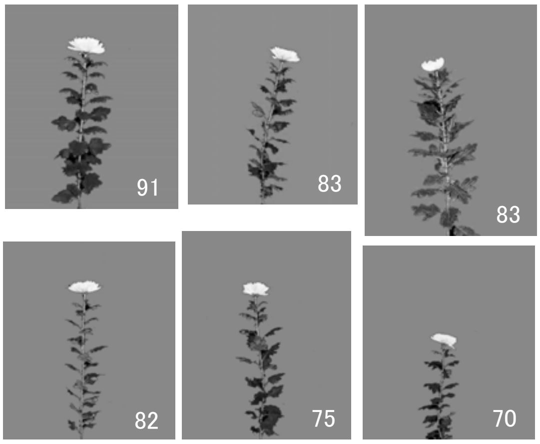

Fig. 1 Chrysanthemum cut flowers and their scores.

An evaluation system for chrysanthemum cut flower with spray formation using a machine vision and neural networks have been already studied by our research group (Kai et al; 1995a, 1995b, 1996). However, the evaluation criteria of the cut flower with spray formation are different from those of cut chrysanthemum with a single flower. In this paper, a consideration on experts' quality evaluation for chrysanthemum cut flower was conducted to quantitate the ambiguous evaluation criteria based on human sense. In addition, machine vision system and neural networks were used to automatically evaluate the cut flower.

2. MATERIALS AND METHODS

2.1 Cultivation method

To obtain many cut flowers with various morphological characteristics, chrysanthemums were planted in 10 boxes positioned as shown in Fig. 2 and several treatments were conducted: Treatment No. 1, 6, and 10 are usual method to grow. In No.2 and 5, more plants were grown. In No.3 and 4, density of fertilization was changed, while irrigating condition was changed in No.8 and 9. To get dwarfed plant, growth retardant was treated in No. 7.

As representative plants, five cut flowers were picked from each box and their appearances were recorded using a video camera. The image of each cut flower was shown for 5 seconds to two experts later and they evaluated the cut flowers by their own criteria (One's full score was 100, while the other's was 5).

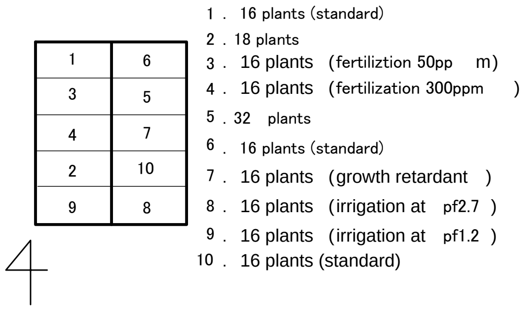

Fig. 2 Cultivation conditions of chrysanthemum cut flower.

2.2 Expert's evaluation

Generally speaking, it is said that chrysanthemum cut flower whose appearance meets the following things is given high score in expert's evaluation:

1) Length of cut flower is long.
2) Main stem diameter needs appropriate size.
3) Main stem is not bent.
4) Stem length between flower and the first leaf needs appropriate size.
5) All node lengths are appropriate and are same size.
6) All leaves are not withered and have deep green color.
7) All leaves have similar lengths.
8) Flower has a single color.
9) Sizes of leaves are well balanced with size of flower.

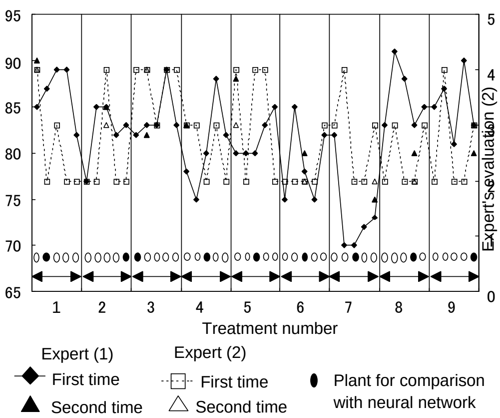

Fig. 3 Expert's evaluation result.

Fig. 3 shows results of experts' evaluation. From the results, it was observed that their results showed different tendency each other and that their second evaluation scores were often different from their first

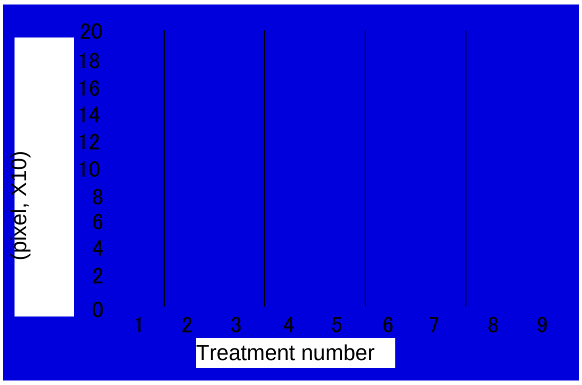

Fig.4 Result of area of leaves and stems.

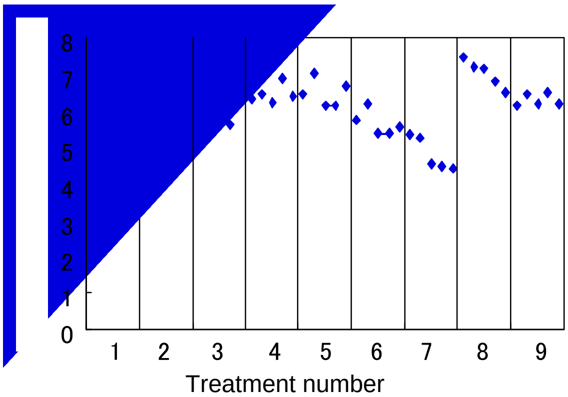

Fig.8 Result of main stem diameter.

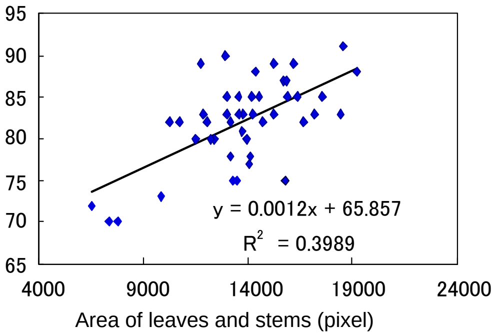

Fig.5 Relation between area of leaves and stems and expert's evaluation.

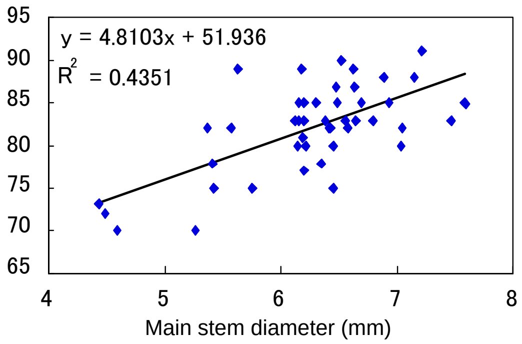

Fig.9 Relation between main stem diameter and expert's evaluation.

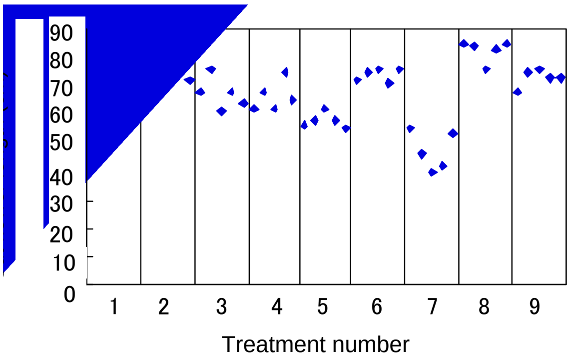

Fig.6 Result of cut flower length.

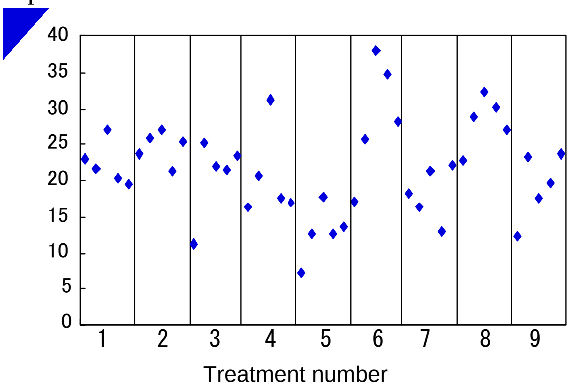

Fig.10 Result of top node length.

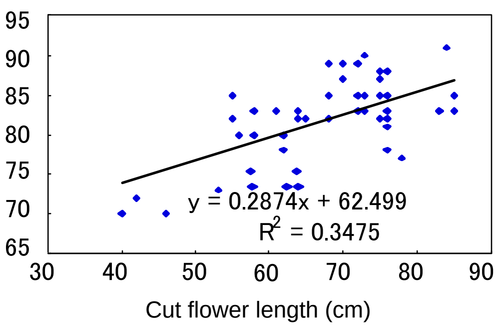

Fig.7 Relation between cut flower length and expert's evaluation.

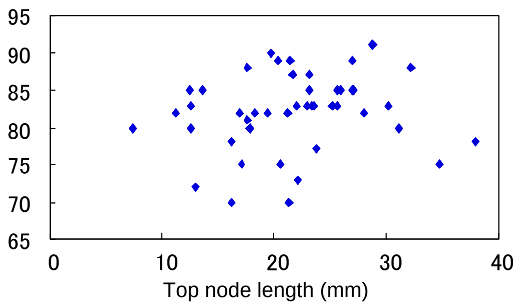

Fig.11 Relation between top node length and expert's evaluation.

scores. This implied that human evaluation was ambiguous and uncertain and that the human evaluation is different from time to time and from place to place. In addition, area of leaves and stems, cut flower length, main stem diameter, top node length (length between flower and uppermost leaf), main stem bend, average internode length, and leaf length were measured to investigate relation between experts' evaluation and cut flower characteristics. In this study, area of leaves and stems was extracted from binary images, while the other features were manually measured.

Fig.4-11 show the some results of them. From the results, it was shown that most measured features corresponded to experts' evaluation criteria, but that co-relation between each feature and experts' evaluation was not high so that evaluation by use of a single feature seemed difficult. In the Fig.4, 6, 8, and 10, treatment number 10 was omitted, because the plant features in treatment number 10 were similar with in treatment number 1 or 6. From these results, it was considered that combination to use the features was necessary and that a system in which learned itself using teaching data like neural networks was required to automate the cut flower evaluation process.

2.3 KNT Neural network

Fig.12 shows an example of constitution of neural networks used in this study. Some features were selected among area of leaves and stems, cut flower length, main stem diameter, top node length, top leaf length, and stem bend as input parameters of neural networks whose output parameter was evaluation score. In this study, 4 or 5 features from above features were inputted to input layer, while hidden layer unit number was changed from 2 to 6. As the output parameter, the scores of expert (1) were used after the data were standardized between 0 and 1.

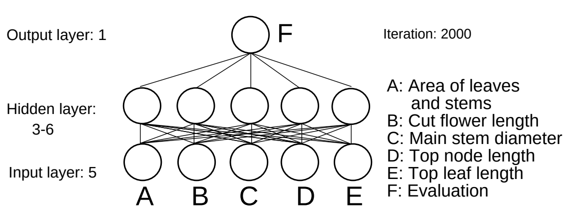

Fig.12 Constitution of neural network.

The neural networks were trained by KNT (Kalman Neuro Training) method (Murase et al; 1994, 1998). The input can be expressed in a vector form as $\{T\}=\{t_1,t_2, ...,t_k\}$. The i-th component of the inputs vector $\{T\}$, i.e., t_i, that comes out from the input unit i is transferred to a hidden unit j (j=1,2,....,m) through the synaptic weight W_{ij}. Since each hidden unit has a summation function operating on inputs, the total input u_j received by the hidden unit is

$$u_j = \sum_{i=1}^{k} W_{ij} t_i \qquad (1)$$

The hidden unit i also has a transfer function that performs a nonlinear transformation on the total input u_i, and then gives an output which becomes the next input fed into the output unit j (j=1,2,...n), which also has a summation function, through another synaptic weight V_{ij}. The total input received by the output unit j becomes directly its output s_j expressed as

$$s_j = \sum_{i=1}^{m} V_{ij} f(u_i) \qquad (2)$$

The outputs can be given in a vector form as $\{S\}=\{s_1, s_2,....,s_n\}$. Overall, what this neural network does is to perform a nonlinear transformation on $\{T\}$ as expressed in the following equation.

$$\{S\} = F(\{T\}) \qquad (3)$$

Once those nonlinear functions (transfer functions) of hidden units are specified, the behavior of the network can be identified by determining all synapse weights contained in the network. The sigmoid function is often employed for the transfer function. The learning of the neural network is a procedure to determine optimal values of synaptic weights by adjusting them step by step using known input data and their associated output data called training data.

3. RESULTS AND DISCUSSIONS

Fig.13 shows a comparison between expert and neural network whose input parameters were area of leaves and stems, cut flower length, main stem diameter, top node length, and hidden layer unit number was two. Horizontal axis indicates treatment number of cut flower, while vertical axis indicates standardized evaluation value. From this figure, it was observed that the output value from the neural network followed the human evaluation scores well and that the output errors from the neural network were smaller than human errors in Fig. 3.

Fig.14 shows a result of neural network whose input parameters were added the top leaf length to the neural network used in Fig.13 and hidden layer unit number was four. Also when stem bend was inputted in stead of the top leaf length, a similar result was obtained.

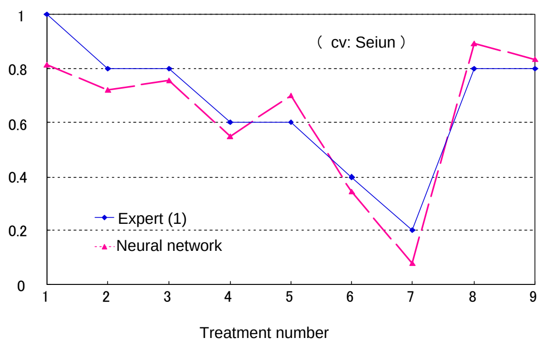

Fig.13 An evaluation result (1).

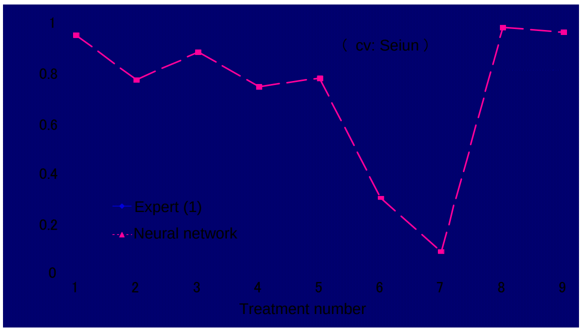

Fig.14 An evaluation result (2).

From the results, it was observed that neural network was effective for handling the ambiguous features used in human evaluation and that the error was less than the human error resulted from the human double check procedure. It was considered that a feasibility to automate cut flower evaluation system was found by investigating features used in human evaluation.

In this study, only area of leaves and stems was extracted from binary images, while the other features were manually measured. To construct an automatic evaluation system, it is necessary that all the features are extracted from images or that other appropriate features to be able to be extracted are investigated if it is difficult to extract the features used in this study.

4. CONCLUSIONS

Neural networks can handle relationship between multi-input and multi-output, even if it is non-liner relation. Machine vision system has a potential to replace human inspection. From these view points, it is appropriate to combine them to use for chrysanthemum cut flower evaluation. This study showed the feasibility not only to automate the evaluation system, but also to add subjective evaluation based on season's and district's requirements to the system. As a future work, features which are equivalent to human evaluation indices and are able to be extracted from images should be investigated for determining the input parameter of the neural network.

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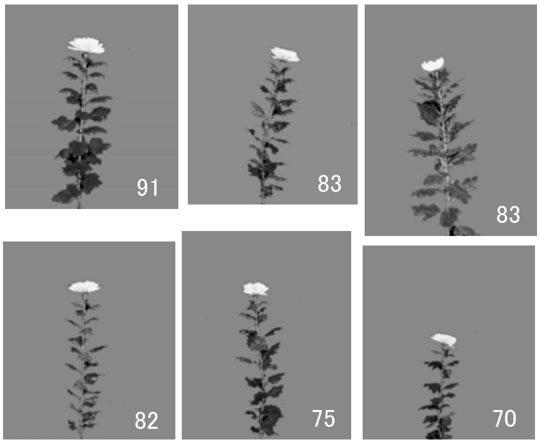

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