The application of digital image processing in grading of begonia pot plants

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Abstract

Digital Image Processing (DIP) is a potential tool for measuring and classifying pot plants in various growth stages in an automatic, objective and consistent way, with a high capacity and low labour input. In the research described in this paper we analysed the features of begonia cuttings which could be relevant for grading. Images of unrooted and rooted begonia cuttings were acquired and analysed with DIP. The various parts of the cuttings were identified and measured using knowledge based image processing. These measurements were shown to be consistent and to be well correlated with the features measured in conventional ways. Experts graded the rooted begonia cuttings into three classes: small, medium and large. The effect of grading unrooted cuttings and growing them with similar-sized cuttings was still apparent four weeks later: the rooted cuttings in graded units were more uniform than those in random units. Two models were constructed to determine the quality of the rooted begonia cuttings based on DIP measurements: one based on multiple linear regression and one based on a neural network. Both were able to grade at least 75% of the rooted cuttings in the same class as the expert. The neural network based model performed slightly (5%) better, especially for the classification of small and large plants. The lack of objective quality criteria is a major obstacle for the development of grading models for pot plants.

Keywords: begonia; image processing; pot plants; grading; cuttings; quality assessment; neural networks.

Introduction

Grading pot plants

Full-grown pot plants are commonly graded before they are sold because the quality of individual pot plants and the uniformity of the total group determine the price of a group of plants. Young and half-grown pot plants are usually not graded. Still, grading of these stages could provide many advantages. 1) Bad plants can be excluded in an early stage so that greenhouse space, energy, nutrients and labour input can be reduced; 2) The interaction between the plants within a graded group will be more uniform so that small plants will experience no competition from larger plants; 3) Treatments, such as application of growth regulators, can be tuned better to the stage of development so that consumption of growth regulators and other chemicals can possibly be reduced; 4) A complete compartment can be harvested in one operation, and completely filled with new plants so that labour input for harvesting can be reduced and the greenhouse space can be used more efficiently; 5) A uniform production process offers more possibilities for automation; and 6) Planning and management of the production cycle can be improved, since the number of plants in the various development stages are known.

Grading also has disadvantages. 1) Grading is labour intensive (Van Der Schilden & Hendrix, 1990). Grading is always combined with other operations such as planting or respacing. The work speed of these operations is reduced. 2) Grading involves a redistribution of the plants over groups. Thus, additional operations are needed. 3) The management of the production process becomes more complicated when different groups require different treatments.

To obtain good results, grading should be based on objective criteria and should be consistent. Humans can not grade objectively nor can they grade consistently. Grading by people is affected by the following factors. Firstly, grading criteria are based on specific and personal experience, and are difficult to be transferred to other people. Each grader tends to use his own criteria. Secondly, the accuracy and speed of the grading operation depends on the experience of the worker and on his physical and mental condition. Thirdly, the mean size of the plants (the reference) has an influence on the classification of the plants; grading by people is not consistent. And finally, the human grader can only grade into a limited number of groups.

Plant grading standards are available from auctions or from organizations like the American Association of Nurserymen. The standards contain specifications for many species in the full-grown stage, but are mostly qualitative. Brons *et al.* (1993) analysed the grading of flowering cyclamen by a panel of experts. They constructed a virtual expert with the use of Principal Component Analysis. When grading the leaves the correlation between the real experts and the virtual expert was rather low (between 64 and 87%), while for the flowers and the general impression the correlation always exceeded 80%.

Grading standards for unrooted cuttings and shoots are not available (because this stage is not commonly graded) and only limited criteria exist for the rooted cuttings and half grown plants.

In this paper we focus on the feasibility of applying DIP for grading unrooted and rooted begonia cuttings. We start with a brief introduction on DIP applications in agriculture. We review the culture process of begonia pot plants and present results of tests which evaluated the consistency of grading by an expert. We discuss the feasibility of using DIP to measure features which are possibly related to the quality of begonia pot plants; both for unrooted and rooted cuttings. The consistency of these measurements is discussed and the relationship with the expert's classification is analysed; the effect of grading unrooted cuttings on the quality of the rooted cuttings is presented and the development and performance of two grading models' are discussed. Conclusions on the feasibility of grading applications based on DIP are presented.

Digital Image Processing in Agriculture

Agricultural grading processes differ from industrial grading processes in a number of ways (Gagliardi *et al.* 1985). Firstly, each grading line has its own characteristics so that each application needs to be adapted to the particular use. Secondly, when inspection standards are available, they are subjective. And thirdly, the features which are used to grade agricultural objects cannot be determined with many commercial DIP products. These differences make it impossible to copy industrial DIP inspection applications directly to pot plants. However, the basic techniques can be applied.

Earlier Hines *et al.* (1986, 1987) performed research on grading container grown azaleas and yaupons based on monochrome signals from a video camera. Their system could give a good estimate of plant size and of top weight, but could nòt describe plant shape well. They suggested that a better plant grading system could be developed by defining a set of statistics, by measuring them and by asking the 'experts' to assign weighting factors to them. Cárdenas-Weber *et al.* (1988) developed algorithms to grade bare-root strawberry plants based on the evaluation of the number and length of the roots and on the size and condition of the root crown. They concluded that the accuracy of their system with 83% needed improvement, but that it was more consistent than human workers. Faster computers or different image processing algorithms would be necessary to enhance the speed of execution of their system. Simonton & Pease (1990) used image processing to identify the structure of unrooted geranium cuttings and the caliper of the main stem of these cuttings. Simonton (1990) used this information to develop a robotic workcell which calculated the optimal grasp location and orientation on the main stem, cut location on the main stem and location of leaves to be removed. The robotic system graded the cuttings into three classes based on their main stem caliper as measured with DIP. Fujiwara (1991) reported research on the evaluation of the quality of carnation seedlings with the aid of DIP. He extracted features from images which he recorded from top and side views with two CCD cameras, and applied fuzzy logic techniques to discriminate between good and poor seedlings.

Application of artificial intelligence techniques for grading full grown ornamentals was investigated by Brons *et al.* (1993). Steinmetz *et al.* (1994) and Timmermans & Hulzebosch (1996). Brons *et al.* (1993) worked with flowering cyclamens and analysed the grading behaviour of human experts with the aid of principal component analysis. They concluded that their panel of experts formed a homogeneous group. Correlation analysis showed that their classification of especially the leaves showed a large variation, while their judgement of the quality of the flowers and of the general plant was less noisy. They applied colour segmentation to process the images and developed a multiple linear regression model (MLR) and a neural network model (NN) to grade flowering cyclamens. The NN performed better than the MLR. Steinmetz *et al.* (1994) developed a system to grade cut roses with the aid of DIP. They applied Bayes decision theory to develop a classifier for straightness and maturity. Straightness was also classified by a NN. Timmermans & Hulzebosch (1996) described research on a grading system for pot plants based on DIP, statistical discriminant analysis and NN's. They showed that colour segmentation alone works well for grading flowering saintpaulia plants, but is not sufficient to qualify green plants such as cactus plants. They concluded that green plants are more complex to classify and require analysis of the structure of the plant.

Objectives

Summarising the above paragraphs, we concluded that grading systems based on objective standards would benefit the efficiency of pot plant production systems. Grading would create a more uniform crop and thus enhance opportunities for application of automated systems, and for increased efficiency of energy, labour, space and chemical input. Grading systems would require a method to measure and judge grading features in an objective and consistent way, with a high capacity and low labour input. Digital Image Processing (DIP), which had been used successfully in industrial application, seemed to be a potential tool for this task. Research on DIP based grading by others had focussed on the plant level.

Dijkstra (1994) concentrated on the system level and investigated the effect of DIP based grading of unrooted cuttings on the uniformity of the resulting pot plant crop. Here we present part of his work which concerns firstly the feasibility of classifying unrooted and rooted begonia cuttings with the aid of DIP, multiple linear regression models and neural network models and secondly, the effect of growing unrooted begonia cuttings among similar-sized cuttings on the uniformity of the resulting rooted cuttings.

Materials and methods

Plant material

The begonia pot plant is a flowering plant which is commonly propagated by specialised companies. These companies grow the mother plants from which cuttings are picked by hand. The cuttings are planted in so-called net pots (small plastic propagation pots with perforated bottom and side), they form roots and start to grow into new plants. After approximately four weeks (in the summer time), the cuttings have a well developed root system, three leaves and a growth tip. At this stage the cuttings are graded, either respaced or sold to other companies and then grown into flowering plants.

The research in this paper was carried out with material from propagation companies, with unrooted and rooted cuttings. We used the cultivar *Begonia (Elatior gr.)* 'Ilona'. Unrooted begonia cuttings have a well-developed 'first' leaf and a 'second' leaf which has started to develop. Rooted cuttings have three leaves and a growth tip.

Grading by an expert

An experienced employee responsible for quality control within a begonia propagation company was invited to be the expert. He was asked to classify one hundred unrooted and one hundred and fifty rooted begonia cuttings. The cuttings were labelled and were each classified five times into three classes. The score for each cutting was registered. In order to avoid the creation of a reference, the cuttings were not grouped but kept in their predetermined random order. The order of the cuttings was changed after each judgement run.

System configuration

The images described in this paper were made with a black and white camera (COHU-4722-2000/000). They were processed with a frame grabber (FG-100-1024 by Imaging Technology Inc.) and a PC by Olivetti (486/33MHz).

Unrooted begonia cuttings
When an unrooted begonia cutting is placed in its natural position on a flat plate, it has a more or less 2-dimensional structure. We placed each unrooted cutting on a diffuse transparent plate with back-lighting and recorded one image. The stem always pointed to the bottom of the image area (see Figure 1).

Rooted begonia cuttings
The rooted begonia cuttings grew in net pots and had a clear 3-dimensional structure. The features could not be captured from one image; instead we recorded and processed a side view and a top view for each rooted cutting. The side views were taken of the rooted cuttings in a fixed orientation. The stem of the third leaf can be located in a plane through the stem of the first and second leaf. This stem plane was always normal to the focal axis of the camera when the image was recorded. A diffuse, uniform lighting system was used as background (see Figure 2).

Figure 1. Image of an unrooted begonia cutting.

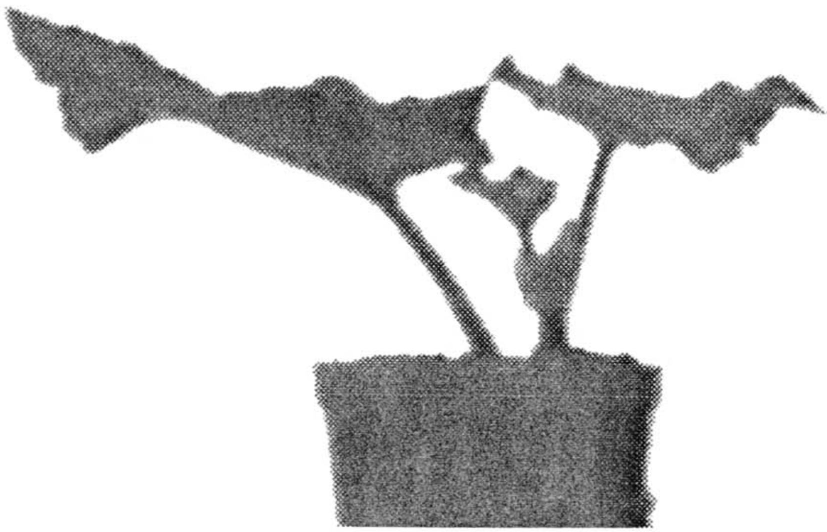

Figure 2. Side view image of a rooted begonia cutting.

All top views were taken from the rooted cuttings after placing them on a dark, light absorbing, background. The cuttings were lighted from above and from the sides with incandescent light tubes (see Figure 3). These light tubes emitted both

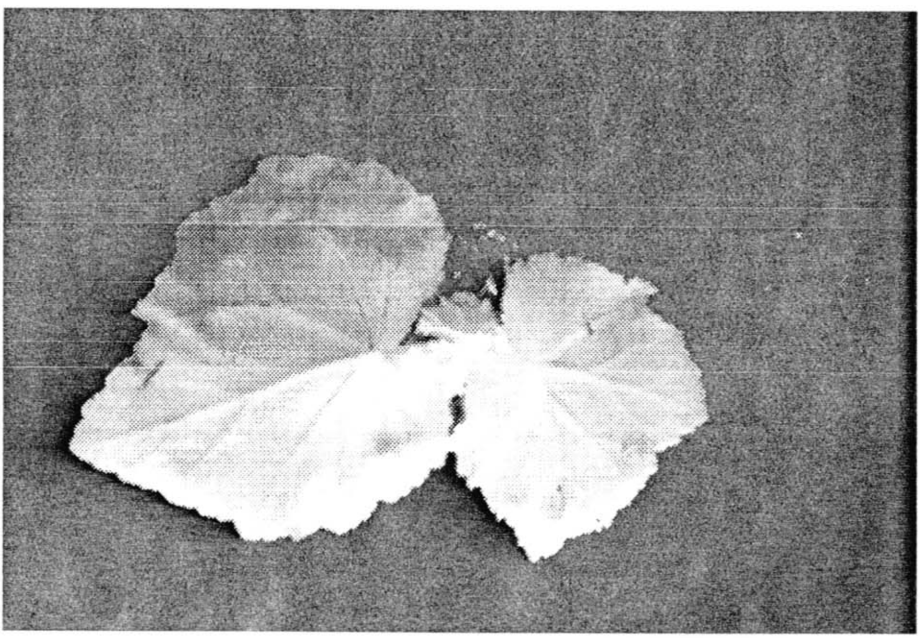

Figure 3. Top view image of a rooted begonia cutting.

visible and near-infrared (NIR) light. This made it possible to segment the plants from the soil, because leaves reflect more NIR light than the soil does.

Quality features and feature extraction

Individual parts of the cuttings, like the individual leaves, were identified and measured with a procedure which is based on models of the unrooted and rooted cutting. The procedure is based on so-called knowledge based segmentation. Simonton and Pease (1990) and Tillett (1991) applied similar procedures to identify the structure of geranium cuttings and of chrysanthemums, respectively. The procedure is described in detail by Dijkstra (1994). The following is a summary.

The procedure involves three steps: two segmentation steps and one identification step. The orientation of the cutting, and the direction of scanning are used in each of these three steps. The first step is called the raw segmentation. Run-length coding and connectivity of runs in adjacent scanning lines are used to identify the potential leaf and stem regions in the image and to estimate the average stem thickness. In the second step (the exact segmentation) the estimated stem thickness is used to reconstruct a stem-leaf structure by grouping the regions into segments. These segments are connected with pointers. The set of segments and pointers are used to identify and measure the individual elements of a cutting in the third step. The identification is based on a model of the structure of the cutting

Rules were developed to process areas which represent leaves which overlap other leaves or stems, holes in leaves and irregularly shaped leaves. Some of these features can be recognised in the unrooted cutting which is shown in Figure 4: it has a ragged first leaf with a hole in it, and a second leaf which overlaps the stem.

Unrooted cuttings
The structure of an unrooted begonia cutting is presented in Figure 5. The following

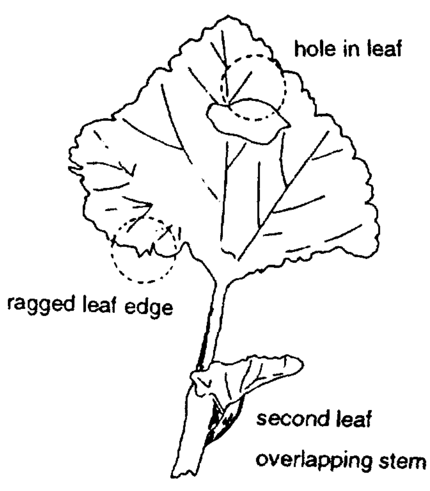

Figure 4. Unrooted begonia cutting with a ragged first leaf which has a hole in it, and a second leaf which overlaps the stem.

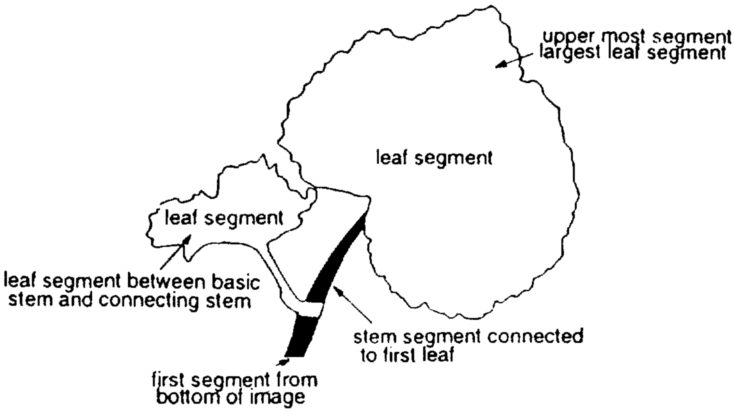

Figure 5. Model of the unrooted begonia cutting.

elements can be identified: the basic stem, which is the lowermost segment in the image; the first leaf, which is the largest, uppermost leaf in the image; the connecting stem, which is the longest stem connected to the first leaf; and the second leaf, which is the leaf between the basic stem and the connecting stem.

A special procedure was developed to determine the area of the leaves. The leaves of begonia cuttings are rugged, they may overlap other leaves or part of the stem, and they may be partly curled over. This means that the projected leaf area will not always give a good estimate of the real leaf area. A better estimate of the leaf area was obtained by exploiting the fact that begonia cuttings are not completely opaque so that overlapping and curled-over parts of the leaves occur as darker areas in transmission images than single flat leaves. These can be detected through analysis of the grey value histogram of a transmission image. The relation between the grey value and leaf 'thickness' is not linear. The grey value histogram was divided into 5 intervals of unequal length and weight factors were assigned to each of the intervals to calculate the corrected leaf area. The procedure was described in more detail by Dijkstra (1991). The procedure was limited to unrooted cuttings, since no transmission images were recorded from the rooted cuttings.

After segmentation and identification, the following features were calculated as indicated:

- Total corrected area of the cutting: the sum of the corrected area of all segments.
- Total corrected leaf area of the cutting: the sum of the corrected area of all leaf segments.
- Total corrected area of the second leaf: the sum of the corrected area of the segments identified as the second leaf.
- Projected area of the cutting: the sum of the pixels of all segments.
- Length of the cutting: distance between the uppermost and lowest point of the cutting. This feature is very sensitive to the orientation of the cutting.
- Width of the cutting: distance in the horizontal direction between the left most and right most point of the cutting. This feature is also sensitive to the orientation of the cutting.

- Ratio between length and width of the cutting: an indication of the roundness of the cutting.
- Ratio between length times width and total area of the cutting: an indication of the density of the cutting.
- Length of the connecting stem according to method 1: distance between the start and end points of the connecting stem.
- Length of the connecting stem according to method 2: distance between the end point of the connecting stem and the start point of the second leaf.
- Thickness of the stem: area of the longest stem segment divided by its length.
- Distance from the tip of the basic stem of the cutting to the optical centre: an indication of the density of the cutting.
- Mean distance of mass: the Euclidian distance of each plant pixel towards the optical centre. Another indication of the density of the cutting.

Rooted cuttings
New procedures were developed to segment and identify the features of rooted begonia cuttings. They are based on the structure of the rooted cutting as is shown in Figure 6. The approach was similar to the one for unrooted cuttings, but a redesign was necessary because of 1) the two views of each rooted cutting, 2) the varying orientation of the leaves, 3) the presence of a pot and 4) the existence of a third leaf. Special rules had to be developed to handle roots which extend beyond the net pot, to process large ground particles, and leaves which overlap the pot.

The features of rooted begonia cuttings which were measured with DIP included the following:
For the first, second and third leaf (the first being the oldest):
- the area as the sum of pixels of the projected area of that leaf
- the height as the uppermost point of that leaf, measured from the pot
- the junction as the height of the connecting point of that leaf

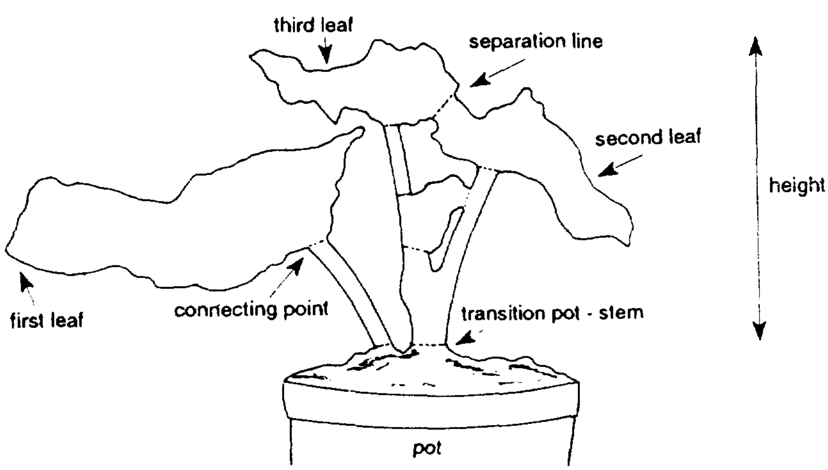

Figure 6. Structure of a rooted begonia cutting.

For the first and second and third leaf combined:
- the area as the sum of pixels of the projected area of both leaves
- the height as the uppermost point of the highest of the two leaves, measured from the pot
- the junction as the highest of the connecting points of the two leaves

For the whole rooted cutting:
- the total area as the sum of all pixels of the projected area of the cutting
- the total height as the uppermost point of the cutting
- the total junction as the highest of the connecting points of the three leaves
- the width as the distance between the leftmost and rightmost points of the cutting
- the height optical centre as measured above the pot
- the area top-view as the area of the largest object in the top-view
- the volume as the product of the area top-view and the total height of the cutting.

The results of the measurements with DIP were compared with those from destructive tests. After the cuttings were measured with DIP, they were cut into pieces. The length and thickness of the stem were measured with a caliper. The area of the leaf was determined by placing the leaf between two glass plates, so that it was totally spread out. The actual leaf area was then measured with DIP as the projected area.

Consistency and range of measurements

When the same cutting is presented to the camera in different positions and the same feature is measured with DIP, then the results will always show some variation. This variation should not be too large. To test the magnitude of this variation, a consistency test was carried out.

The consistency of the measurements for a specific feature can be calculated as:

$$Consistency = (1 - \frac{1}{n} \sum_{i=1}^{i=n} (\frac{1}{m} \sum_{j=1}^{j=m} \frac{abs\,(x_{ij}-\bar{x}_i)}{\bar{x}_i})) * 100\% \qquad (1)$$

where
m = number of observations for each cutting
n = number of cuttings
x_{ij} = measured value for the feature of cutting i in observation j
$\bar{x}_i$ = mean value for the feature of cutting i for all observations

A potential grading feature should have a consistency of at least 90 percent.

A feature can only serve as a grading criterion if it has a certain range. If the length of a cutting can be measured with a high consistency, but all cuttings have the same length, then length cannot be used for grading. The range of a feature can be calculated from its minimum and maximum value. The distribution function of the values was assumed to be normal.

The consistency and range of the DIP measurements were calculated from observations on fifty unrooted and twenty rooted begonia cuttings. All measurements were repeated five times.

Statistical methods

Correlation

Consistent DIP measurements with a satisfying range do not necessarily imply a good estimate of the feature. Comparisons with conventional methods are necessary. SPSS-PC was used to determine the Pearson correlation coefficients between the measurements with conventional methods and those with the DIP method. All r's were 2-tailed significant with an uncertainty of $\leq 0.1\%$.

Multiple linear regression analysis

Multiple linear regression analysis (MLR) was performed with the stepwise input selection method. The expert's classification was used as the dependent and the DIP features as the independent variables. The levels of uncertainty to enter and exit a feature were set at 5% and 5.5%, respectively.

Regression analysis can only be carried out on scalar variables. Therefore, we translated the expert's classifications of 'small', 'medium' and 'large' into the values 1, 2 and 3, respectively. The computer scores ranged between 0.5 and 3.5. A score below 1.5 was interpreted as small, between 1.5 and 2.5 as medium, and above 2.5 as large.

Grading experiments

With the objective to evaluate the influence of growing unrooted cuttings among similar-sized ones as opposed to growing them in a random mixture of all different sizes, we set up an experiment in two equal-sized growing units. For each unit we labelled 360 unrooted cuttings, measured them with DIP and planted them in net pots. The pots were placed in a square of 20 by 18 plants. The two units were set up in different ways: the first was graded, the second ungraded. The 360 unrooted cuttings in the two units were divided into 5 growth groups of 72 cuttings each. In the graded unit the growth groups contained cuttings of ascending corrected leaf area, so that growth group 1 held the smallest unrooted cuttings and growth group 5 the largest ones. In the random unit each growth group contained unrooted cuttings of all sizes. The experiment was carried out in duplicate; the first series was carried out between May 23 and June 17 of 1991, the second between June 7 and July 2 of 1991. Unfortunately, the usual expert was not available to grade the second experiment.

Size ratio

After a period of 4 weeks, the experts graded the rooted cuttings into three classes: small, medium and large. In order to compare their classification for the different growth groups, we determined the 'size ratio' from the percentages of small, medium and large plants as follows:

$$Size\ ratio = \frac{\%\ small * 1 + \%\ medium * 2 + \%\ large * 3}{2} - 50 \qquad (2)$$

Classification strategies

We evaluated two different types of models on their feasibility to grade rooted cuttings. The first type is based on the equations found through multiple linear regression analysis (MLR), the second on a neural network (NN). They are described in the following sections.

MLR
The relations which were found through MLR analysis were incorporated in a model to grade the rooted begonia cuttings automatically. As discussed earlier, the two experts used different features for grading. To model their individual grading, we used for each expert the regression equation which was found for 'their' graded unit so that we worked with two different equations.

NN
A grading model for rooted begonia cuttings was designed based on a NN. It consists of a three-layer feed-forward NN which learns with the back-propagation generalised delta rule (Rumelhart & McClelland, 1986; and Zhuang *et al.*, 1992). 18 DIP measured features were used as input; the output was defined as small, medium or large. An optimum number of 12 nodes in the hidden layer was found by iteration. A new training set was used for each experiment and for each unit.

Results

Grading by an expert

Unrooted cuttings
When the expert graded the unrooted cuttings a second time, he graded 66% of the cuttings in the same group as in the first judgement. After the third, fourth and fifth judgement the score dropped to 54%, 50% and 48%, respectively. It is not correct to conclude that the expert did a poor job; the main reason for a different classification in two runs was that he changed his standard.

The expert indicated that two features of unrooted begonia cuttings are important in his judgement: 1) the leaf area of the first and second leaf and 2) the length of the stem between the first and second leaf. A 'large' unrooted begonia cutting is dense and its second leave is large enough.

Rooted cuttings
The expert showed a higher consistency in the classification of the rooted cuttings than of the unrooted cuttings. In the first two tests he graded 87% of the rooted cuttings in the same class. After the third, fourth and fifth judgement the score dropped to 79, 73 and 68%, respectively. The expert identified two features as important in his judgement: 1) the development of the second and third leaf and 2) the density of the cutting. The first leaf was not considered to be important.

Feature measurements

Once we segmented and identified the various features of the cuttings, we measured the features with DIP, determined the consistency and range of these measurements and performed a correlation analysis with results from conventional methods. The results are presented in the following sections, first for the unrooted cuttings, then for the rooted cuttings.

Unrooted begonia cuttings

The results of the calculations of the consistency and of the range of the measurements with DIP are presented for the various features in Table 1. These show that all features, with the exception of the area of the second leaf and the length of the connecting stem were measured with a higher consistency than the required 90%. The second leaf is relatively small, and it can point in different directions when the cutting is placed in its natural rest position. The length of the connecting stem poses the same problem. Sometimes this stem is occluded by the second leaf, so that either this stem or the second leaf is not detected at all, and a value of 0 is measured.

The range of values is large enough to grade the plants into different groups. The consistency of the measurements of the corrected and projected leaf areas are similar.

The results of the correlation analysis with the conventional methods are presented in Table 2. These show that the total corrected area of the cutting is a slightly superior estimation of the area of an unrooted cutting over the projected area (r=0.87 vs r=0.82). These results also show that measuring the length of the connecting stem with method 2 (the distance between the end point of the connecting stem and the start point of the second leaf) is a clear improvement over that with method 1 (the distance between the start and end point of the connecting stem). And finally, these results show that the thickness of the stem cannot be measured well with DIP (r=0.50).

Table 1. Consistency of measurements on unrooted cuttings.

Feature	Consistency %	Range	Mean
Total corrected area, pixels	94.7	8,382-40,925	20,399
Total corrected leaf area, pixels	94.1	7,084-40,813	19,526
Total corrected area 2nd leaf, pixels	86.1	0-13,274	2,884
Total projected area, pixels	94.6	8,067-39,487	19,649
Length of cutting, pixels	95.8	109-266	172
Width of cutting, pixels	95.8	197-421	284
Ratio length/width	92.0	0.38-1.35	0.62
Ration length*width/area	94.9	0.21-0.72	0.42
Length conn. stem, method 1, pixels	77.0	2-176	71
Length conn. stem, method 2, pixels	89.7	0-196	110
Tickness of stem, pixels	90.0	5.2-23.1	8.0
Distance optical centre to tip basic stem, pixels	97.7	102-263	176
Mean distance mass, pixels	95.6	51-92	66

Table 2. Pearson correlation coefficient between features of unrooted begonia cuttings measured with DIP and conventional methods.

DIP feature	Conventional feature	Pearson r
Total corrected area	Area of flat cutting	0.87
Total corrected leaf area	Area of flat leaves	0.87
Total corr. 2nd leaf area	Area of flat 2-nd leaf	0.88
Total projected area	Area of flat cutting	0.82
Length conn. stem, method 1	Length of stem	0.70
Length conn. stem, method 2	Length of stem	0.83
Tickness of stem	Tickness of stem	0.50

Rooted begonia cuttings

Most features of the rooted cuttings could be measured with DIP with a consistency greater than the required 90%. Below this target were the consistencies of the assessment of the area and of the junction of the two youngest leaves. The expert indicated that the combined area of the two newest leaves is important in his judgement and this could be measured consistently (91.9%).

Correlation analysis between conventional measurements and those with DIP showed that the features of individual leaves were not measured with a high degree of accuracy (Pearson correlation coefficients around 0.60). The area of the two youngest leaves combined could be determined with an r-value of 0.83. The area in the top-view provided a good estimate of the total leaf area (r=0.90) despite overlapping leaves.

MLR Analysis

The results of the MLR analysis which we performed to reveal the relation between DIP measured features and the qualification by the expert are presented in Table 3. For the second experiment we found stronger relations (multiple r values of 0.81 and 0.76) than for the first experiment (0.69 and 0.68). The analysis also shows that different features are related to the expert's classification in the two experiments. The expert who graded the second experiment indicated that he judged height as an important feature, while the expert for the first experiment valued the area of the second and third leaf. Since height was measured more accurately than the area of the second and third leaf, the better relationship could be expected.

Grading experiments

We used the expert's qualification of the rooted cuttings to calculate the size ratio for the five growth groups (see Table 4). The size ratio's in the graded units increased with the growth groups, while in the random units no relation was found. This indicates that the effect of grading unrooted cuttings and then growing them among similar-sized cuttings persists for four weeks in both experiments.

Table 3. Results of the MLR analysis between the expert's classification and the DIP measured features of rooted begonia cuttings.

		Experiment 1		Experiment 2	
Feature		Graded	Random	Graded	Random
Multiple r		0.69	0.68	0.81	0.76
r^2		0.48	0.46	0.67	0.58
First leaf	Area	·	·	·	0.16
	Height	·	·	0.27	−0.18
	Junction	·	−0.20	·	0.31
Second leaf	Area	−0.11	·	0.11	0.18
	Height	·	·	0.23	−0.17
	Junction	0.12	·	·	0.40
Third leaf	Area	−0.19	−0.16	0.46	·
	Height	0.01	0.49	·	·
	Junction	·	·	0.15·	·
Second + third leaf	Area	·	·	·	·
	Height	·	0.32	·	·
	Junction	·	·	·	·
Total area cutting		0.39	·	·	·
Total height cutting		−0.01	·	1.30	1.18
Highest junction		·	·	·	·
Width cutting		·	−0.01	·	·
Height optical centre		·	·	−0.34	·
Area top view		−0.52	·	1.26	1.32
Volume		0.87	0.20	−1.57	−1.64
Number of plants		359	359	346	336

Classification strategies

The numbers of rooted cuttings which were classified as small, medium and large by the expert and by the MLR based model are shown in Table 5. The same cuttings were graded with the NN based model. These results are presented in Table 6. In order to evaluate the performance of the two approaches we calculated the percentages of rooted cuttings which were classified identically (=correct), 1 class differently (=1st order error) or 2 classes differently (= 2nd order error) for both the MLR and the NN models. The results are presented in Table 7.

The regression based model graded approximately 80% of the rooted cuttings in the same group as the expert, while it never graded rooted cuttings with 2nd order errors. The performance of the regression models for experiment 1 and experiment 2 were very similar, with 81% and 76% of the rooted cuttings graded in the same class as the expert. The multiple r-values for the two equations in Table 3 were 0.69 and 0.81, respectively. Apparently, the multiple r does not predict the performance of the model.

The NN classified 5% more rooted cuttings correctly than the MLR model did. This improvement was mainly a result of the more correct classification of the small

Table 4. Grading results by the experts for the graded and random units.

Exp.	Growth Group	Graded units				Random units			
		Expert Judgement				Expert Judgement			
		Small	Medium	Large	Size Ratio	Small	Medium	Large	Size Ratio
	1	7%	86%	7%	50	4%	68%	47%	72
	2	5%	92%	3%	49	8%	71%	21%	57
1	3	10%	75%	15%	53	6%	71%	23%	59
	4	4%	56%	40%	68	4%	71%	25%	61
	5	3%	34%	63%	80	4%	73%	23%	60
	1	31%	56%	13%	41	18%	23%	59%	71
	2	37%	41%	22%	43	12%	29%	59%	74
2	3	9%	38%	53%	72	1%	43%	56%	78
	4	6%	27%	67%	81	13%	36%	51%	69
	5	6%	18%	76%	85	3%	28%	6%	83

and large cuttings. The NN made 2nd order errors in experiment 2. Most of the cuttings involved proved to be irregular in shape and the expert was ambiguous in their classification.

Discussion

Measurements with DIP

The DIP measurements of the unrooted cuttings showed a higher correlation with the conventional measurements than those for the rooted cuttings. This could be a result of the orientation of the leaves in relation to the camera which is less well-defined in

Table 5. Numbers of rooted begonia cuttings judged in classes by the regression equations and by the experts.

Experiment	Expert judgement	Regression judgement					
		Graded units			Random units		
		Small	Medium	Large	Small	Medium	Large
	Small	8	13	0	6	13	0
1	Medium	2	228	16	4	218	19
	Large	0	38	54	0	39	61
	Small	36	25	0	13	18	0
2	Medium	10	104	12	3	87	17
	Large	0	35	124	0	29	169

Table 6. Numbers of rooted begonia cuttings judged in classes by the neural network and by the experts.

Experiment	Expert judgement	Neural network judgement					
		Graded units			Random units		
		Small	Medium	Large	Small	Medium	Large
	Small	15	6	0	10	9	0
1	Medium	0	240	6	2	223	16
	Large	0	35	57	0	30	70
	Small	40	18	3	29	2	0
2	Medium	6	82	38	4	91	12
	Large	0	6	153	2	29	167

Table 7. Performance of the regression models and neural network.

	Experiment 1				Experiment 2			
	Graded		Random		Graded		Random	
	MLR	NN	MLR	NN	MLR	NN	MLR	NN
Number of cuttings	359	359	360	360	346	346	336	336
Correct, %	81	87	79	84	76	79	80	85
1st order error, %	19	13	21	16	24	20	20	14
2nd order error, %	0	0	0	0	0	1	0	1

the rooted cuttings. The individual parts of the rooted cuttings were identified correctly in 99% of the cases. The presence of certain parts is more important than their individual size. The routines described in this paper can only be applied to plants with a clear stem-leaf structure. In more complex plants such as a twelve week old begonia plant, the individual leaves and stems cannot be distinguished. The work by Timmermans & Hulzebosch (1996) suggests that grading of this growth stage would still be most successful on the basis of the analysis of the structure of the plant.

Grading experiment

In our experiments we found that the effect of grading unrooted cuttings and growing them with similar-sized cuttings, resulted in a more uniform crop. Whether the unrooted stage is the optimum stage for grading is another question which is interesting to investigate.

Classification strategies

The experts were more consistent in grading the rooted begonia cuttings than in that of the unrooted cuttings. This was not unexpected, since unrooted begonia cuttings are not commonly graded and the experts had little or no experience with grading this growth stage.

The experiments showed that the two experts apply different criteria in grading begonia cuttings. This agrees with the results of Brons *et al.* (1993) who found that a homogeneous panel of experts graded flowering cyclamens with a considerable variation. This was especially true for the quality of the leaves. This suggests that human grading of cuttings will always show a large variation, since these can only be graded on the basis of the quality of their structure and of their leaves. Hence, it would be desirable to perform grading experiments with cuttings with a larger group of experts so that the variation in their evaluation can be processed. The problem of the availability of such experts remains. Development of objective quality criteria would solve this problem.

Both the MLR and the NN classified more than 75% of the cuttings in the same group as the expert. In the study on the consistency of the experts we found that in two consecutive judgements they classified 87% of the rooted cuttings in the same group. Thus, part of the difference in classifications by the models and by the expert is probably caused by a 'misclassification' by the models, while an other part is 'misclassified' by the expert. Again, a larger panel of experts or objective quality criteria would facilitate the development of these models.

In these experiments we used three discrete qualification groups: small, medium and large. Brons *et al.* (1993) asked the experts to grade their flowering cyclamen in such a way that the results could be translated into a numerical grade. Their approach offers the possibility to order the plants in a continuous way which facilitates the comparison of the qualifications by the experts and those of the models. The question remains whether this approach is feasible for begonia cuttings, since experience with grading this growth stage is limited or non-existent.

Both the MLR and the NN showed to be useful tools for grading rooted begonia cuttings, where the NN performed slightly better than the MLR. This agrees with the findings by Brons *et al.* (1993) in their experiments where NN was also superior over MLR for grading flowering cyclamen. Timmermans & Hulzebosch (1996) also found that NN performed better than discriminant analysis for the classification of cactus plants, while both approaches showed similar performances in the grading of flowering saintpaulia plants. All these experiments on application of artificial intelligence techniques suggest that the performance of NN's in grading green, flowering, full-grown or young pot plants makes up for the disadvantage of the black-box approach.

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