APPLICATION OF DIGITAL IMAGE PROCESSING FOR POT PLANT GRADING

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APPLICATION OF DIGITAL IMAGE PROCESSING FOR POT PLANT GRADING

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flowering Saint Paulia's

Abstract

The application of digital image processing for grading of pot plants has been studied. Different techniques e.q. plant part identification based on knowledge based segmentation, have been developed to measure features of plants in different growth stage. Growth experiments were performed to identify grading features and to test whether it is possible to grade pot plants in homogeneous groups. Judgement experiments were performed to test whether it is possible to grade plants as good as man do. For the grading experiments decision models based on regression equations and neural networks have been developed.

Stellingen

1. Sorteren van potplanten in een vroeg ontwikkelingsstadium leidt tot een betere beheersing van de teelt.
   - Dit proefschrift

2. De menselijke waardering van potplant kenmerken is verre van consistent: zij lijdt onder vervagend normbesef.
   - Dit proefschrift

3. Door een sorteerder in een objectieve discussie de subjectieve kennis over kwaliteitsnormen te laten uitleggen, neemt het kwaliteitsbesef toe.
   - Dit proefschrift

4. De computer overtreft de mens niet met betrekking tot de nauwkeurigheid bij het beoordelen van een individuele potplant; echter hij is wel consistenter.
   - Dit proefschrift

5. Voor een meer reële uitbetaling aan de bietenteler kan het vaststellen van de hoeveelheid winbare suiker beter gedaan worden op basis van de gehele biet, dan op basis van een na-gekopte biet.

6. De stelling van Hofstede dat "In the design of planning systems, the chances of producing a system that is valued by users are highest if the first step is the development of a user-system interface that is understood and accepted by the user" is nog volledig houdbaar.
   - G.J. Hofstede, Modesty in modelling, proefschrift Landbouwuniversiteit (1992).

7. De kennis van de banen van kunstmestkorrels is nog onvoldoende om strooibeelden te berekenen. De variatie in grootte en vorm van de korrels maakt een sorteeractie om de uniformiteit te vergroten noodzakelijk.

8. Bij het schrappen van het voorvoegsel Landbouw verliest de Landbouwuniversiteit de grond van haar bestaan.

9. De consistentie waarmee een sorteerder potplanten beoordeelt is vergelijkbaar met de consistentie waarmee een begeleider een stuk tekst beoordeelt: een ruw concept kan vergeleken worden met een stek en een uitgewerkte tekst met een bloeiende plant.

10. Voor serieus programmeerwerk is een programmeertaal als C onontbeerlijk.
    - Automatiserings Gids, 28 oktober 1994.

11. In navolging van files op een zonnige zondag op de autosnelweg richting kust, ontstaan er op een regenachtige zondag files op de digitale snelweg richting amusements "programma's".

Stellingen behorende bij het proefschrift van Jouke Dijkstra:
Application of digital image processing for pot plant grading.
Wageningen, 22 december 1994

Voorwoord

Een proefschrift kan niet tot stand komen zonder de hulp en inspiratie van vele mensen. Daarom wil ik de volgende personen bedanken voor hun inzet en inbreng in het onderzoek:

mijn directe begeleider ir. Jan Meuleman voor zijn enthousiaste inzet voor het onderzoek. Ook op onmogelijk tijdstippen en afgelegen lokaties is Jan nog steeds enthousiast te krijgen. Een nimmer ophoudende bron van inspiratie voor nieuwe ideeën waar je het niet altijd mee eens hoeft te zijn, maar er blijven voldoende ideeën over,

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Contents

1 Introduction

'All animals are equal, but some are more equal than others'. But how about plants? Looking at a group of plants of the same species, an observer may say that they all are equal. Inspecting the plants more closely, differences between individual plants may be noticed. Is there any need to separate these plants from each other and is it possible to perform this separation without human interaction?

Research at the Experimental Research Station for Flower Research at Aalsmeer, the Netherlands, showed that the harvesting of pot plants is inefficient and labour intensive (van der Schilden et al., 1990). Pot plant production is also affected by the inefficient use of greenhouses. By increasing uniformity in groups of plants, harvesting should be more efficient because these groups can be harvested at the same moment. This results in a more efficient use of greenhouse space.

To create uniform groups, plants have to be graded. It has been shown that human graders have problems with grading consistently and continuously. Therefore other techniques should be developed. A potential solution to the problem of grading without human interaction is digital image processing (Meyer et al., 1985; Hines et al., 1987; Cardenas-Weber et al., 1988; Chen et al., 1991; Brons, 1992).

In 1985, the Department of Agricultural Engineering and Physics at Wageningen Agricultural University (WAU) became involved in the application of digital image processing in grading processes. A research project on the application of digital image processing for grading tasks in horticulture was started in co-operation with the Experimental Research Station for Flower Research in 1988. The initial results of this project are presented in this thesis.

1.1 Grading

Processing of agricultural products is closely tied to grading operations. There are hardly any products on the market that have not undergone some sort of grading operation. Grading in this context includes all operations which segregate a material with a mixture of attributes, 'raw material', into distinctive groups or grades. The concentration of the material with particular attributes in these groups is much larger than in the raw material. Some common examples of grading operations involving agricultural products are cleaning and sizing seeds, separating grain from chaff, separating out clods and dirt, sizing and sorting fruit and vegetables, and sizing eggs by weight. (Peleg, 1981).

Horticulture also involves considerable grading. In pot plant cultivation most grading is done manually. The quality and size of pot plants are defined by visually determined features. The human vision system in itself is superior to any other vision system however the opportunities for a human to classify using his vision system are limited. Man are good at comparing two objects but as soon as they have to classify individual objects without seeing other objects or a standard, their classification will vary over time because of changing subjective 'standards'.

In Figure 1.1, a classic example of human misinterpretation is translated to the pot plant situation.

Grading is a tedious job and requires constant concentration. In addition to the problems associated with applying the correct standards, it is hard to find people who are able to perform the grading task satisfactorily. The main reasons for this are the relatively low wages paid and the uncomfortable work environment. Training people for the grading task can sometimes take six months and many graders quit after one or two years. Nevertheless, the market demands products of standardised and uniform quality which cannot by produced by humans so it should be searched for automated systems using objective 'standards'.

Before discussing the need for automatic grading in pot plant cultivation and the concept of computer-camera systems, there is a brief description of horticulture in the Netherlands. This is followed by a discussion of the possibilities for introducing automatic grading systems into horticultural production given the present state of the art in greenhouse automation.

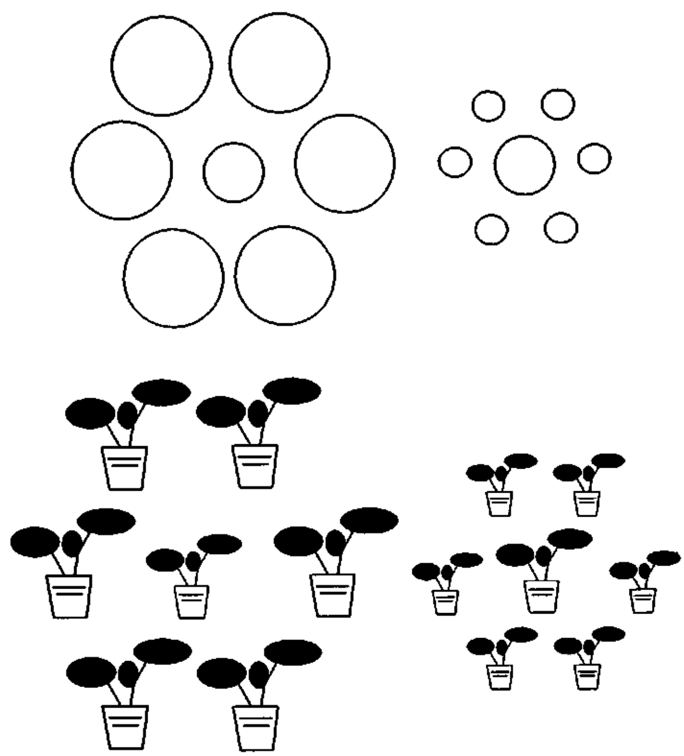

Figure 1.1 Human misinterpretation in grading pot plants

1.2 Pot plant cultivation in the Netherlands

Many Dutch greenhouses are to be found in such horticultural areas as 'het Westland' and 'de Kring' in Aalsmeer. In 1989 the Dutch greenhouse industry occupied about 9500 ha, 10 percent of which was used for pot plant production. It is the fastest growing sector in the greenhouse industry. From 1970 to 1990, the annual growth rate was about 10 percent (Ploeger, 1992). Pot plants are cultivated in plastic or earthenware pots and are produced for ornamental use in offices and homes. The ornamental value of the pot plant is determined by its leaves, its flowers or both. Pot plant production is divided into two categories: flowering plants and green plants. Table 1.1 shows the area of greenhouse space occupied by each category from 1970-1991. Although there is a decrease in the number of nurseries, the area they cover is increasing. The number of large nurseries - more than 10.000 m^2 - has grown very quickly in the last decade and this type of nursery is highly mechanised and automated.

Table 1.1 Area of pot plants in greenhouses, divided in green and flowering plants (Ploeger, 1992).

year	flowering plants (ha)	green plants (ha)	total (ha)	number of nurseries	nurseries > 10.000 m^2
1970			145		
1980	282	272	554	1832	101
1985	301	385	686	1680	
1990	425	559	983	1765	311
1991	447	598	1045		

The Netherlands is one of the worlds leading pot plant producers. In 1992, production from the 1700 pot plant nurseries was valued at 1.5 x 10^9 NGL and a large proportion came from export (80 %). The nurseries themselves are very specialised. The mean number of different species at large nurseries (>5000 m^2) is 3.0. Thirty-five percent of these nurseries grows one specie. A new type of nursery with division of labour, an extensive process automation, and up to fifty employees is becoming more prevalent. Size and profitability of pot plant nurseries are strongly correlated (Hofstede, 1992).

There are over a thousand different registered products and almost all of these require a specialised production process. According to Bots (1991) the products differ in number of cultivation stages, density per stage, stage length, number and nature of manipulations, climate requirements, light-, water-, nutrition requirements, treatment against diseases, growth regulation, and the way they are reproduced. All these details make the products quite different from each other. New products are also being introduced frequently, so it is hard to get exact data on pot plant production, cultivation, and grading strategies.

The main difference between pot plant production sector and other branches of the agricultural industry is its high rate of innovation and the independence of the individual pot plant grower as entrepreneur. The successful operation of a large pot plant nursery depends to a large extent on adapting innovations (Alleblas, 1987). Initiatives by pot plant growers include setting up nurseries in Brazil or Spain, planning labour peaks during school holidays, creating a brand name or a new product, setting up their own genetic research, as well as following Paris fashion magazines to determine what colours to cultivate. (Hofstede, 1992).

Figure 1.2 gives an example of a nursery lay-out. Usually a nursery is not so straightforward as the figure and there may be greenhouses of different ages, size and technical cultivation systems.

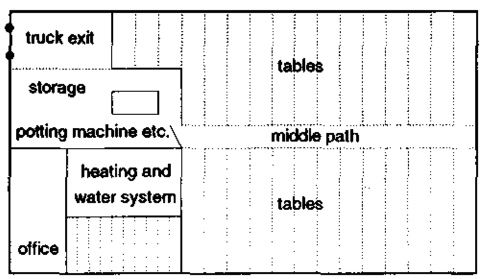

Figure 1.2   An example of a nursery lay-out

1.3 Automation in pot plant production

Production systems for pot plants differ. They can be grown, for example on the ground, on concrete floors, on fixed tables that can be rolled aside, or tables that can be automatically transported ('containers'). Table 1.2 shows the percentage area devoted to these different production systems. Depending on the nature of the production system in use, the plants are transported to a central location for each manipulation. This occurs most frequently when internal transport is automated, e.g. by containers or conveyor belts.

Table 1.2 The percentage of area of pot plants per production system in 1989 (Ploeger, 1992).

Production system	Percentage
Ground	34%
Fixed tables	18%
Concrete floors	14%
Movable tables	14%
Containers	11%
Tempex plates	6%
Others	3%

Climate control in most greenhouses is highly automated (opening and closing of windows, the regulation of the CO_2-level, light, temperature, and watering). Manipulations such as making cuttings, planting cuttings, grading plants, and preparing the final products for transportation have hardly been automated at all yet. The potting machine is the most common item of mechanisation in nurseries. Over 80 percent of the large nurseries (> 5.000 m^2) use a potting machine. Most spacing is still done manually, even in the large nurseries (Table 1.3). This is because there is a lack of good automatic systems (Ploeger, 1992).

The internal transport of pot plants in nurseries has become a lighter task because plastic pots are used instead of earthenware ones. However, without mechanisation it is a physically heavy task and little mechanisation has been introduced so far (Table 1.4).

Table 1.3 The percentage nurseries in the Netherlands per size class using different methods for spacing in 1989 (Ploeger, 1992).

area in m^2	unknown	manual	manual/ mechanical	mechanical	no spacing applied
< 1 000	10 %	81 %		1 %	8 %
1-2 000	9 %	83 %	2 %	2 %	4 %
2-5 000	1 %	87 %	1 %	6 %	5 %
5-10 000		79 %	6 %	10 %	5 %
>10 000	1 %	69 %	5 %	22 %	3 %
average of all nurseries	3 %	80 %	3 %	9 %	5 %

Table 1.4 The percentage of nurseries in the Netherlands per size class using different methods for internal transport in 1989 (Ploeger, 1992).

area in m^2	unknown	manual	manual/ mechanical	mechanical	automatic
< 1 000	10 %	87 %		3 %	
1-2 000	9 %	89 %		2 %	
2-5 000	1 %	84 %		15 %	
5-10 000		68 %	2 %	27 %	3 %
>10 000	1 %	49 %	4 %	40 %	6 %
average for all nurseries	3 %	77 %	1 %	17 %	2 %

From Table 1.4 it can be concluded that automatic transport is only implemented in nurseries larger than 5.000 m^2. This can be explained by the high cost of implementation (Ploeger, 1992).

In chapter 2 it is discussed that for a successful implementation of an automatic grading system additional handlings should be avoided. This means that the internal transport has to be automated. Another important condition for the implementation of automatic grading is that large batches of plants are processed. This reduces the number of switchings in the system. Grading for example, has to ensure that groups of plants are large enough to fill a whole compartment. Large nurseries, with only a few different plant species, meet this condition. As mentioned before, the mean number of different species on large nurseries (>5000 m^2) is 3.0. Given the increasing number of large nurseries (Table 1.1), it can be assumed that the possibilities for implementing automatic grading systems will increase in the coming years. Chapter 2 discusses the question of in which stages grading should take place in the production process and the conditions that have to be taken into consideration.

The main research hypothesis in this study is:

Grading of pot plants by means of digital image processing at (a) certain stage(s) of growth results in more homogeneous groups of plants.

The following research questions have been identified:
1. Why should plants be graded? Grading of plants should increase their value or may improve the efficiency of the production process. An analysis of the grading process is given.
2. At which stage of growth should plants be graded? Although grading of plants can be applied at all stages of growth, grading at particular growth stages may be more efficient. An analysis of the potential grading points is given.
3. Why should grading be done automatically? At the moment grading is mainly done by man based on a complex set of features. The problems concerning the human grader are discussed.
4. Is it possible to measure features of plants using digital image processing? Digital image processing has already been in use for several years for medical and military purposes and has been implemented in the electronic and automobile industry, but is in development for the agriculture. Methods have to be developed to measure complex agricultural objects which have no predefined shape.
5. Which features should be measured in order to grade plants into uniform groups? At the moment grading is done visually by man using subjective criteria. An analysis concerning the identification and testing of grading features is presented.
6. What is the effect of grading plants at different stages of growth? Case studies using different plant species are performed to test the effect of grading at different stages of growth.
7. Is it possible to grade plants using digital image processing qualitatively as good as when grading is done by human beings? Different decision systems are presented for performing the grading operation and these are compared to the results of human grading.

1.4 Scope of the study

Digital image processing has been chosen as the sensor technique for measuring plant features. This technique can be applied to measure features of all kind of plants. In this study, the focus is on pot plants. This decision is based on the following:

1. The measurement of plant features in singularised plants is already complicated. The measurement of features in images with multiple overlapping plants would be even more complicated. It has been decided to use singularised plants to ensure that the project could be carried out.
2. The system is fixed in one place because it is necessary to control the environment for the image acquisition. This means that the plants have to come to the system.
3. To measure the effect of plant grading, plants should grow in a controllable environment which should remain the same throughout the experiment. This is possible in a greenhouse.
4. In a later utilisation stage, the system is most profitable when used in the context of a year round cycle.
5. In order to develop a grading system, it must be possible to compare the results collected to particular standards.

Pot plant cultivation meets these criteria. They can be treated as individual units, can be transported, are grown in greenhouses, are produced the whole year round, and already many of the grading operations are done by human beings.

1.5 Structure of the thesis

In Chapter 2, the need for grading in pot plant cultivation and the stages in the growth cycle when grading should be carried out are discussed. In Chapter 3, the use of digital image processing in agriculture, especially in horticulture, is discussed, including the setting-up of a grading system. An important part of digital image processing is the identification of grading features. This is discussed in Chapter 4. The lack of knowledge about suitable grading features and decision rules makes it necessary to perform growth and judgement experiments. The experimental set-up and methods for these experiments are explained in chapter 4. In Chapter 5, 6, and 7 experiments using different species are discussed. In Chapter 8 the results of experiments with different species are used to draw general conclusions about using digital image processing as a grading tool.

2 Grading in pot plant cultivation

2.1 Introduction

In Chapter 1, the possibilities for implementing automatic grading in the pot plant cultivation has been discussed. This chapter analyses the grading problem. It discusses the reasons for grading and the need for automatic grading, indicates when it should be done and how grading is carried out in the present production process. Basic requirements for an automatic grading system are formulated on the bases of these considerations.

Plant grading in agriculture is already used for research purposes. Its objective is to test plants against predefined quality standards in order to assign individual plants to different groups. Uniform groups are created and poorly developed plants are removed in this way. Major applications are (Cardenas-Weber et al., 1988):
- selecting and measuring plants for a research experiment;
- determining which plants are ready for planting in a nursery;
- classifying plants for marketing purposes.

The grading processes discussed in this thesis are performed on pot plants which are reproduced by cuttings or shoots, because this is the most common way of reproduction here. Other reproduction techniques, like tissue culture and seedlings, are beyond the scope of this study.

2.2 Why grade in pot plant cultivation

The general objective in pot plant cultivation is to produce full-grown plants of the desired quality as efficiently as possible. By grading the plants in different stages in the growth cycle, this objective can be achieved in a more efficient way. Grading at the beginning and during the growth cycle has major advantages:
- possibility of excluding bad plants at an early stage. If it is known which plants will not develop into marketable plants, they can be excluded and the amount of energy and space needed can be reduced. Since these plants need not to be removed during the growth cycle or at the harvest, labour is saved;
- reduction of plant interaction effects. If a small plant is placed between large plants, competition will affect its growth response. A more favourable situation is when the plant is placed in a group of plants of uniform size. After grading, small plants will get better opportunities to develop into marketable plants because they are not in competition with large ones.
- the right action can be taken at the right moment. For instance growth regulators can be used at the right stage of development. Besides, regulators can be used more efficiently which may cause a reduction in the total amount of regulators that need to be applied.

- if it is known which parameters determine the growth of the plant, measurements can be taken to produce the 'optimum plant'. This can result in different treatments for smaller and larger plants;
- reduction of labour during harvest. Manual picking of plants one by one from the greenhouse is labour intensive. Uniform growth groups enable a group of plants to be harvested at the same time.
- better possibilities for automation of the whole process. In automated systems where plants are harvested by pick and place robots, no additional grading and transportation is needed to sort out plants that are not yet ready for market;
- better space utilisation. If a group can be harvested at one time, no plants will be left in the compartment and the whole compartment can be filled with new plants;
- better possibilities for managing the production cycle. The number of plants as well as their development stage are known.

Plants are also graded at the full-grown stage before being sold. Here the price of a group of plants is determined by the quality of the individual plant and the uniformity of the total group. Therefore, consistent grading is important in the full-grown stage to create groups of a constant quality.

Grading also has disadvantages. It is labour intensive and it slows down the speed of the operation, e.g. during the separation of shoots or re-spacing of half-grown plants. Decisions concerning plant size take time. Grading also involves a redistribution of plants over groups, and so additional operations are needed to separate the groups of plants. The operation in the greenhouse becomes more complicated when there are more groups of plants needing different treatment.

Theoretically, grading at the young stage should be sufficient to create uniform quality groups at the full-grown stage. However, in practice there are many external factors which influence plant growth. It can be stated that, in order to optimise the growth process, grading should be carried out several times during the growth cycle. From an economic and logistic point of view, the number of operations should be minimised and, therefore, the best points in the growth cycle to perform grading are those which can be combined with other physical operations. A physical operation means that a plant is moved and so redistribution over different groups can be accomplished easily. Section 2.3 describes such physical operations. Research related to the most optimal grading points with respect to the profit and cost of the grading operation is beyond the scope of this study.

2.3 Where to grade in pot plant cultivation

Processing in a greenhouse was studied in order to determine the physical operations involved in pot plant cultivation. To find points for the integration of grading within the total production process, three categories have been defined. These are mainly based on the different growth stages:

1. operations carried out at the young stage: operations at the beginning of the growth cycle, e.g. planting of cuttings or shoots;
2. operations during the growth cycle: operations during plant growth, e.g. transplanting and re-spacing;
3. operations at the full-grown stage: operations at the end of the growth period, e.g. collecting the plants from the greenhouse and preparing them for the auction.

In Figure 2.1 the operations at the different growth stages, including grading points, are shown. Grading points are identified by a physical operation during which the plants are singularised. The grading points which are discussed are potential ones.

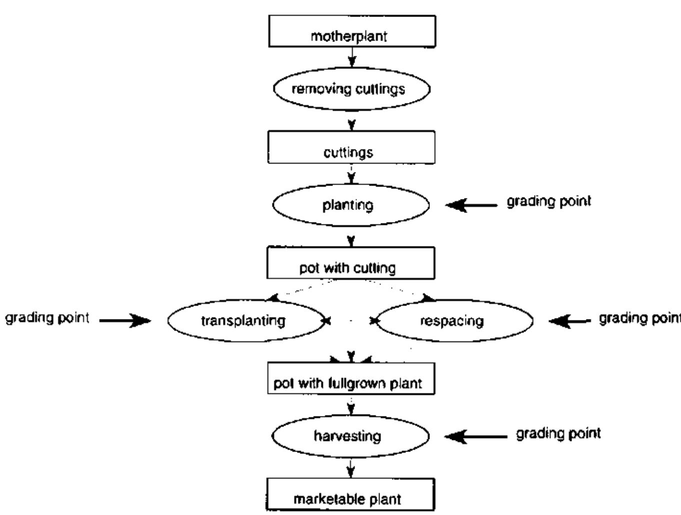

Figure 2.1 Operations at the different growth stages.

1. Physical operations and grading at the young stage.
   To supply the growers with new plants for production, so-called mother plants are grown. Depending on species, plants are either multiplied by cuttings or shoots.
   The first potential grading point is the moment when cuttings are taken from the mother plant or when shoots are separated from a cluster of plants. When grading is done at this stage, it is performed manually. The need for grading in this stage depends on the nature of the plant material.

   Shoots are graded more often than cuttings, due to the origin of the plant material. At a certain moment a cluster of shoots, consisting of plants of different sizes, is separated. This implies that the variation in the group of young plants is reasonably large. Cuttings are removed from the mother plants. The workers can decide which cuttings they remove and which ones will remain on the mother plant for another growth period. As a result, the group of young plants has a reasonable uniformity.

   The next potential grading point is the planting of the cuttings or shoots in the growth medium. Grading at this point is done by removing 'exceptional' plants. Grading between picking and planting, a transition stage, is difficult. The shoots and cuttings are packed together in containers immediately after picking or separation. Then they are transported to the planting location or temporary storage. The production of cuttings and shoots is not necessarily performed by the same firm as the production of full-grown plants. During this stage the cuttings and shoots are not singularised. To avoid additional manual operations, they should be separated automatically. The mechanical separation of cuttings or shoots has not yet been successful.

2. Physical operations and grading during the growth cycle.
   At the start of the growth cycle, small plants are put in a pot or other medium. This medium will not necessarily be the same for the whole growth cycle. During the growth cycle different physical operations are performed like transplanting and re-spacing. At these points grading can be carried out to create uniform growth groups or to exclude bad plants. For example during re-spacing, a group of plants is regraded into two groups based on features such as leaf area, number of leaves, length of internodes, branch points, development of certain parts, colour, number of flowers, development of flowers, and height. At the moment, the grading operation is performed manually even in locations where the internal transport of plants is highly automated and pick and place robots and transportable tables are used.

   The entire growth cycle does not necessarily takes place in the same greenhouse or at the same firm since some growers specialise in part of the growth cycle. This involves additional physical operations combined with grading to move the plants from one location to another.

3. Physical operations and grading in the full-grown stage.
   At the end of the growth cycle, plants are removed from the greenhouse. When the plants are removed from the greenhouse with the help of automation, e.g. on containers and by pick and place robots and conveyor belts, workers take the marketable plants from the conveyor belt. Plants which are not ready for market, go back to the greenhouse for another period. After picking, plants are modified manually and spoiled leaves and flowers are removed. During the modification process the plant's grade is determined.

The present state of the art shows that most grading is done manually, since there are no automatic systems available. At the young stage hardly any grading is done at all. From interviews with growers it appeared that there is not much objective knowledge available about the grading of cuttings and shoots. In the half-grown stage some grading is done but also not much objective knowledge is available about the criteria to be used. In the full-grown stage there is more information available on grading because of the standards, e.g. set by the auction.

2.4 Why grade automatically

Quality grading in pot plant cultivation is difficult to describe in terms of objective and subjective criteria. Objective quality is the quality standard based on objective specifications and measurements, e.q. height and diameter. Subjective quality is quality conform its usefulness, e.q. ornamental value. Suitability for use depends on the subjective judgement of the consumer (Steenkamp et al., 1986). The producers' approach to quality is more objective than that of individual consumers (Oprel, 1989).

The problem is that the human judgement is based on subjective criteria, while optimal grading operations require objective and constant judgement. The grader has to inspect and grade several hundred individual plants per hour. He visually determines the size of the plant, the number of flowers and its colour. It is a repetitive and very tedious job which requires constant concentration and effort. The main problem is to get people who are able to grade plants according to uniform and objective standards. In pot plant cultivation human grading has the following disadvantages:

1. the accuracy of the grading operation depends on the experience of the worker, his physical and mental condition, his work rate and his motivation. Therefore, the quality of grading will vary from day to day and even within a day itself;
2. the human grader divides plants into different groups. If the mean size of the plants (the reference) differs during the day the grading result will also be affected;
3. the human grader can only grade into a limited number of groups. Too many groups will affect grading capacity and quality negatively;
4. grading criteria are based on specific and personal experience which is difficult to transfer to other people. Due to the lack of objective criteria, each grader tends to use his own criteria.

In large commercial greenhouses grading operations are performed by more than one grader. Combining the same quality groups of different graders will decrease the uniformity of the resulting quality group because of the different grading criteria of individual workers. Experiments with human graders are described in Section 2.5.

Today's greenhouse entrepreneurs are confronted by the following:
1. the uniformity of plants in the greenhouse during the growth cycle becomes more important for economic reasons and for increasing of automation;
2. the standardisation of quality in the full-grown stage is very important for marketing reasons;
3. labour costs in the Netherlands are very high;
4. it is difficult to get qualified people for the grading operation.

Given these facts, the automation of grading operations becomes highly desirable.

As already mentioned, no automatic grading systems are available yet. Therefore such systems have to be developed right from the start. The system requirements are as follows:
1. the grading results should be at least as good as the results produced by human graders;
2. for logistic and economic reasons the grading operation should not cause additional operations in the production process carried out in the greenhouse;
3. the system should be able to operate without human supervision.

2.5 The consistency of the human grader

2.5.1 Introduction

In Section 2.4 problems related to the human grader have been mentioned. Consistency tests with unrooted cuttings and half-grown Begonia and Dieffenbachia plants were carried out in order to obtain more information about the consistency of the grading operation. The objective of this experiment was to test the reproducibility of the human grader with unrooted cuttings and half-grown plants. Reproducibility means that the plant is graded into the same group each time the plant is judged.

2.5.2 The experimental set-up

One hundred randomly selected plants were used for the unrooted cuttings. More cuttings would result in too much dehydration during the grading experiment because of exposure to air. The cuttings were presented to the human grader in a computer-determined random order in one line. The grader was asked to grade the cuttings into the following classes: small, medium, or large. The plants were not grouped when judging was being carried

out. In normal processing, the grader also sees a limited number of plants at the same time. In this way the grader was not able to compare the current plant with reference plants in a group. To avoid the effect that the grader would define the plants in such a way that each group would contain almost the same amount of plants, the actual number of plants in each group was not disclosed. Each cutting was labelled but the label could not be seen by the grader. After grading, the cuttings were shuffled so the way the cuttings were ranked was changed. Labelling ensured that the score given to each plant during the different runs could be registered without the grader being informed. Grading had to be carried out five times per experiment.
The same procedure has also to been applied for the half-grown plants. The number of plants was increased because the effects of dehydration is less here. Due to the limited amount of time for a single experiment (one day) the maximum number of plants that could be used was 150 plants.

Two experts were consulted, one for Begonia and one for Dieffenbachia plants. These experts have a long term experience in grading plants and are responsible for the quality of the plants at that particular location. Judgements were made under normal light conditions and this was constant throughout the series of judgements involved in each experiment. Since the number of plants was rather small, it is assumed that the experiments were not affected by the expert becoming tired or loosing concentration.

2.5.3 Experimental results

In Table 2.1 the scores of the grading experiments for both the unrooted and the half-grown plants are presented. The score is based on the percentage of plants classified into the same group during the judgements.

It is possible that the grader remembers the classification made in the previous judgement (learning effect). The learning effect is tested by comparing the scores of the pairs of judgements (e.g. comparing the score of the 1st and 2nd judgement with the score of the 2nd and 3th judgement). If the score of the pairs is almost the same, it is defined that no learning effect is present. The expert classifies a same amount of plants in another group during the next judgement.

Another test for the learning effect is by comparing the scores after three, four and five judgements. It is defined that a learning effect is present when the score after three judgements is almost the same as after five judgements. The expert recognises the plants and during the last judgements he knows how he graded the plants during the previous judgements. In some cases it was noticed that the grader recognised plants with an unusual shape.

Table 2.1 Percentage of plants classified into the same group during the judgements.

	Begonia unrooted cutting	Dieffen-bachia unrooted	Begonia half-grown	Dieffen-bachia half-grown
1st and 2nd judgement	66	76	87	66
2nd and 3th judgement	73	80	85	69
3th and 4th judgement	84	56	87	77
first three judgements	54	63	79	55
first four judgements	50	38	73	50
all five judgements	48	29	68	47
number of plants	100	100	150	150

When the pairs of judgements are considered, it can be seen that for unrooted Begonia cuttings the agreement between two judgements increases during the experiment (66%, 73%, 84%). An explanation for this is that despite the cuttings being randomised after each judgement, the expert was able to recognise the cuttings from a previous judgement. Each unrooted cutting has its own particular shape and the grader is able to learn these shapes. After three judgements, most cuttings are recognised and the percentage misclassification does not change very much (after three judgements 54 % and after five judgements 48 %). To exclude the learning effect, the first, second and third judgement can be taken into consideration. Sixty-six percent of the cuttings will be classified in the same way during the first and second judgement. In the second and third judgement, 73 percent of the cuttings are classified in the same way. This second group of 73 percent is not the same group as in the first judgement pair because when these three judgements are compared, only about 54 percent of the cuttings get the same classification. The grader has problems with grading 46 percent of the cuttings consistently into the same group. This does not mean that the grader is not able to grade. The main reason for misclassification is the changing standards which are used by the expert during each judgement run. This is compensated by the learning effect.

The shape of unrooted Dieffenbachia cuttings is much more uniform than that of the Begonia cuttings and therefore more difficult to remember. The score for the pair of first and second judgement is better than in the case of unrooted Begonia cuttings (76% to 66%), but the number of cuttings which are classified in the same way during all judgements decreases continuously during the runs. Only 29 percent of the cuttings were classified in the same way after five judgements. The expert obviously changed the boundaries of the group because of an absence of a predefined standard. In the case of unrooted Dieffenbachia cuttings no learning effect could be noticed. The 80 percent classified in the same way between the second and third judgement is an outlier in this case.

The differences between the smallest and largest cutting are greater for unrooted Dieffenbachia cuttings than for unrooted Begonia cuttings. The number of cuttings about which the expert doubts is smaller because the distance between the class boundaries is larger. Therefore the number of cuttings close to the class boundary is smaller. This results in a higher score for the first pair of judgements for the Dieffenbachia cuttings than for the unrooted Begonia cuttings for which the number of cuttings close to the class boundary is larger.

For the half-grown Begonia plants, the number of plants assigned to the same group between two judgements is more constant. Between 85 and 87 percent of the plants are assigned to the same group during a subsequent judgement. After three judgements, the overall score is 79 percent, and after five judgements 68 percent. Again the number decreases due to changes in class boundaries and the absence of absolute quality standards. The effect of the expert recognizing the plants is less because the score is still decreasing after three judgements.

For the half-grown Dieffenbachia plants, the grader is less consistent than for half-grown Begonia plants because the grading standards for half-grown Dieffenbachia plants are less explicit. The score after five judgements (47%) is much lower when compared with the half-grown Begonia plants after five judgements (68%). When the score after three, four and five judgements (55%, 50%, and 47% respectively) is considered, some learning effect can be identified. For half-grown Begonia plants, the development of certain parts of the plant is judged. For half-grown Dieffenbachia plants the compactness and the size of the plant are important. These features are less well defined. It does not mean that the grader is not able to grade plants, but he needs better standards if he has to grade in a constant way, especially for the half-grown Dieffenbachia plants.

From the results reported in Table 2.1 it can be concluded that human judgement is not constant and consequent.

2.6 How to grade pot plants

What represents quality in horticultural plants, can be interpreted in different ways: plants which are larger or heavier, have a better flower or leaf colour, a better tenability, etc. Due to these differences in interpretation, establishing quality is difficult while at the same time, the number of different interpretations continues to increase. The common objective in all interpretations is to establish better definitions of quality (Oprel et al., 1985).

At the Experimental Station for Flower Research at Aalsmeer, the Netherlands, research was carried out to the identification of subjective and objective quality criteria for pot plants (Benninga et al., 1991; Oprel et al., 1985; Vogelezang et al., 1988; Westerhof, 1987). Growers and consumers were asked to give scores (between 0 and 10) for 12 features (see Table 2.2) and for overall quality. Plant features such as height and diameter were also measured. Analyses, using multiple regression techniques, were carried out with the overall impression of the plant as a dependent variable and the

measured features as independent variables. The mean score of the total impression per plant and the mean score of the individual features per plant were also determined. The analyses showed that human judgement is not consistent (Vogelezang et al., 1988).
This Station has carried out research on the identification of objective quality criteria for Begonia, Dieffenbachia, Saintpaulia and Ficus:

Table 2.2 Features of Begonia plants which were used by the Experimental Station for Flower Research to identify quality criteria.

- height	- colour of leaves
- area of plant	- colour of flowers
- ratio between height and area of plant	- roundness
- volume of leaves	- distribution of flowers
- volume of flowers	- maturity
- number of shoots	- total impression

It appeared to be difficult to judge the colour of the flowers and leaves. Analyses of objective measurements combined with a panel judgement showed that less tall plants were the most appreciated; 30 cm seems to be the optimum height. This height is the same as the height of the sticks in the pot. Furthermore, a larger smallest diameter in top-view (see Figure 2.2), more shoots with flowers and a smaller ratio between largest and smallest diameter in top-view (more round) are also better appreciated.

From a second experiment it appeared that the number of open flowers, the number of shoots, a smaller largest diameter of the top half of the plant in side-view, and a larger smallest diameter of the bottom half of the plant in side-view were better appreciated. A possible explanation for the difference between the two judgements is the difference in the time of the year (Vogelezang et al., 1988).

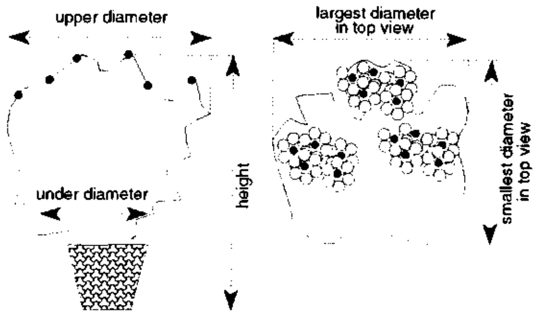

Figure 2.2 Feature of a Begonia plant (Vogelezang et al., 1988).

A correlation analysis was carried out to define relations between the overall judgement and the features (see Table 2.3). Following Pearson correlation coefficients (r) between the overall judgement and some features were found: maturity 0.98, distribution of flowers 0.97, number of flowers 0.90, and ratio between length of flower stem and length of leaf stem 0.98. Besides, there seemed to be a general tendency towards a better appreciation of compact plants (Oprel et al., 1985).

Table 2.3 Features of Saintpaulia plants which were used by the Experimental Station for Flower Research to identify quality criteria.

- volume of the leaves	- distribution of flowers
- volume of the flowers	- colour of flowers
- length of the flower stem	- colour of leaves
- length of the leaf stem	- maturity
- ratio between flower stem length and leaf stem length	- overall judgement

In the full-grown stage of the Dieffenbachia the length (height) of the plant is considered as a quality feature together with the shape in top-view (the more round the better), as well as the shape in side-view. The shape in side view is highly determined by the number of shoots, three or more shoots is best (Oprel, 1986).

The Ficus is graded into length groups in the full-grown stage (Benninga et al., 1991). In Table 2.4 features which influence the quality are noted.

Table 2.4 Objective features of the Ficus which influence the quality for a particular length group (Benninga et al., 1991).

- area of the plant per cm length
- ratio between half of the length of the plant and the number of shoots in the plant's lower half
- ratio between total length and total number of shoots
- ratio between total length and leaf area
- width of the plant
- roundness of the plant

It can be concluded that the features for plant grading are based on human visual perception. As already has been mentioned the human grader has problems when he has to grade objects based on visual perception. His classification will vary in time and is blurred by external influences. To ensure that the grading is done in a constant way, a system which is based on objective criteria is needed. Digital image processing (DIP) seems to be an interesting alternative for the human eye-brain combination. It allows non-destructive measurement with hardly any effect on plant growth.

To implement an automatic grading system in pot plant production, grading operations need to be studied in more detail. It is important to know which features and which quality standards are used and how decisions are taken.

2.7 Automatic grading system for pot plants based on DIP

DIP requires a computer-camera system which is able to measure plant features. DIP has already been used to measure plants for the development of growth models. In situ leaf area, stem diameter and internode length were measured in this way (Meyer et al., 1985). The area of the individual leaves measured with DIP showed a strong relation to the area measured by a more traditional electronic-optical method (coefficient of correlation $r=0.99$). Meyer et al. (1989) estimated the wet and dry plant weight using DIP. They found a coefficient of correlation (r) of 0.98 between the leaf area measured with DIP and the wet weight, and a coefficient of correlation of 0.95 between the leaf area measured with DIP and the dry weight.

In the U.S.A. much research has been done on grading tree seedlings. Rigney and Kranzler (1988) used DIP for grading pine tree seedlings. Projected root area, stem diameter and shoot height were used to distinguish between seedlings that could be automatically accepted or rejected. Misclassification ran at about 5.7 percent. Suh and Miles (1988) measured tree seedlings in a similar way. The correlation coefficient (r) between the DIP measurement of the shoot height and the manually measurement of the height was 0.99. The correlation coefficient between the DIP measurement of the stem diameter and manually measurement of the stem diameter was 0.98. The projected area of roots measured by DIP was compared to measured root volumes. A correlation coefficient of 0.80 was found. The projected area of the whole seedling was highly correlated to weight ($r=0.95$).

Grading of cuttings by means of DIP has been described by Cardenas-Weber et al. (1988). Bare-root strawberry plants were graded upon the number of their roots and root length. Good plants should have at least 10 roots of 76 mm or longer. Eighty-three percent of the plants were graded correctly. This was a higher score than the human grader could achieve. Simonton et al. (1990) described a system for measuring the plant features of Geranium cuttings by identifying the branching stem structure, including main stem and petioles. The results of the measurements were used to grade the cuttings and to guide a robot system for trimming and planting.

Hines et al. (1986, 1987) investigated the feasibility of DIP in grading container-grown ornamental plants. The features for grading were shape, size, foliage density and colour. Bennedsen et al. (1991) used DIP based on colour images for the inspection of pot plants. Cyclamen plants were measured by taking a top- and side-view image. Parameters like area of flowers, area of leaves, centre of gravity for flowers and leaves and the circumscribed rectangles of the flowers and leaves were used.

Most applications of automatic grading which have been reported use vision as a sensor. In all these publications no figures are given about the effect on grading using the features mentioned.

Research at the Dutch Inspection Department for Ornamental Plants showed the effect of grading on weight. It is assumed that the assimilation capacity of young plants is related to the weight of the cutting (Greef, 1989; Westerhof, 1987). It should be mentioned that weight is only one grading feature. Features like leaf area and length of the stem cannot be determined from weight. The weight of the plant is also affected by dehydration and contamination by soil and roots. DIP is able to recognise features like stem length, number of leaves, and leaf area. In Chapter 3 the possibilities of DIP are discussed more in detail.

A strong feature of a DIP system will be its objectivity. The system is able to measure the size of a plant in an absolute value. For a human being it is hard to give an absolute number to an object without having a standard to compare with.

2.8 Conclusions and discussion

Grading during and at the end of the growth cycle has many advantages. However grading also introduces additional operations. From an economical and logistical point of view, the number of operations should be minimised. Therefore the best points to grade are those where physical operations are already carried out on the pot plants. In the growth cycle many different physical operations are performed so grading can be applied at many different points.

Up to now grading in pot plant cultivation has been mainly done manually. In the full-grown stage most plants are graded in conformity with the quality standards set by e.g. the auctions. At the beginning and during the growth cycle, grading is not done on any considerable scale because a lack of information about grading standards. In these stages, more knowledge is needed about grading features which determine the growth potential and (shape) development of the plants.

Grading is a labour intensive operation which requires constant concentration. In addition, the human grader has problems with consistency. Grading experiments with unrooted Begonia cuttings showed that 66 percent will get the same classification when the same group is graded for the second time. The half-grown Begonia plants showed better results: 87 percent were classified in the same class after a second grading. Nowadays pot plant cultivation demands more uniformity during the growth cycle in order to be able to profit from automation and commercially there is a greater demand for more uniform and standardised products. The labour costs in the Netherlands are high and it is difficult to get qualified people for grading operation. Therefore, automation of grading is desirable.

Considering the way the grading operation is being carried out at the moment, one can state that digital image processing (DIP) is a valuable technique for the development of a grading system. The grading operation is based on a complex set of features which are mainly visually determined. Literature shows that DIP is used to measure and grade plants. It can be concluded, therefore, that automatic grading using DIP is a possible solution.

Two different sensor systems can be considered to provide features for a decision system for classifying plants: a computer-camera system or a weighing system. In Table 2.2 the advantages and disadvantages of the systems based on the system requirements are shown.

Table 2.2 Comparison of different grading systems leads to following conclusions:

	Human	Mechanical	
		Weighing	DIP
Operate autonomously		yes	yes
Objects presented non-singularised	yes	no	no
Consistent grading result	no	yes	yes
Grading on complex set of features	yes	no	yes

The most important advantage of mechanical grading over human grading is its consistency of the grading results. The most important advantage of DIP over weighing is its capability to measure a complex set of features of the plant. Therefore in this research the ability of DIP for consistent grading based on a set of complex features is investigated. The only problem with DIP is how the objects are presented to the grading system. This has to be solved in the processing of the plants.

3 Digital image processing in the agricultural environment

3.1 Introduction

In the previous chapter it was concluded that digital image processing (DIP) is a suitable technique for the measurement of plant features on which a grading system can be based. This chapter discusses the application of DIP in an agricultural environment especially in pot plant grading.

DIP, also called computer vision, studies the underlying principles of human visual perception and attempts to provide a computer-camera system with the visual capabilities (Varghese et al., 1991). DIP was introduced for image interpretation for military purposes, for image reconstruction and image interpretation in medical research, and in the automobile and electronics industry for process automation and quality control. It has just started to develop in the agricultural environment (Gagliardi et al., 1985). The applications of DIP in agriculture can be subdivided into three categories (Kranzler, 1985); Image interpretation (e.g. remote sensing), Robotics vision (e.g. for apple and citrus picking), and Inspection (grading of apples). The grading of pot plants is a typical inspection application.

3.2 Digital image processing applied in a grading application in agriculture

Industrial DIP inspection applications have potential use in the grading of agricultural objects. However they cannot simply be applied to the agricultural environment because of such problems as the biological variability of objects and the difficulty in interpretation of unstructured environments. A number of difficulties in agricultural applications have to be considered (Gagliardi et al., 1985).

1. Difference between applications. Each grading line has its own specific characteristics, so each application needs to be adapted for a particular use. This makes it difficult for the system supplier to develop off-the-shelf applications.
2. Lack of objective inspection standards. Many manual on-line inspection stations rely on subjective inspection criteria. This makes it difficult to implement objective criteria in an automatic inspection application.
3. Unique inspection parameters. The features for grading agricultural objects demands vision systems that are not compatible with many commercial DIP products.

These differences make it necessary to develop a grading application for pot plants from the very beginning. Basic techniques developed for industrial applications can be applied. However, for most steps in the development of an application, modifications are necessary in order to make them suitable for agricultural applications. The configuration of a DIP system as it is commonly used in agriculture nowadays is presented (see Figure 3.1).

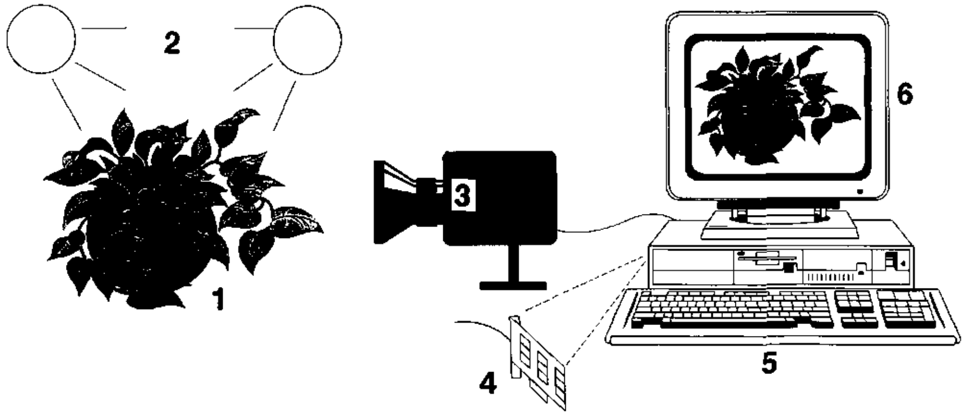

Figure 3.1 Example of a DIP system configuration in agriculture.

The following sub-systems can be distinguished in a DIP application (Figure 3.1).

1. Object and background.
2. Lighting system including lenses, diffusers and other tools to manipulate light.
3. Recording device like a CCD (Coupled Charge Device) camera.
4. Digitiser and frame store.
5. Computer including tools to speed up the image processing.
6. Output devices such as:
   a - terminal to communicate with user and system;
   b - image display for representation of the image to the outside world;
   c - printer for a hard copy of the results;
   d - disc to store programs, data, and images.

In order to discuss grading system development, it is divided into sub-systems. For a pot plant grading system a conversion is needed from the plant to a classification. In this conversion several sub-systems are identified. They are based on specific processes and problems.

1. Scene processing.
   Scene processing, also called image construction, deals with the process of image building, before the image is captured. It concerns plant position, background, the lighting system, and the camera position.
2. Image processing.
   Image processing deals with images from just after recording to feature extraction. It concerns the recording of the image, separation of the plant from the background in the image (segmentation), and the preparation of the image for measuring features.

3. Feature extraction.
   Feature extraction deals with the extraction of features from processed images. It results in a list of features measured in the plant image. In some applications the division between image processing and feature extraction is hard to define because there is an interaction between both sub-systems.
4. Feature processing.
   Feature processing deals with the decision structure which assigns a classification to a plant based on the features provided by the feature extraction.

3.3 Scene processing

3.3.1 Introduction

Objects in the agricultural environment are less easy to describe than objects in the industrial situation. The colour and shape of each object may vary. Therefore it is important that the objects are clearly visible in the scene. For instance, the presentation of a plant in its environment can be very different if it has an irregular shape. Poor lighting conditions or a background which is very similar to the plant make image segmentation much more complicated and time consuming than when a plant is presented with a sharply contrasting background. It is not possible to reconstruct the plant on the basis of a standard plant. Some properties of the plant can be enhanced by using special lighting systems. Therefore it is important to know about the spectral properties of the plant.

Information that is lost during the recording of an image cannot be reconstructed afterwards. The quality of the image is also important for the speed of the grading system (Paulsen et al., 1986). In order to obtain a fast grading system, the amount of image enhancement has to be minimised.

3.3.2 The scene set-up

Object, background, camera position, and lighting system together are defined as the scene. The following limitations have to be taken into consideration.

1. Number of objects in the scene.
   A single object in the image makes the segmentation between object and background easier than when more objects are present. Therefore the plants in a grading system have to be presented one by one to avoid time consuming object separation routines.
2. Controllability of the background.
   Controllability of the background is determined by the opportunities to manipulate the background. The presentation of tree seedlings as light objects on a black conveyor belt using front lighting is an example (Rigney and Kranzler, 1988). To improve the quality of the segmentation, it is preferable to present dark objects on light backgrounds for a high contrast and visa versa. A uniform lighting system can also

serve as a background (Rigney and Kranzler, 1988; Berlage et al., 1988; Awa et al., 1988). The image acquired with such a system is called a 'shade' image.
An example of an uncontrolled background is a full-grown plant with flowers and these flowers have to be separated from the leaves.

3. Orientation of the object.
Agricultural objects have a three-dimensional shape. The area visible to the camera depends on the orientation of the object. Wolfe et al. (1985) described the measurement of red bell peppers, using six different views to see the whole pepper.
4. Type of feature to be measured.
The features of the object can be divided into two groups: spectral and geometrical features. Depending on the type of feature to be measured, different lighting systems and background have to be chosen.
Spectral features: The colour of an agricultural object is not based on the direct reflectance of the object, but on the interaction between the light and the pigments in the object (Mohsenin, 1984). Light enters the upper layer of the objects and if certain pigments are present in this layer, they absorb specific wavelengths. The reflected light, called indirect reflection or body reflectance, misses these wavelengths, which is seen as a colour (Birth, 1976).
Geometric features: This group consists of such features as shape of object, area, perimeter, length, width, and curvature.
5. Type of lighting system.
Two types of lighting systems are distinguished, back-lighting and front-lighting.
Back-lighting systems : Back-lighting systems produce high contrast images. Incandescent lamps gave better results than fluorescent lamps (Awa et al., 1988). The peak sensitivity of the CCD-camera (between 700 and 850 nm) matches the light production of incandescent lamps better. By using incandescent lamps, interference between the lamps and the camera can be avoided. Uniformity of light distribution is achieved by applying diffusers to the front of the lamps. This system is suited for the measurement of geometrical properties because of the sharp edges between object and background. During the segmentation very little uncertainty about the location of the edge is introduced.
Front lighting systems : Front-lighting systems are used to enhance the spectral features of the object. Band-pass filters, cut-on filters, cut-off filters and colour camera's provide the DIP system with spectral information on the object, e.g. the position of apples in a tree (Slaughter et al., 1989). Shading and direct reflection are a problem with front-lighting systems and therefore diffuse light sources have to be used (Paulsen et al., 1986, Tillett, 1991). Front-lighting is also used to measure geometric features, but the measurement is affected by the lack of sharp edges. A small change in threshold value results in a relative large change in the location of the edge.

3.3.3 The use of spectral properties of objects in DIP

To enhance plant parts in an image, information is needed about the spectral properties of plants. The main factors which determine the transmittance properties of healthy green leaves are scattering caused by cell walls and the presence of water, chlorophyll and carotenoids. For green leaves Norris (1965) found the following:

- below 500 nm there is low transmission due to carotenoids, chlorophyll and scattering;
- around 675 nm also low transmittance due to absorption by chlorophyll.
- between 700 and 1200 nm high transmission;
- above 1500 nm there is a low transmission due to absorption by water.

Leaf reflectance in the near-infrared (NIR) range (700-1100 nm) is mainly determined by the leaf structure. Leaves with compact mesophyll arrangement have lower reflectance than leaves with porous mesophyll, i.e. a mesophyll with many cell wall-air space interfaces. This is because light passes more often from hydrated cell walls to air spaces in a porous mesophyll, which causes more light scattering with subsequent increase of reflectance. Internal discoloration of leaves or a black coating on their surface will cause a decrease in NIR reflectance, because more NIR light will be absorbed by the black coating (Gausman, 1973).

Most plants have two distinctive groups of pigments; the green/blue-green chlorophylls and yellow-orange carotenoids. During the growing season chlorophylls "a" and "b" play an important role in the photosynthesis and are dominant in the plant leaves. They absorb light in the red and blue wavelengths. Therefore the plants are observed as green. Later on in the growing season the carotenoids, i.e. predominantly xanthophyllous and carotene, cause leaves to appear more yellow and brown. This appearance results from the fact that chlorophylls break down much more rapidly in the leaves than carotenoids (Troyer et al., 1990). Coloured plants like Poinsettia have a third group of pigments, the red/white anthocyanins, which cause the upper leaves to turn into bright colours (Meyer et al., 1960).

These spectral properties are used to segment leaves and flowers from the background. Figure 3.2 shows that in the visible light region (400 - 700 nm) soil has a higher reflectance than leaves, but in the NIR region, the leaves have a higher reflection. Guyer (1986) used this difference in reflectance in a DIP application to segment plants from the soil.

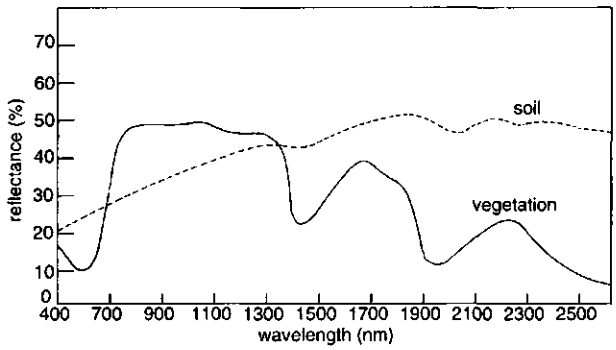

Figure 3.2 The spectral properties of leaves and soil (from Guyer et al., 1986).

3.3.4 The scene set-up for a pot plant grading application

From the above explanation it can be seen that many factors may influence the scene set-up. Therefore each growth stage requires its own scene set-up based on the features to be measured and the way plants are presented.

1. Young stage.
   The young plants are presented singularised in their natural rest position using back-light. The plants have a pre-defined orientation to reduce the amount of image processing. The features which have to be measured are geometric ones. A black and white camera system is suitable for this growth stage.
2. Half-grown stage.
   The half-grown plants are presented singularised in a pot. Top- and side-view images are recorded. In this growth stage geometric features are important. The top-view image is recorded using a front-lighting system and a background which is very different from the leaves. One top-view image is enough to get all the information about the top-view of the plant. The side-view image is recorded using a back-lighting system. The orientation of the plant towards the camera is random. Several images are needed to get all the information from the side. This is accomplished by rotating the plant or by using more black and white cameras taking images under different view angles in the horizontal plane.
3. Full-grown stage, green plants (without flowers).
   Full-grown green plants are processed in the same way as half-grown plants.
4. Full-grown stage, flowering.
   Since flowers have to be segmented from leaves, front lighting is needed. This holds for both the top- and side-view. The background has to be different from the leaves and flowers. The flowers and leaves are separated using a colour camera or spectral filters.

3.4 Image Processing

Image processing is the manipulation and analysis of images. Its major sub-areas include (Rosenfeld and Kak, 1982).

1. Digitising which is the conversion of images into a discrete (digital) form, and compression which is the efficient coding or approximation of images to save storage space or channel capacity.
2. Enhancement and restoration which is the improvement of degraded (low-contrast, blurred, noisy) images, and reconstruction which is the creation of images from a set of projections.
3. Matching which is the comparison of images, description which is the segmentation of images into parts and measuring properties of and relationships among parts, and recognition which is the comparison of the resulting descriptions to models that define classes of images.

The basic principles of image processing and image analyses are extensively described by, e.g. Rosenfeld and Kak (1982), Ballard and Brown (1982), Gonzales and Wintz (1987), and Pratt (1978).

Considering a grey value image where 0 represents black and 255 represents white, an important step in image processing is the segmentation of the objects of interest from background or extraneous objects. The simplest way to segment an image is by using a threshold. Any pixel (picture element) with a grey value above the threshold is classified into one group, and any pixel with a grey value less or equal to the threshold is classified into the other one. The grey level histogram of the image should have peaks corresponding to the two grey level ranges. Thresholding works well with high contrast images captured under controllable lighting conditions. It is used for many applications (Keefe et al., 1986; Rigney and Kranzler, 1988; Berlage and Cooper, 1988; Reid and Searcy, 1988).

In a colour system, pixels are classified on the bases of their colour. This generally yields into a much more refined classification, since it is based on several features rather than a single one. Bennedsen et al. (1991) used a threshold in the Red, Green and Blue image (RGB) to segment between leaves, flowers and background. Another possibility is to look at clusters in the colour space. This is a useful method when lighting conditions are variable or when multiple threshold is applied (Slaughter and Harrell, 1989; Miller and Delwiche, 1989).

The threshold technique is satisfying for simple global features like total leaf area and total height. More complex features like the point where a side stem branches away from a plants' main stem is difficult to describe mathematically and to locate reliably (Onyango and Davis, 1989). Some knowledge is needed in the program to perform the segmentation in order to locate such features.

The knowledge base incorporated into images is derived from models of the real world. These can be models of physical phenomena or rules which represent the relationship between objects in the real world. The concept of using a rule or expert system for the segmentation of images is already well established (Ballard and Brown, 1982). The so-called low level operators are able to isolate elements of an image. To understand the results of the segmentation, decision rules on a higher level are needed. The higher level contains knowledge about the objects' size, shape, and the connectivity between the elements to form objects. In this way clusters of pixels are labelled as elements of an object or disregarded as noise or background.

An example of knowledge based segmentation is given by Tillett (1992) for the identification of key features like the stems and leaves of chrysanthemum plants grown together in a container. These images are quite complex because the plants overlap each other. It is hard to identify individual plants in the image. Stem finding in the image is done by looking for relatively long thin segments in the image. For identification as a stem, the segments have to meet the following criteria.

1. The thickness of the segment is between 2 and 10 pixels. A maximum of 10 pixels is large enough to accommodate the double thickness of two stems laying next to each other.
2. The length of the segment is at least 3 pixels. Segments are initiated as pairs of vertical edges and tracked downwards until the thickness criterion is no longer satisfied, or until one of the sides deviates suddenly by more than one pixel to either side.
3. The angle of the stem to the vertical is less than 22 degrees. This distinguishes the stem from most of the leaf branches.
4. A continuous path of pixels can be found downwards connecting the stem to the bottom of the image.

These criteria allow each segment to be tracked for testing on stricter requirements.

The knowledge based segmentation is partly integrated with feature extraction. The procedure classifies the different parts of the image into, e.g. stems, leaves, pots, and background. The use of a relational model of the objects provides identification and calculation of the individual parts.

The result of segmentation is a labelled image. To reduce the processing power requirements of the grading system, the image is coded so less information has to be processed by the system. A commonly used technique is run-length coding (Rosenfeld and Kak, 1982; Simonton, 1989). A run represents a line with the same values. To represent this line the starting coordinate, the length of the run and the value of the run are needed. A test is carried out to check whether two runs are connected to each other. Two runs are connected if the starting point of the first run is at the left side of the ending point of the second and the ending point of the first run is to the right of the starting point of the second one (Figure 3.3).
In formula form :

Connectivity : if (start run 1 < end run 2) and (end run 1 > start run 2)

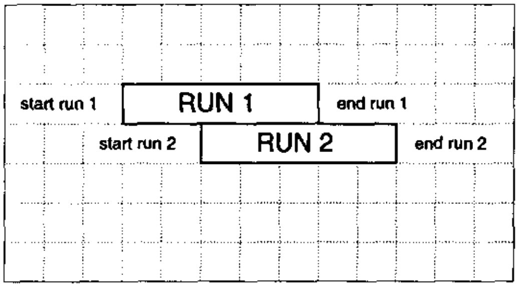

Figure 3.3 Connectivity between two runs

3.5 Feature extraction

Feature extraction involves the measurement of the object. Two main categories of features are distinguished.

1. Features with dimensions like:
   - Area : number of pixels classified as object.
   - Length : distance in pixels between two points in the image located at the endpoints of a line representing the length.
   - Width : distance in pixels between two points in the image located at the endpoints of a line representing the width.
   - Perimeter : length in pixels of a curve representing the boundary.
   - Convex hull area : number of pixels of the area found by drawing a convex line around the object. Concave holes in the edge of the object and holes inside the object area are included.
   - Moments : computation of the $_{ij}$th moment of M_0 around point x_0 and y_0 is done by:

$$M_0 = \Sigma\ (x_0 - x)^i (y_0 - y)^j$$

   The optical centre (x_0, y_0) is found by calculating the first order moment around a reference point. In that case the equation of the first order moment is zero.

Measurement of features with dimensions of objects always implies the need for calibration.

2. Dimensionless features.
   - Roundness : a common definition is the ratio between the length and the width.
   - Density ratio : the number of object pixels inside the perimeter divided by the number of pixels classified as object pixels. Another definition for density is the area of the object in pixels divided by the convex hull area of the object.

   The advantage of dimensionless features is that no calibration is needed.

The features to be measured strongly depend on the application. Fujiwara, (1991) described an application for the grading of seedlings. A top-view image was captured to extract the top leaf area, leaf length, leaf width, and the number of leaves. The side leaf area, seedling height, and the seedling direction were extracted from the side-view image. In Figure 3.4a the top-view, and in Figure 3.4b the side view are shown.

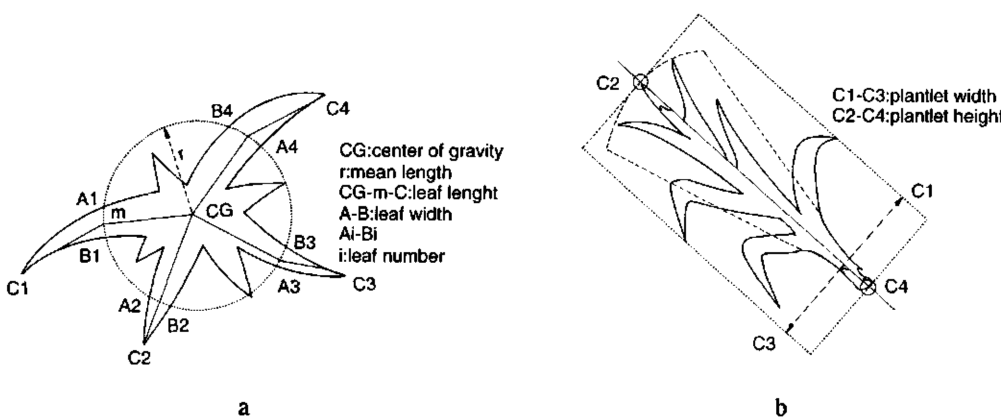

Figure 3.4 Features measured of a cutting (a) top-view image, (b) side-view image (according to Fujiwara, 1991).

Measurement of cuttings has been described by Cardenas-Weber et al. (1988). A list of visually measurable plant features is presented (Table 3.1) like shape, stage of development, and health. Some features can be measured directly (e.g. length of roots and number of leaves). Others are relative and have to be evaluated qualitatively (e.g. shape, texture). Some features are not directly visible and instead measurements of related features are used. For instance absence of fungus indicates a healthy plant, a thick stem indicates high water content, and the projected root area predicts the root volume.

Table 3.1 List of visually measurable plant features (Cardenas-Weber et al., 1988).

shape	symmetry complexity elongation moments of inertia leaf serration venation pattern
stage of development size :	length : roots, stem diameter : crown, stem area : roots, leaves perimeter sturdiness ratio
stage of development number of parts :	branches flowers roots leaves
health	diseases change of colour mechanical damage: (holes, breakages, etc.)

Simonton et al. (1990) described a system to measure features of Geranium cuttings. They identified the branching stem structure including main stem and petioles. The analysis was based on the creation of a directed graph data structure which contained the information required to perform rapidly plant part identification. The classification of objects as plant parts was based on size, shape, and location data. Identification of the main stem, petioles, growth tip, and geometry of the interconnections of the plant parts was performed successfully. Overlapping sections (e.g. petiole crossings) and occlusions (e.g. leaves over stem segments) contributed to identification errors. An analysed image is shown in Figure 3.5.

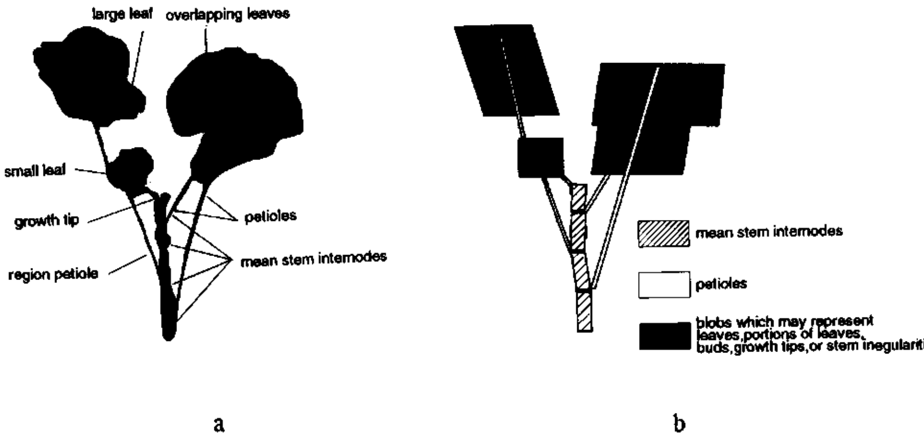

Figure 3.5 Image of Geranium cutting (a) original image, (b) analysed image (according to Simonton et al., 1990).

Hines et al. (1986, 1987) analysed the feasibility of DIP in grading container-grown ornamental plants. Two views, 90 degrees apart in the horizontal plane using back-lighting were captured. For the spectral information two other views using front lighting and different filters were captured. Colour was determined by the ratio between the number of pixels in the plant using an interference filter (520 nm) and the number of pixels in the plant using an infrared filter. Figure 3.6 shows the features extracted.

The following features were chosen for plant measurement.

- Height
- Width
- Size : the projected area of the plant.
- Shape: described by the following features:
  - rectangularity : cross-sectional area divided by the product of height and width
  - circularity : squared perimeter divided by the cross-sectional area
  - elongatedness : cross-sectional area divided by the squared plant width
  - triangularity : 2*area/(height*width) - 1
  - ratio between height and width
  - perimeter
- Foliage density : percentage of plant pixels within the perimeter of the plant
- Symmetry : the standard deviation of the plant pixels around a theoretical axis of symmetry.

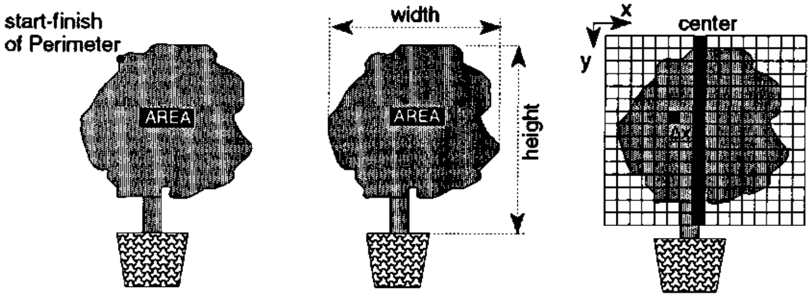

Figure 3.6 Features extracted from a full-grown plant (according to Hines et al., 1986).

Red cyclamens were measured by taking a top-view and a side-view image. Global features like area of flowers, area of leaves, centre of gravity for flowers and leaves and the circumscribed rectangles of the flowers and the leaves were extracted for inspection (Bennedsen et al., 1991).

From the literature it can be concluded that feature extraction depends on the growth stage of the plant. At the young stage the features are detailed, for example, the stem structure. At the full-grown stage they are global like overall leaf area and distribution of flowers.

3.7 Feature processing

After feature extraction, a list of features with their values becomes available. The classification of the plant is based on one or more grading feature(s) processed in a linear or non-linear mathematical model, called the decision model. The nature of the decision model depends on the availability of a target classification or the existence of explicit rules.

If rules are known these can be implemented in a classification rule system, for instance, an expert system (McClure, 1983). An example of a simple, single rule system is the grading of tree seedlings. Seedlings with a stem diameter of seven pixels or more were considered as plantable seedlings (Tohmaz et al., 1990).

If the rules for classification are not explicitly known, techniques are needed which are able to detect the features to be measured for target classification. For the development of the decision model, the target classification of the plant (for instance, an expert's judgement about a full-grown plant) is related to features measured with DIP. Cluster analysis is a possible solution for separating two objects. The points in the feature space have to be clustered. Thus regions can be distinguished which belong to a certain object class based on similarity-rules (similar to a 'standard'). The features of pot plants, however, show a homogene distribution in the feature space and no clusters can be distinguished (Hines et al., 1987). In such cases a linear model is a possible solution. For the development of these linear models, multiple linear regression analysis can be used as a method for finding weights which have to be combined with features. The output of the equation determines the classification of the plant. This method is useful for grading a group plants into different quality classes.

For non-linear cases, decision models can be developed using fuzzy logic and neural networks. Fujiwara (1991) reported on the grading of seedlings on size and development. By applying fuzzy logic in the decision model 97 percent of the seedlings were classified correctly.

A neural network shows good properties as decision model because of its capacities to process complicated sets of data and its 'learning capacities' (Ben Hanan et al., 1991, Zhuang et al. 1992). When the target classification and the measured features are presented simultaneously to the network it 'learns' the weights which have to be assigned to each feature (Kohonen, 1982). A commonly used type of neural network is the multi-layer back-propagation learning network (Rummelhart et al. 1986). The input nodes, points were the features enter the network, are connected to output nodes which provide the classification via an internal network of connections and nodes. The weight of each connection determines the strength of the transmission of a feature to a next layer. The knowledge in a neural network is stored in the weights between the nodes. It learns the weights of the connections via the generalized delta rule by back-propagation. A major disadvantage of a neural network is the interpretation of the weights of the connections. It is difficult to interpret which features are used for the classification and how they are combined.

The use of pot plant classification with DIP and neural networks has been reported by Brons (1992). He concluded that the expert could best be approached by a neural network with eight variables as input obtained from a set of 40 variables. The variable reduction method was based on principle component analysis and linear regression. The training of the network was performed by judging the plants on their quality of leaves, quality of flowers, and the general quality of the plant.

3.8 The development of the image processing for a grading system

On the basis of the different components in a grading system based on DIP, a strategy for the development of such a system is proposed in this thesis.

The grading operation has to result in a division into groups, called the Grading System Target Output (GSTO). This target output determines the objectives of the grading operation. These objectives are called the grading task. The general set-up of the grading system is determined by the grading task. The grading task determines which features have to be used. The grading features together with knowledge about the sub-systems determine the set-up. In Figure 3.7 the sub-systems including the image flow and knowledge flow are shown in the system development stage.

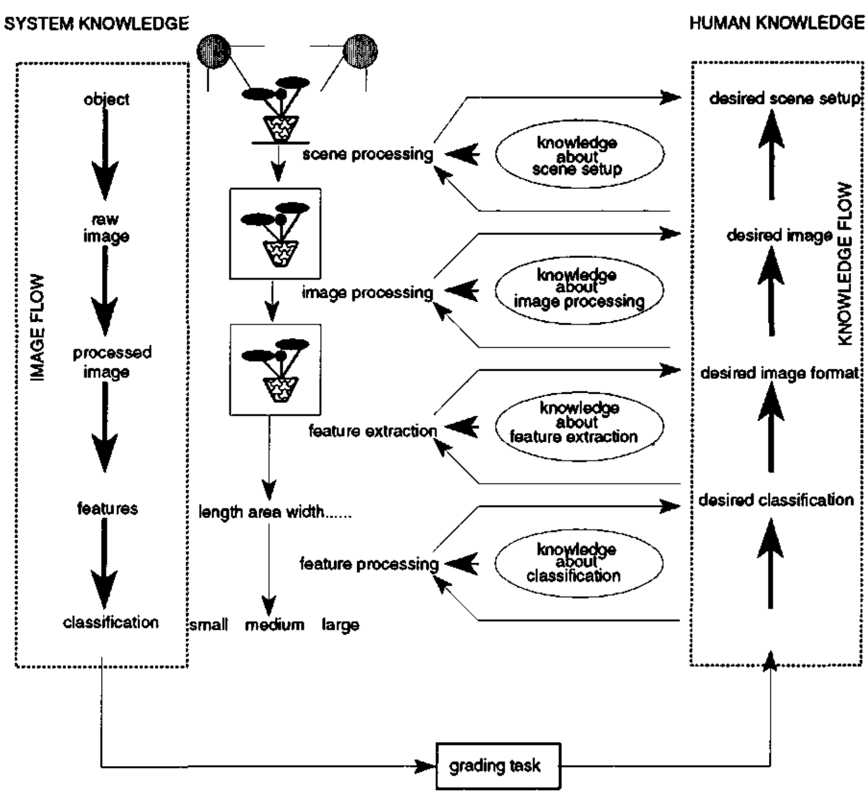

Figure 3.7 Image and knowledge flow in the grading system set-up.

There are two layers. The 'lower' level represents the image flow with the features. The 'upper' level represents the knowledge flow. The human knowledge about the grading task is embedded in the knowledge flow. The system knowledge about the grading task is embedded in the image flow. The knowledge flow goes from the overall impression of a population of plants to the single feature of the plant. Humans are able to distinguish plants in a population, based on comparison. They are not able to measure features of a single plant without tools. The image flow goes from the single features of a plant to the overall impression of a population of plants. The DIP system is capable of measuring single features of a plant. However it is not able to compare plants in a population without additional knowledge. During the development stage of a grading system the two flows interact with each other in the sub-systems. A combination of the desired output of a sub-system with knowledge about the sub-system leads to the desired input of that sub-system.

The grading system needs rules for grading which are embedded in a decision system. Knowledge about the decision system combined with the GSTO results into a list of desired features. The desired features for the decision system are extracted from one or more images. Knowledge about feature extraction combined with the desired features results into one or more desired images for the feature extraction. The camera system hardly ever provides images which are directly suitable for feature extraction. Image processing is needed to enhance these. Knowledge about the desired images combined with image processing results in the characteristics of the input image. The input image has to contain information about the desired features. Knowledge about scene processing combined with the desired image characteristics results into a scene set-up.

An important characteristic of a grading system is its autonomous operation (Tao et al., 1991). For a proper system operation, control is needed over the decisions of the grading system. In figure 3.8 an automatic grading system is shown. Each sub-system makes decisions in the image flow. The status of the decision is reported to the 'super-vision layer'. If an error status is reported by one of the sub-systems analyses are stopped and the image has to be recaptured, for instance, the same object with another orientation. In this way the system is prevented from taking decisions about objects that do not meet the standards.

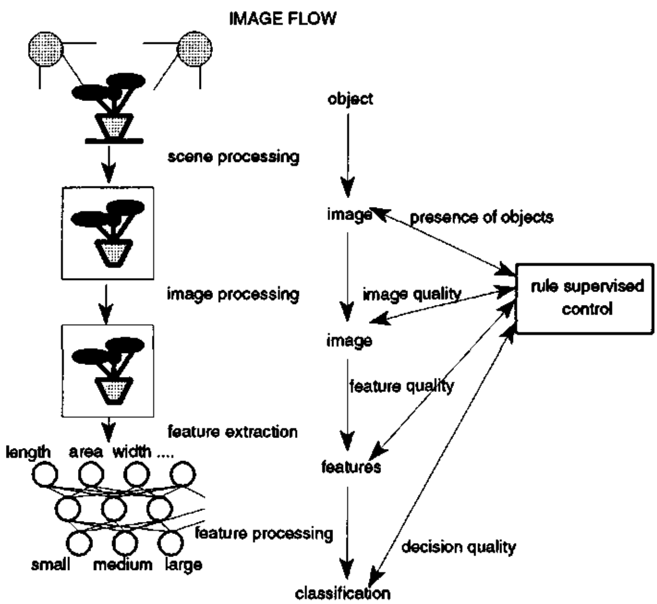

Figure 3.8 Grading system with sub-systems.

3.9 Image processing in agriculture and its sources of error

In all sub-systems, errors are introduced into the measurements. The several sources of error have their individual influence on the reliability of DIP measurement results. The objective of this section is to make an inventory of the most important sources of error in the DIP in agriculture. Some sources of error can be minimised by choosing the correct set-up. Other sources are difficult to influence and have to be taken into consideration during measurements.

When applying DIP to the measurement of plants, four stages can be identified. In Figure 3.9, the four stages are shown.

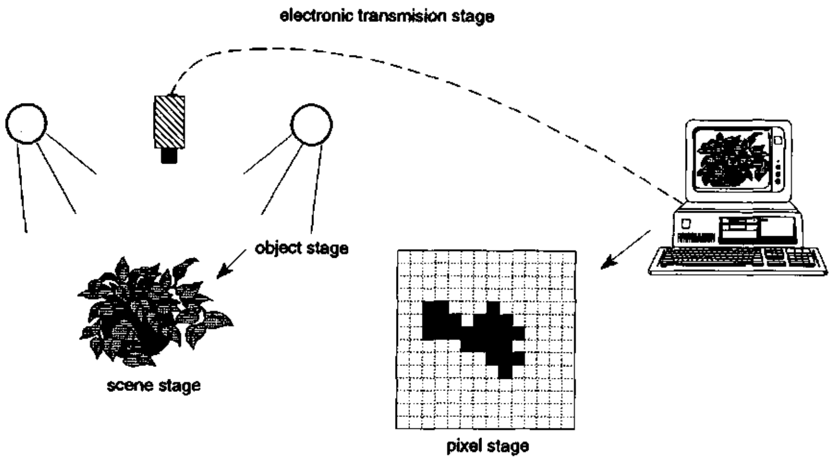

Figure 3.9 Different stages in image processing

1. Object stage.
   The object stage is the stage before recording takes place. The source of error in this stage is due to the variation in the plants. This is discussed in the section dealing with the set-up of the growth experiments in Chapter 4.

2. Scene stage.
   The scene stage is the stage of projection of a 3-dimensional object onto a 2-dimensional image plane. Sources of error at this stage are occlusion of relevant parts, variation in illumination, aberration of the lens, focusing of the object and motion of the object. By taking these sources into consideration during the scene set-up these errors can be minimised.

   Another major source of error is the distance between the camera and the object. From Figure 3.10 it can be seen that the variation in distance from the camera results in variation of length.

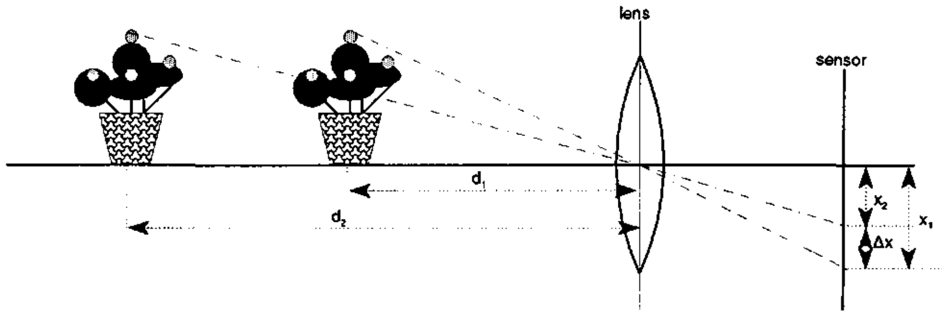

Figure 3.10 Variation in projected length related to the distance between camera and object.

The relative error is expressed as :

$$\Delta x = (1 - d_1/d_2)$$

in which :

- x_1 = length measurement of object on distance 1 to camera (pixels)
- x_2 = length measurement of object on distance 2 to camera (pixels)
- d_1 = distance 1 between camera and object (m)
- d_2 = distance 2 between camera and object (m)
- Δx = relative difference in length measurement for an object on different distances to the camera $(x_1\text{-}x_2/x_2)$

To reduce the error, the ratio d_1/d_2 has to be large (close to 1.0 which means that the relative difference between d_1 and d_2 is small). This can be accomplished by increasing the distance between the camera and the object. However, an increase in distance results in a decrease in resolution. This affects the accuracy of measurements too. In this case a compromise has to be found.

3. Electronic transmission stage.
The electronic transmission stage is the stage in which the CCD-element is charged and the signal is transmitted to the frame-grabber for sampling and quantification. High quality systems give errors that can be ignored.

4. Pixel stage.
   The pixel stage is the stage in which the processing of the image is involved. The most important source of error in this stage is thresholding. Small objects have a relatively large number of edge pixels. Different threshold levels change the area measurement. High accuracy measurements (errors of less than one percent) require at least 50 pixels of length. Less than 20 pixels per length measurement result in relatively large errors (see Figure 3.11).

The most important sources of error are the differences in distance between the object and the camera and the resolution of the system. Both sources can be influenced in the system set-up by changing the distance between the object and camera so the relative difference in distance becomes smaller and by changing the resolution. This requires a lens with a suitable focus.

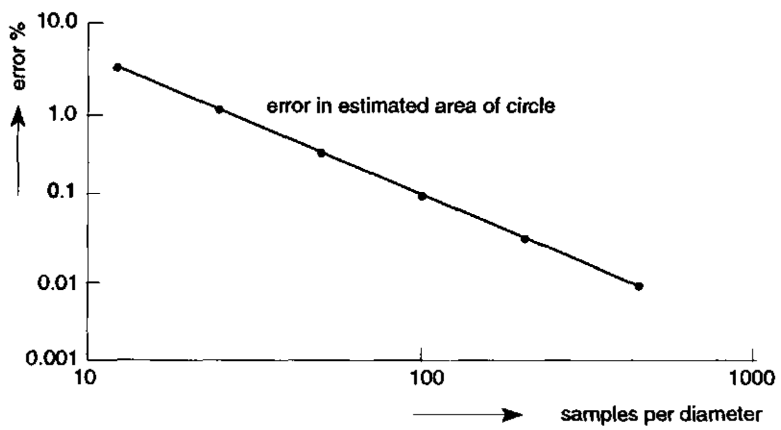

Figure 3.11 Error in the estimate of area of circle (according to Young, 1988).

3.10 Conclusions and discussion

In this chapter the application of Digital Image Processing DIP in an agricultural environment, in this case for pot plant grading applications, is discussed. In industry different applications have already been developed. They cannot be directly applied in agriculture because of the difference in objects. Therefore most applications for grading have to be developed from the very beginning. Rules and features are required to meet the classification objective. In pot plant production these are unknown, since the quality judgements are performed by man.

To set-up a grading system a grading task has to be formulated. The introduction of sub-systems reduces the complexity of the system set-up. An important part of the development of a grading system is the information about features that have to be measured and their processing in a decision model to come to a classification of the plant. In some cases the desired features are not measurable in the input images. Then other features have to be found which can replace or represent them. Sometimes the development of a grading system is an iterative process. Problems in one sub-system, like the uniformity of the lighting system, can result in a different set-up in another sub-system to solve the problem, like an other light source.

The strong point of DIP when used for grading is its ability to measure many features in an objective way. However this is also DIP's weak point because it requires considerable knowledge to interpret the relation between the features. Humans however, are good in analysing complex images and comparing them with each other.

Errors in the system set-up results in a non-satisfactory Grading System Target Output (GSTO). The errors can occur in all the different sub-systems and have the following character;

- the resolution of the object is insufficient;
- the variation in distance between the camera and object is too large;
- the threshold results are not consistent because of shading;
- the essential features in the image are not to be seen;
- the features used in the decision model are not the correct ones, so the decision about the object is not optimal.

4 Identification and testing of grading features

4.1 Introduction

In Chapter 3, the importance of knowing which plant features have to be measured in order to develop an automatic grading system for pot plants is discussed. This chapter concerns the identification and testing of the quantitative and qualitative properties of grading features and their performance in a grading system.

A grading feature is a characteristic of an object measured by Digital Image Processing (DIP). These features are used to grade objects into different groups or classes. The grading operation has to result in the Grading System Target Output (GSTO). This is determined by the experts because no other standards are available at the moment. The expert is a person who is supposed to know the grading standards. The GSTO determines both the grading features and the decision model. The grading features interact with the decision model. A bad decision model, using the correct features, does not result in a good classification and visa versa. Therefore a test is made of the quality of the grading features by applying correlation analysis. Then the decision model is tested. In this way the relation between individual features and the judgement of the expert is tested first. Then the identification of the decision model based on a set of correlated features is carried out.

The main objective of the pot plant production process is to produce full-grown plants of the desired quality. In all stages, the grading operations have to result in groups of plants which develop into uniform groups of full-grown plants of the desired quality. There are different grading tasks involved at each growth stage.

a. Young stage: unrooted cuttings, shoots and plantlets. Grading is performed here to create uniform growth groups. In the young stage, the speed of growth of the plants is important and grading focuses on the growth potential of the plants. The same growth potential means that plants grow and develop equally fast. A uniform growth group means that a group of plants will grow and develop at the same rate.
b. Half-grown stage: plants that are in between the young stage and the full-grown stage. Grading is performed here to improve the uniformity of groups. At this stage not only growth speed is important but also the expected ornamental value of the plants. Therefore, grading takes account of both the growth potential and the shape of the plants since the latter influences the shape of the full-grown plant.
c. Full-grown stage: marketable plants at the end of the growth cycle. Grading is performed here to create uniform quality groups with respect to the ornamental value of the plants. Features like number and distribution of flowers as well as the shape are important. The size of the plant is less important.

A grading point is chosen based on the considerations raised in Chapter 2. Then the grading features are selected and tested so that the grading task can be performed. In order to identify and test the grading features the following steps have to be carried out.

1. Identification of the grading features which have to be measured for a particular grading task.
2. Testing to see whether the desired features are measurable in the image.
3. Testing the quantitative properties of the grading feature, for example, consistency and range.
4. Testing the qualitative properties of the grading feature, for example, its relationship with growth potential and the quality of the plant.
5. Testing the performance of the grading feature in combination with a decision system.

4.2 The identification of grading features

A first step in the identification of grading features is to interview graders. However the graders give subjective answers as:
- "this cutting looks nice";
- "the heart of the plant is well developed";
- "the plant is compact".

The result of the interviews is not a list of objective criteria which can then be implemented as grading features in a DIP system. A problem with the identification of quality determining features is that decisions are based on a complex set. The features which have to be used differ from specie to specie and sometimes the experts have different opinions about quality-determining features and the quality of the plant.

Hines et al. (1986, 1987) concluded that the development of a grading system based on a set of statistics which corresponded to the experts' standards caused problems when it came to interpretation. They suggested to define a set of features which could be measured with DIP. Groups of experts would then have to assign weight factors or other relationships to this set. The features recommended for inclusion in such a set are: height, width, foliage density, rectangularity, product of height-width, computed growth index, elongation and triangularity. These features, and their assigned weight factors, would determine the grade of each plant.

Brons (1992) used a set of standard features such as area, perimeter and convex hull. These features were related to the judgements given by experts by using linear regression, principle component analyses, and a neural network.

A second step in identifying grading features is to study the literature. Chapter 2 and 3 refer to features from the literature on the subject. However, there are no figures reported on how useful these features are as grading features. The literature shows that the nature of features change during the growth cycle. Detailed features are measured in the young stage. These include the leaf area of individual leaves and stem thickness. Looking at the growth system of the plant, which is determined by its chlorophyll, leaf area might be expected to have an influence on growth potential. A larger leaf area normally has more active chlorophyll. Growth in the early stage is little affected by the maintenance of existing leaves and a high percentage of the photonic energy can be used for the growth of the plant. In the full-grown stage, global features like total projected leaf area, shape parameters and flower distribution are measured. These features are responsible for the overall look of the plant.

A third step in identifying grading features is the study of growth models. The growth of plants however, is described in terms of an increase in dry weight or the leaf area index. The 'input plants' all have the same size and the features of individual plants are not taken into consideration. Therefore, growth models do not provide information about grading features for individual plants. The development of growth models for pot plants is still under study and DIP systems can be a tool capable of providing the models with information.

A fourth step is to make judgements and experiments with growing plants. These are defined as 'growth and judgement experiments'. Judgement experiments imply that the features of individual plants are measured with DIP and that these measurements are related to the judgement of the experts. Growth experiments imply that the features of a group of plants are measured with DIP at a certain growth stage and related to the judgement of the expert after a certain growth period. The difference between the judgement experiment and the growth experiment is the availability of the judgement at the moment of measurement. Judgement and growth experiments are discussed in Section 4.5.

4.3 Measurability of grading features

After having chosen a set of grading features, a check has to be done whether the features can be measured with DIP or not. The features mentioned by the grader are sometimes hard to measure. These features have to be replaced by features which are strongly related to the features mentioned, for example, the volume of a plant is replaced by a combination of the projected area of the plant from two or three images. It has also to be checked whether the image contains information on the desired features.

In Chapter 3, scene processing has been discussed including the enhancement of certain features by using the spectral properties of the object or by choosing the correct background.

4.4 Quantitative properties of grading features

The quantitative properties of a grading feature describe its reproducibility, called 'consistency', its range and its relationship to the actual value of the features.

1. Consistency.

   When agricultural objects are presented to the camera in different positions, the measurements obtained with DIP can give varying values for the same feature. In grading, it is important that repeated measurements of the same features on the same plant result in a similar value. To test this property of a particular grading feature a so-called consistency test is carried out. A number of randomly selected plants from a particular population are presented to the grading system and each plant is measured a few times. To simulate normal processing, it is important that the presentation of the plant is independent from the occasions on which it was presented. In this way repeated measurements of the features of the same plant can be carried out. In the test, the plants are presented to the camera by humans. It is possible that this can cause some dependencies between measurements and, therefore, a procedure has been developed to minimise this dependency. The objects are labelled in a way which does not influence the measurements. Then they are presented to the camera in their natural rest position. The 'natural' rest position means that a certain predefined orientation exists similar to the rest position of a cutting. After all the plants have been measured once, the measurement is repeated, beginning with the first plant. There is a time delay between the measurements being made of the same plant. Because of this, the plants' last measurement orientation is unknown. The size of the test set and the number of repetitions is limited because of plant dehydration. After the measurements have been made, the variation in the value of each feature of the same object is determined and this leads to its relative inconsistency.

   Relative inconsistency within object i is defined as:

$$relative\ inconsistency_i = \frac{1}{m} \sum_{j=1}^{j=m} \frac{abs(x_{ij} - \bar{x}_i)}{\bar{x}_i} \qquad (4.1)$$

   m = number of repetitions for one object per feature
   x_{ij} = measured value of the feature of plant i in repetition j
   $x_{i.}$ = mean value of the feature of plant i for all repetitions.

   A relative inconsistency of 0 means that measurements can be carried out without variation. Values larger than 1 occur in extreme situations and mean that the feature can not be measured.

The sum of the absolute difference between the measured value and the mean value is taken as a measure of deviation. In normal variance analysis, the square root of the sum of squares of differences between the value and the mean value is taken, but here one outlier would greatly affect the inconsistency. To standardise the value representing the size of the different objects, results are divided by their mean value, so a relative difference is calculated.

Overall inconsistency for all plants is defined as:

$$\textit{overall inconsistency} = \frac{1}{n} \sum_{i=1}^{i=n} \textit{relative inconsistency}_i \tag{4.2}$$

n = number of plants

The consistency of a feature is defined as:

$$\textit{consistency} = (1 - \textit{overall inconsistency}) * 100\% \tag{4.3}$$

A high consistency (over the 90%) for a feature means that it can be measured repeatedly without much variation.

2. Value range of the grading feature.
   It is important that individual plants can be distinguished when grading plants into groups. Therefore the range of values for the features of the group being presented has to be large enough. For instance the height of the plant can be measured with a high consistency. But if the height of a group of plants is the same, height cannot be used as a grading feature for distinguishing individual plants. The range of a feature is calculated by taking the minimum and the maximum value for that feature in the sample chosen for the consistency test. It is assumed that the distribution function of the values is a normal one.

3. Relation to the actual value of the feature.
   Tests are performed to analyse the relations between the values of the features measured with non-destructive DIP and the actual values of these features in order to interpret the results of the DIP measurements in the growth and judgement experiments. The actual values are determined with destructive DIP measurements or other techniques. For example, in order to determine the relation between the projected leaf area of a cutting and the wet weight and actual leaf area, the projected leaf area of the cutting is first measured in the natural rest position with DIP. Then the cutting is weighted and next flattened between two glass plates to measure the actual leaf area.

The quantitative properties of the features determine whether the feature can be used as a grading feature. Only features with a high consistency and a large range can be used in the decision models otherwise results will be too influenced by uncertainty. This is explained in the discussion on qualitative properties.

4.5 Qualitative properties of grading features

4.5.1 Introduction

The qualitative properties of a grading feature describe its relation to the Grading System Target Output (GSTO). The better the relation of the feature to the GSTO, the higher its quality as grading feature.

The expert determines the GSTO, but his knowledge about the grading standards changes for the different growth stages.

a. Young stage.
   In the young stage there is little information available on GSTO. The grading task in this stage is to create uniform growth groups which are still uniform in the full-grown stage. The quality of a feature in the young stage is determined by its relationship to the quality of the plant in its full-grown stage. At the moment of grading, uniformity and quality in the full-grown stage are unknown. Therefore, growth experiments are carried out to investigate the relationship between features in the young stage and the quality and size of plants in the full-grown stage. A problem is that the relation between features in the young stage and quality in the full-grown stage will decrease due to disturbing influences which may occur during growth cycle.
b. Half-grown stage.
   Just as in the case of young plants, GSTO is not available immediately and so growth experiments are carried out. The shorter the period between grading and the full-grown stage, the fewer disturbing influences will affect the growth process.
c. Full-grown stage.
   The quality of the features in the full-grown stage is determined by their relationship to the expert judgements.

4.5.2 Growth and judgement experiments

The objective of growth experiments is to identify grading features at different stages of growth. These features are used to grade plants into uniform growth or development groups. The objective of judgement experiments is to identify grading features which determine the quality of plants according to expert judgement.

An effective way of identifying features which have to be measured for experiments is to mix the steps referred to in Section 4.2. The first step is an interview with the expert about important grading features. The next step is to observe the expert during the grading operation and to examine whether or not the features mentioned can be identified in the grading result. Grading features are defined on the bases of these results as well as on the basis of information drawn from the literature.

Features are also depending on plant type, for example, structure and size. The number of leaves on a cutting can vary considerably between two different species. These features, combined with standard features such as length, width, and area are measured in both judgement and growth experiments.

After they have been measured, plants are put in a growth medium. At the end of the growth cycle, the individual plants are judged by the expert and again measured with DIP. The experiments are divided into three stages.

1. Start stage : the grading and planting of the starting plants.
2. Growth cycle : the growth of the plants in the experimental blocks.
3. Final stage : the harvesting and grading of the plants in the end stage.

The growth experiment does not necessarily has to begin with cuttings or shoots neither does it has to continue till the full-grown stage has been reached. However, in the final stage, the expert should be able to grade the plants to get a GSTO. In Figure 4.1 the different stages and the relationships between the different measurements and judgements are shown.

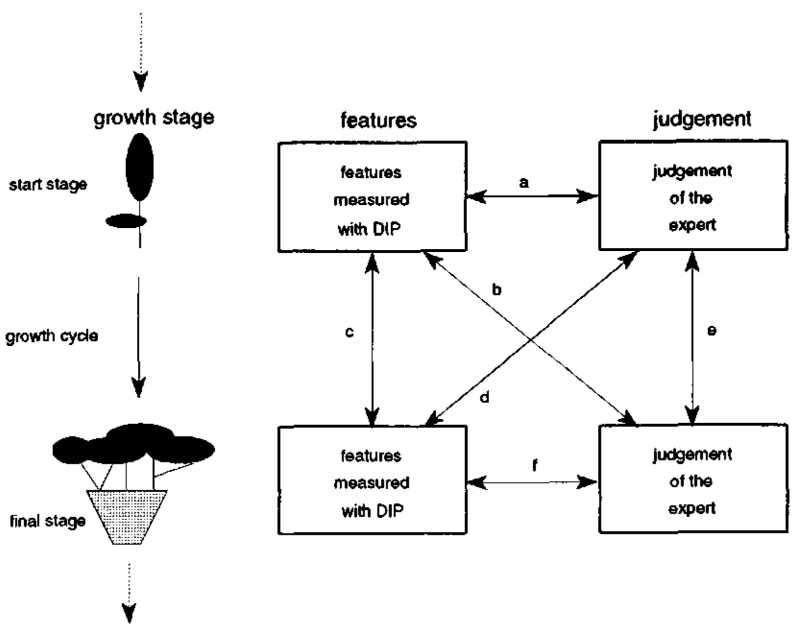

Figure 4.1 Relationships between the different measurements and judgements (explanation given in Section 4.5.3).

4.5.3 Relationships in the experimental set-up

The objective in analysing the relationships given in Figure 4.1 is to determine the qualitative properties of the grading features at the different stages. The following relationships (see Figure 4.1) are distinguished.

- Relationships during the start stage :

a. The relationship between features measured with DIP in the start stage and expert judgement. This relationship provides information about features in the start stage which can be used for grading plants into uniform growth groups in accordance with expert judgements.

- The relations between the start and final stage :

b. The relationship between expert judgement in the final stage and the features measured with DIP in the start stage. This relationship provides information about the grading features in the start stage which are related to the quality and size of the plant in the final stage. The identified grading features are used to grade the plants in the start stage into uniform growth groups.
c. The relationship between features measured with DIP in the final stage and features measured with DIP in the start stage. This relationship provides information about the relation between certain parts of the plants at both stages.
d. The relationship between features measured with DIP in the final stage and the expert judgement in the start stage. This relationship provides information about the expert's knowledge concerning growth potential and its effect on further development of the plant.
e. The relationship between expert judgement in the start stage and expert judgement in the final stage. This relationship provides information about the expert's knowledge concerning the future quality of the plant.

- Relations in the final stage :

f. The relationship between features measured with DIP and the expert judgement in the final stage. This relation provides information about the grading features which are used in the final stage. In this stage the plants are graded into uniform size and quality groups according to the opinion of the expert.

Relationships a and f in Figure 4.1 are found by performing judgement experiments. The other relationships are found by performing growth experiments in combination with judgement experiments.

Figure 4.1 can be extended by introducing more measurements during the growth cycle. The introduction of additional measurements results in more relationships. The decision to perform additional measurements depends on the length of the growth cycle and relevancy for measuring the plants during the growth cycle. Measurements during the growth cycle can provide more information about the development of plants and the uniformity in the growth groups. If the uniformity in the growth groups disappears during the growth cycle, the point at which this happens can be examined. In this way an indication can be given about the point where regrading should be carried out in order to retain uniform growth groups.

In practice not all relations in Figure 4.1 can be analysed. One problem is the expert judgement in the start stage. In the normal course of events, plants are not graded in the start stage so the expert has no experience with grading in this stage. This means that the relationships a, d, and e in Figure 4.1 cannot be analysed.

The expert also does not provide much information on grading standards when additional measurements are introduced during the growth cycle. Therefore some of the relationships introduced by additional measurements cannot be analysed.

Analyses of the results of the remaining relationships are carried out in reverse order: from final stage to start stage. The main reason for this is the fact that, in the final stage, the most information is available on the GSTO. The earlier in the growth stage, the less knowledge is available about GSTO.

The analysis starts with the correlation analysis between the features and the expert judgement in the final stage (relation f in Figure 4.1). This results in Pearson correlation coefficients between individual features in the final stage and expert judgement. A higher correlation coefficient means a better qualitative property of the feature for grading. In Section 4.4, it is mentioned that the quantitative property of a feature affects the qualitative property. If the consistency of a feature is low, it will not show high qualitative properties because variation has been introduced. It has to be taken into consideration that the expert judgement is a categorical variable. This means that the expert judgement has discrete values. The correlation coefficients which are found are less high then when the expert judgement would have been recorded as a continuous variable because of the quantification effect. The analysis can only be carried out when the relationship between the individual features and the expert judgement can be considered as linear. This is tested in Section 5.5.3.3.

The next step is to perform a multiple linear regression analysis. This analysis is done to investigate whether a set of features in the final stage has a relationship with expert judgement in the final stage. The expert judgement is used as dependent and the features as independent variables. The same restrictions which are mentioned for the correlation analysis apply to this analysis. The multiple r indicates the strength of the relationship between a set of features in the final stage and expert judgement in the final stage. The set of features with the best relationship to the expert judgement can be used in a decision model in order to get a classification of full-grown plant.

Then a correlation analysis between expert judgement in the final stage and the features in the start stage (relation b in Figure 4.1) is performed. This analysis is done to investigate the qualitative properties of the grading features in the start stage. The regression analysis with expert judgement in the final stage as dependent and the features in the start stage as independent variable, indicates the strength of the relationship between a set of features in the start stage and expert judgement in the final stage. The set of features with the best relationship can be used in a decision model to grade plants during the start stage into uniform growth groups.

The relationship between features in the start stage and features in the final stage (relation c in Figure 4.1) provides information about how the plant develops during the growth cycle. An investigation can be carried out to see how a single feature in one stage is related to a single feature or set of features in another stage. Understanding of the relationship between a set of features in the start stage and a set of features in the final stage is more difficult. In this case a multivariate input/output model is needed. In order to understand a set of features in the final stage, these features have to be related to expert judgements, otherwise no interpretation can be carried out. The set of features in the start stage is then related to that set of features in the final stage. However this does not provide additional information.

4.5.4 The set-up of the growth experiments

When analysing relationships in the growth experiments, it is important that there is as little disturbance from external factors as possible. During the set-up and performance of experiments, sources of disturbance have to be minimised. To describe these disturbances and how they can be minimised, the growth experiment is divided into three stages as defined in Section 4.5.1.

Start stage parameters :

- Plant species : the shape and size of each species are different. Results for one species cannot be used for other species without verification.
- Plant breed : The response of different breeds to grading can be different: every breed is unique. The same breed per species should be used for a series of experiments in order to be able to compare the results.
- Origin of the start plant : each grower uses specific methods to produce plants. Westerhof (1987) stated that the origin of cuttings has an influence on the growth potential of the plant. Therefore, the origin of cuttings has to be the same for one series of experiments.

- Location on the mother plant: The location of cutting on the mother plant influences the development of the cutting (Westerhof, 1987). For the experiments cuttings should be used from mother plants of the same age, grown in the same compartment of the greenhouse, and removed from the same location on the mother plant. The treatment of the mother plants with hormones should be the same or should be avoided.
- Treatment of the start plant : the growth potential of the start plant can vary if the plant storage period varies. Therefore all the start plants involved in one experiment should have had the same treatment. Cuttings should be removed at the same time and by the same person.

It can be stated that by excluding all sources of disturbance, start parameters, with the exception of size, are the same for all plants.

Growth cycle parameters :

- Climate.
  - The temperature differs between greenhouses and even within compartments.
  - The water supply may show variation because of the supply system in the greenhouse.
  - The supply and concentration of nutrients can differ at different locations.
  - The amount of illumination depends on the season of the year and location in the greenhouse. Some parts are shadowed by construction elements.
  - The distribution of CO_2 can vary within compartments depending on the distribution- and ventilation system.

  To reduce these influences experiments are performed in the middle of the greenhouse. By putting experimental blocks close to each other, the influence of climatic differences can be reduced. Special attention should be paid to ensure a uniformity of light supply and to avoid obstacles intercepting light. The experiments should be performed during different seasons to examine whether the same relations are found.
- The use of growth regulators : growth regulators are used to stimulate or reduce the growth. To reduce the effect of variation in dosage of growth regulator per plant, the use should be minimised or avoided.
- The time after which a young plant starts to grow may vary. The reason why some cuttings root faster than others is unknown but it does cause differences in the growth speed. For that reasons it is better to start with plants that already have roots.
- The interaction between the plants. The development of a plant depends on the size of its neighbours. For example a small plant between large neighbouring plants will be overshadowed (see also Section 2.2). When plants are positioned between plants of the same size, competition between plants will be more equal.

Final stage parameters :

- The growth response of plant parts may differ. Developments in size are non-linear. An example is the development of a leaf when it opens. As a result the shape of the plant can change substantially within a short period.

It can be concluded that growth experiments should be done in growth chambers where all climatic conditions can be controlled and environmental influences can be excluded. Moreover the plant interactions should be standardised and the influence of the grower minimised. In this research, however, the objective is the development and testing of a plant grading system with DIP, under normal conditions. Therefore the experiments are performed in commercial greenhouses.

The only source of variation in the growth experiments should be the size of the plants and the interaction between plants. Therefore different types of blocks are created to investigate plant interaction: those having homogeneous and those having heterogeneous environment respectively. Homogeneous means that the size of the plants standing next to each other is almost the same. The same size means that the values of the features for which the plants are graded are similar.

- Block 1: The ordered experiment, homogeneous environment.
  Plants in the start stage are measured with DIP, then labelled with a unique code and put in a pot. The plants are ordered and placed in the greenhouse based on one or more grading features. The plants are put in a square, so the number of edge plants is minimised. The square is filled up row by row. In this way the difference between plants standing next to each other is minimised and the environment is highly uniform. All plants compete in almost the same way. Ordering plants is preferable to grading plants into uniform groups. If groups are created, plants of the same group will be neighbours, but the size of the neighbouring plants can be very different. This depends on the smallest and largest plants assigned to that group. The border between two growth groups introduces additional heterogeneity in the environment.
- Block 2 : The random placed experiment, heterogeneous environment.
  Plants in the start stage are measured with DIP, then labelled with a unique code, put in a pot, and placed in a random order in a square in the greenhouse. By using a random order, the normal processing in greenhouses is simulated. Plants can have all kinds of neighbour plants so the environment for the plant is heterogeneous. The plant will endure different competition.
- Block 3 : The free-spaced experiment, no interaction.
  Plants in the start stage are measured with DIP, then labelled with a unique code, put in a pot, and placed in the greenhouse with a surplus space around the individual plants. In this way there is no interaction between plants. This situation is not common in a greenhouse. This experiment was carried out to see what would happen if the plant would not endure competition.

The difference in strength between the relationships in the start stage and the final stage of the different blocks indicates the influence of differences in environment.

The judgement given by experts on the plants in the final stage needs some preprocessing. As mentioned in Section 2.6 experts can be very subjective. To avoid that the size of the preceding plants has influence on the judgements of the expert on the current plant, plants should be presented in random order. This is especially the case when the final plants are judged from the ordered experiments.

4.6 The sources of error in the testing of grading features

During the testing of grading features and the growth experiment, errors occur which influence the results of the growth experiments and the identification of the grading features. In Figure 4.2 the different sources of error in the growth and judgement experiments are shown in a qualitative way.

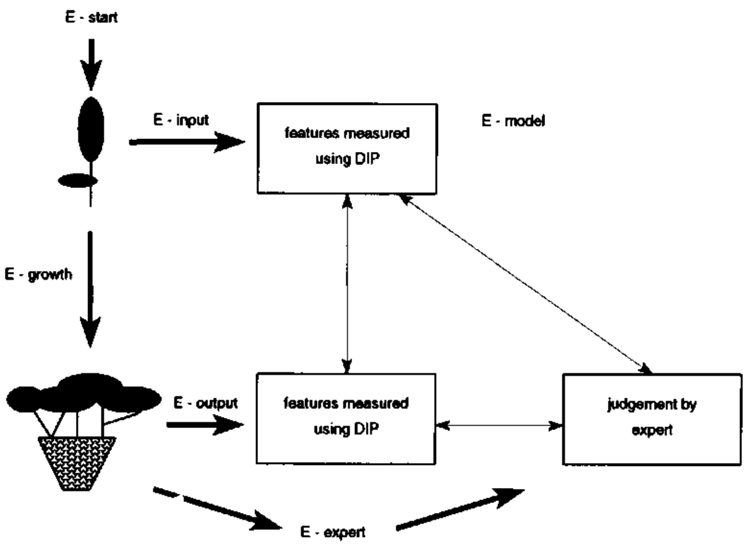

Figure 4.2 Error sources in the growth and judgement experiments.

1. E - start
   Error caused by differences between the starting plants due to variation in origin such as mother plants, cutter, and treatment (Section 4.5).
2. E - input
   Error due to making measurements using DIP in the start stage. The magnitude of the error is determined by consistency tests (Section 4.4).
3. E - growth
   Error due to variation in climate, for example, water supply, light supply, and different location (Section 4.5).

4. E - output
   Error due to measurements using DIP in the final stage. The magnitude of the error is determined by consistency tests (Section 4.4).
5. E - expert
   Error due to classification errors made by the expert. This error includes three major sources:
   - The consistency of the expert. By judging the plant again the classification may be different. Those plants which fall in between two adjacent classes are particularly susceptible to being classified differently.
   - If the mean size of the plants differs in time, the classification also differs in time. The standards which are used by the expert are changing.
   - The expert gets tired and is influenced by his environment. Concentration breaks down and this results in a less consistent plant classification (Section 2.7). Experiences with large groups of plants showed that the expert sometimes assigns plants to totally different classes.

6 - E - model
   The model is a description of the reality which inherently results in an error. It is not possible to describe the reality completely, special not in biological cases.

The errors 1 to 5 are controllable (Section 4.5.4) and have to be minimised. The error in the overall model for the growth of plants is unknown. In the statistical analysis of the growth experiments a part of the variation not explained by the statistical analysis is due to this unknown error. In Figure 4.3 the overall identification and testing of grading features is shown.

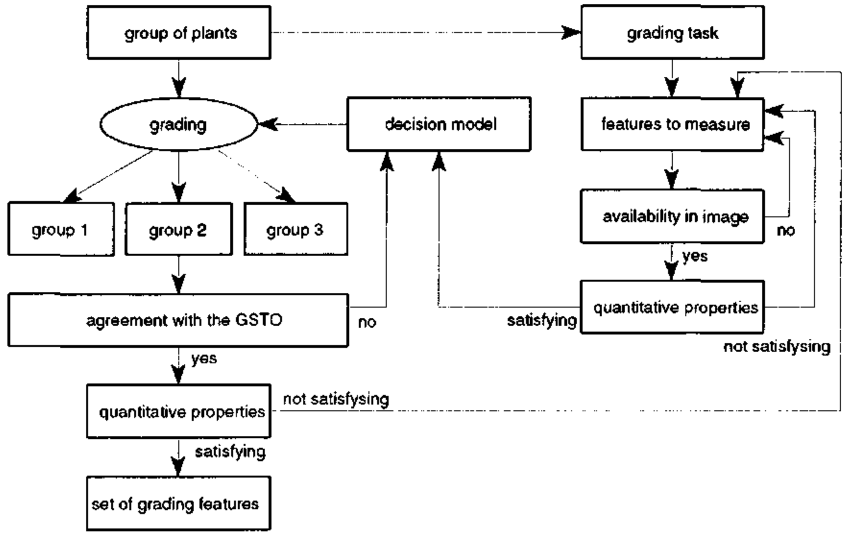

Figure 4.3 The identification and testing of grading features.

4.7 The performance of grading features in combination with a decision model

4.7.1 The decision model

After the qualitative properties of a set of plant features have been determined, their performances are tested in decision models. The development and testing of decision models is not the same for all growth stages. The availability of Grading System Target Output (GSTO) has a considerable effect.
In the full-grown stage the GSTO is immediately available. It is based on standards determined by the auction or other commercial institutions. Because the GSTO is available, techniques like statistical classifiers or neural networks can be used. As a result decision models based on more complex sets of features can be developed. Such a decision model can be used more often because the quality standards for the plants do not change.

In the young stage, however, there is not much information available on GSTO because no standards are available for grading. The expert has some basic ideas about the grading of young plants, for example, the importance of the leaf area. However, as discussed in Chapter 2, classifications performed by human graders are not consistent.

An additional problem is the difference between groups of young plants. Shape and size can vary since they are influenced by the 'harvest' date of the young plants, the season of the year, and the location in the greenhouse (Westerhof, 1987). Therefore it is hard to establish standard sizes for the young plants. Even when growth experiments are performed to identify relations between features in the young stage and quality of the plant in the full-grown stage. In all these cases it is not possible to develop complex decision models. The number of grading groups is determined by the processing that takes place in the greenhouse. The number of plants in each group has to be large enough to be treated as a unit. For example during re-spacing, one unit is divided into two groups which fill up a compartment. In operational situations it is very common to grade into equally sized groups. To accomplish this, a sample from the group is taken and based on one feature or a combination of relative features (for example, ratio between length and leaf area) the feature space is divided in such a way that it results in equally sized groups. A relative combination of features can be determined by performing growth experiments.

In Figure 4.4, the change in feature measurements, the knowledge of GSTO, the objectives of the grading task, and the complexity of the decision model in relation to the growth stage of the plant, is shown. In the stages between young plants and full-grown plants, decisions are made on the basis of a mixture of these factors.

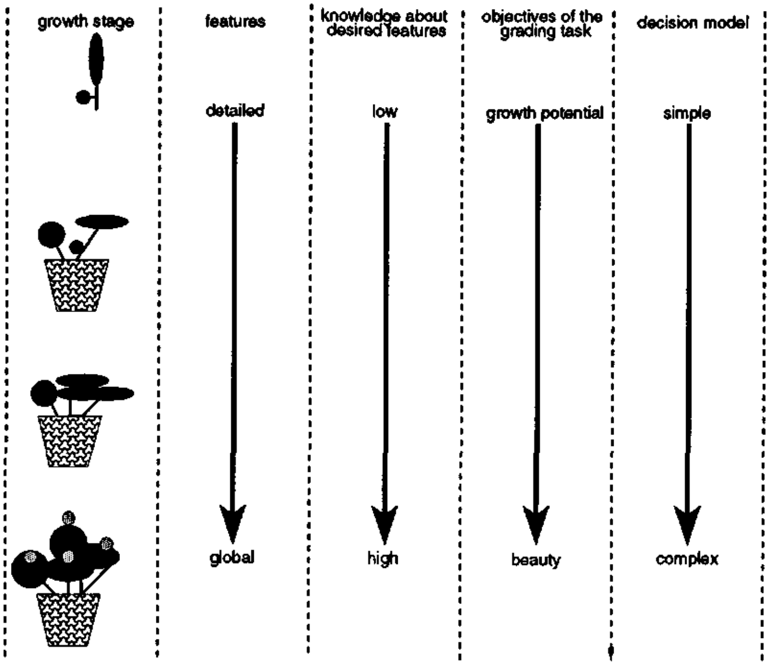

Figure 4.4 The change in feature measurement, knowledge of GSTO, objective of grading task and complexity of a decision model in relation to the growth stage of the plant.

4.7.2 The performance of the decision model in a grading system

The performance of the grading features and the decision model in a grading system are tested by experiments. The grading system and the expert both grade the same set of plants. The results of the decision system are compared with the judgement of the expert, the GSTO. If the computer decision is the same as the expert's judgement, the decision is defined as correct. A difference between the expert's judgement and the decision of the grading system of one class is defined as a first order error. This error can be caused by plants close to the limit of two classes. A difference of more than one class is defined as a second order error. These are serious errors.

The performance of a grading system is determined by :

$$performance = \frac{number\ of\ equal\ classifications}{total\ number\ of\ plants} * 100\% \tag{4.4}$$

By determining the performance, different decision models are evaluated.

In order to test the performance of a decision model at points where no GSTO is available (e.g. the young stage) a judgement is made about the plants after a certain growth period. The experimental blocks are divided into growth groups. The plants are assigned to a growth group based on the rank in the experimental blocks. For the ordered blocks this means that the first growth group consists of the smallest plants and the last one out of the largest plants. In the random blocks, all different sizes of plants are present in the growth groups. The size ratio of each growth group is then determined by the percentage of small, medium and large plants (see Formula 4.5).

$$size\ ratio = \frac{\%\ small*1+\%\ medium*2+\%\ large*3}{2} - 50 \tag{4.5}$$

For example when all plants in a group are judged to be small, the size ratio is :

(100*1 + 0*2 + 0*3)/2-50 = 0

When all plants were judged large, the size ratio is :

(0*1 + 0*2 + 100*3)/2-50 = 100

The size ratio gives an indication about the average size of a growth group. When the decision model performs well, it is to be expected that in the ordered blocks the distribution of the small, medium and large plants changes for the growth groups. E.g. the 'smallest' growth group should contain more small plants resulting in a smaller size ratio. For the random placed blocks, the size ratios of the different growth groups should be the same. Problems will occur if for instance, 100% is judged as medium in one group and in another group 50% is judged as small and 50% is judged as large. The growth ratio is the same, but in practice this situation is quite unusual.
Division into growth groups can be simulated by ordering the experimental blocks for any feature. It should be taken into consideration that for the simulation of a different order, the growth environment is not homogeneous for that particular feature.

4.8 Discussion and conclusions

In this chapter the identification of grading features and the testing of the grading features for their quantitative and qualitative properties and their performances in a grading system were discussed.

The grading features are identified by interviewing growers, from literature and by performing growth and judgement experiments. The grading features used by the experts may differ from those used in Digital Image Processing (DIP). In the interpretation of the decision model, it is useful to create a set of features that can be interpreted by plant physiologists.

A problem that arises in the identification and testing of grading features is the availability of a Grading System Target Output (GSTO). When there is little information available on the GSTO, the development of a decision model and the testing of grading features in a decision model is more difficult than when standards are available.

In the full-grown stage, standards are available and the performance of judgement experiments provides information about qualitative properties of features measured with DIP. These standards imply that complex decision models, like neural networks, can be developed.

In the young stage and during growth there are no standards available. Therefore growth experiments are performed in order to investigate the qualitative properties of features. In order to get the strongest relation between the features and the GSTO, the size of the plants should be the only variation in the growth experiments. Ordered and random blocks are created to study the influence of the plant interaction effect. Because of the absence of standards in the young stages and during growth, only simple decision models can be developed. These are based on values derived from random samples, using a single feature or the ratio's between features.

The quality of a feature is determined by the strength of its correlation with the GSTO. The quantitative properties of a feature also influence the qualitative properties. Low consistency and a small range weaken the correlation.

Grading features can be measured more accurately in industry than in agriculture. The definition of the objects is much better in industry than in the agriculture and this means that the measurements can be performed more accurately. The consequences of false classification in agriculture are, in general, not so serious as in industry because of the relatively low prices of the objects and the low penalty cost.

The features and availability of the GSTO varies in different growth stages. A system which would be able to measure the plants in all growth stages based on the same features and decision model would be complex. Therefore, it is better to develop a grading system for each growth stage.

5 Case study on Begonia plants

5.1 Introduction

The Begonia plant is a flowering plant which is grown for its ornamental value. It is propagated by removing cuttings from mother plants. Cuttings have a well-developed 'first' leaf and are starting to develop a 'second' leaf. The removing of cuttings is done manually. In spite of the fact that the human cutters are trained to harvest cuttings that are almost of the same size, results are heterogeneous. In Section 2.7 experiments are described in which man did grade unrooted Begonia cuttings. These experiments show that man are not able to grade cuttings in a consistent way during a longer period.

The first objective in this case study is to identify and test features of unrooted Begonia cuttings measured by DIP. These features are used to grade the cuttings into uniform growth groups which are expected to have a high degree of uniformity after a growth period of four weeks. The second objective is to identify and to test features which describe the size and development of the four week old Begonia plants measured by DIP. These features are used to evaluate the uniformity of the growth groups after this growth period and to grade the plants into uniform development groups according to the standards set by the experts. The procedures for identifying features and describing relationships are discussed in Chapter 4.

After discussing the way Begonia cuttings are processed, the DIP used to measure its features is described. For the unrooted stage, a routine has been developed to estimate the leaf area. This is based on the grey values of the object pixels. Segmentation of the individual parts of the unrooted and half-grown plant is knowledge based. Therefore, a model of the plant is used to identify the individual parts. The features are identified by performing growth and judgement experiments. After the presentation of the results, different decision models for grading four week old Begonia plants are discussed.

5.2 Flow chart of growth and processing points

The propagation of Begonia plants is done by specialised firms. These firms grow the mother plants and ensure that the Begonia cuttings are rooted. Then the plants go to other growers who bring them to the flowering plant stage. Figure 5.1 gives a flow chart showing the growth of Begonia plants.

In the growth experiments, plants were measured three times in a growth period of four weeks. They were measured at the unrooted stage, after a growth period of three weeks, and after a growth period of four weeks. When they were in the four weeks old stage, they were also judged by experts.

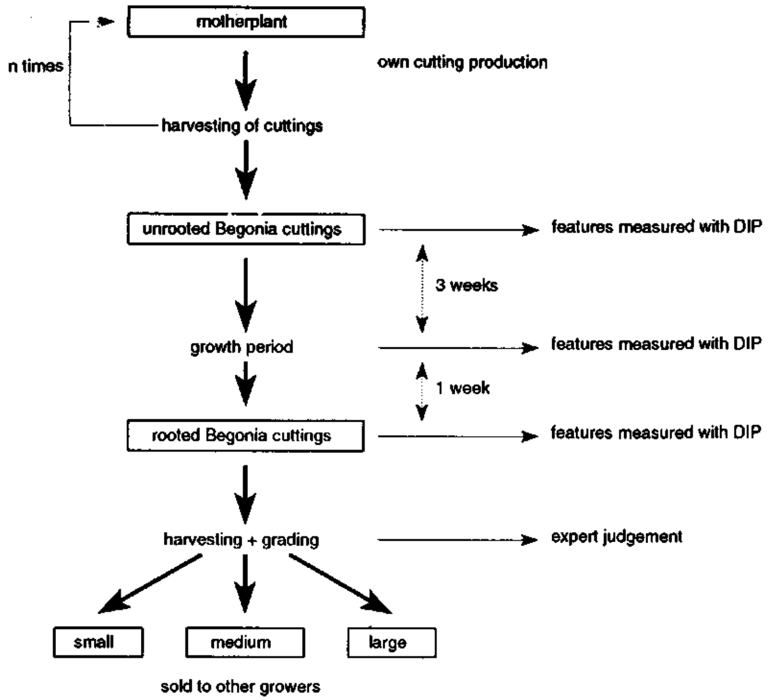

Figure 5.1 Flow chart of Begonia cultivation.

Figure 5.2 The unrooted Begonia cutting.

5.3 Unrooted Begonia cuttings

5.3.1 Introduction

Figure 5.2 shows an unrooted Begonia cutting on a diffuse transparent plate with back-lighting. The parts to be identified are noted in the figure.

According to the expert the leaf area of the first and second leaf is important for the growth potential of the cutting. The length of the stem between the first and second leaf gives information about the compactness of the cutting. Experts state that cuttings with relatively small leaves and a long stem should be removed.

Leaves and stems can be distinguished by their geometric properties and their position in relation to the structure of the cutting. The individual parts are identified and measured by implementing this structure in image processing and feature extraction. In this section the possibilities of measuring the features of unrooted Begonia cuttings and their quantitative properties are investigated.

5.3.2 Scene processing

The Begonia cutting has a three-dimensional structure. Measuring the leaf area by only determining the projected area causes errors. The cutting cannot be flattened or processed during measurement because of possible damage to the cutting. Therefore, the cuttings are put in their natural rest position on a diffuse transparent plate with back-lighting (Figure 5.2). In this way, geometric features can be extracted well. The cuttings are oriented in such a way that the tip of the stem is always at the bottom of the image. This is done to reduce the calculation time involved in the experiments. The main stem is allowed to have a deviation of 30 degrees from the vertical axis.

The projected leaf area of the cutting in the natural rest position is not equal to the actual leaf area. Since the Begonia cutting is not totally opaque, transmission information can be used to get information about leaf orientation in the image. In this way a correction can be made for the calculation of the actual leaf area of overlapping or tilting leaves.

In the experiments the cuttings are presented one by one. The distance between the camera and a cutting varies between 0.97 m and 1.03 m. The error due to differences in distances between camera and cutting is negligible (Section 3.9). The largest cutting just fits in the camera's field of view (512*512 pixels).

5.3.3 Image processing

The measurement of the leaf area of the cutting independent of its orientation is based on the grey value information of the cutting using light transmission. The grey value of the object pixels provides information about the thickness of the leaf. The method is based on the fact that lower grey values represent more leaf material between background and camera than higher grey values.

The Lambert-Beer law defines the attenuation of the transmitted light ray in a homogeneous, non-diffusing, absorbing medium. Unfortunately, the Lambert-Beer law cannot be applied to suspensions with particles and cellular materials because a light ray transmitting through a material with internal interfaces which has absorbers in discrete volumes cannot be defined with sufficient accuracy. Successful mathematical models have been developed for single particle scattering. No comparable models have been developed employing basic physical laws to a light ray transmitted through a cellular structure such as a plant leaf. In this case the gross effect would be measured (Birth, 1976).

The reduction in intensity of the light ray is related to the thickness of the leaf material between the light source and the camera (Dijkstra, 1991). To compare the transmittance at different points in the image, it is essential that the background is homogeneous and the light intensity is constant. The measurements have to be done in the intensity range of the camera for which the relation between intensity and grey value is linear.

The relation between the grey values and the 'thickness of the leaf' is studied by presenting the same cutting five times in natural rest position to the camera. This number of presentations is a compromise between the need for adequate information and the danger of physical damage through dehydration. The calculated leaf area of the cutting in all five recordings has to be the same. The projected leaf areas will be different because of different orientations. The grey value histograms of the cuttings show that between the five cuttings there is a difference in the distribution of grey values. It has already been mentioned that pixels with a lower grey value correspond with more leaf material between camera and background than pixels with higher grey values. The leaf area is estimated by using a weight factor that is related to the grey values.

The most proper way to estimate the leaf area is to calculate a weight factor for each grey value of the grey value histogram. However, the histogram is divided into five intervals, beginning with the threshold level and ending with the grey value of the lowest possible object pixel in order to reduce the amount of calculation time. The intervals have different lengths because it is expected that the function is exponential (like the Lambert-Beer law). The intervals with the lower grey values are shorter than when higher grey values are involved. The length is determined interactively which will be explained in the error minimisation of the overall function. After a set of interval limits has been calculated, the number of pixels in each interval is calculated (Equation 5.1).

$$x_{ijk} = \sum_{l=i_l}^{l=i_h} histogram[l] \tag{5.1}$$

x_{ijk}	=	number of pixels in grey value interval i for cutting k and repeating number j
histogram[l]	=	number of pixels with grey value l
i_l	=	lower limit of grey value interval i
i_h	=	upper limit of grey value interval i

The estimation of an optimal set of weight factors starts with a certain set of weights w_i. Each part of the grey value interval x_i is multiplied by its particular weight factor which results into a computed area (Equation 5.2).

$$x_{jk} = \sum_{i=1}^{i=i_{tot}} (w_i * x_{ijk}) \tag{5.2}$$

x_{jk}	=	calculated area of cutting k record number j
i_{tot}	=	total number of grey value intervals
w_i	=	weight factor for grey value interval i

The average area of the cutting is determined after calculating the area with this particular set of weight factors. If the weight factors are correct, the differences between the five measurements should be very small. If not, the error is calculated by adding the absolute difference between the calculated area and the average area (Equation 5.3). Since the size of the cuttings differ the error is standardised. The error is added for all cuttings in the test.

$$E = \sum_{k=1}^{k=k_{tot}} \sum_{j=1}^{j=j_{tot}} \frac{(x_{jk} - x_k)}{x_k} \tag{5.3}$$

x_k	=	mean calculated area of cutting k
E	=	standardised error cumulated for all cuttings
j_{tot}	=	total number of repeatings
k_{tot}	=	total number of cuttings

By minimising the error E, a better set of weight factors can be calculated. The error is a function of the weight factors w_i and the interval boundaries i_l and i_h. For five intervals the error is a function of four weight factors (one of the weight factors is standardised on 1, to avoid $E = 0$ for $w_1 = w_2 = .. = w_5 = 0$) and four interval boundaries. (The lower boundary of the lowest interval is known, the lower boundary of the adjacent interval is equal to the upper boundary of the first interval, and so on. The upper boundary of the highest interval is also known). Given the interval boundaries, the optimal weight factors are calculated using the non-linear optimisation procedure as described by Hooke and Jeeves. The weight factor of the interval with the highest grey values is set to 1.0. This section is assumed to be the thickness of a single leaf. All other factors have to be $\geq$ 1.0. The optimum set of weights is used to calculate the corrected leaf area of the cutting. A nested non-linear optimisation procedure, the zero-order procedure of Hooke and Jeeves, is used to vary both weight factors and interval boundaries.

Individual parts of the cutting, like the first and second leaf, are identified by a procedure which automatically determines and measures these parts. This procedure is based on a model of the cutting. This so-called knowledge based segmentation has been described in Chapter 3. Similar procedures have been described by Simonton (1989) to identify the structure of geranium cuttings, and Tillett (1991) to identify stem structures in Chrysanthemum images.

The procedure consists out of three parts. The first part (the raw segmentation) identifies potential leaf and stem regions in the image. The average stem thickness is also estimated. The second part (the exact segmentation) uses the estimated stem thickness to create a stem-leaf structure based on the regions identified in the raw segmentation. The regions are grouped into segments representing plant parts such as stems and leaves. The segments are connected to each other by pointers which define the relationship. The third part (the identification and measuring) is based on the segments and pointers which connect the segments.

Segmentation is based on run-length coding. A run starts if two adjacent pixels are below the predefined threshold. Object pixels have lower grey values than the background pixels because of back-lighting. The run ends if two adjacent pixels are above the threshold. Two pixels are taken to remove noise and small holes in the object. This worked well. In this way, each line is split-up into runs.

In the raw segmentation, runs are classified as 'leaf' run, i.e. runs which belong to a leaf part, or 'stem' run which are runs which belong to a stem part. Scanning is carried out from top to bottom, so the first runs encountered are leaf runs because of the orientation of the cutting. Each run is tested for connectivity with runs in the previous line. When a run meets the following criteria it is identified as a stem run (see Figure 5.3).

1. The length of the run, which represents the thickness of the stem, has to be between a minimum (5 pixels) and a maximum (25 pixels). Runs which do not meet these criteria are classified as leaf runs (see Figure 5.3). The angle between the stem and vertical axis has to be as small as possible otherwise corrections have to be made. For example, if the angle between the stem and the vertical axis is 30 degrees, the actual stem thickness is 0.87 times the length of the run (cosine 30 degrees).
2. The length of the run and the length of the three previous connected runs must be almost the same. A difference in length of one pixel between two runs is permissible. This one pixel is needed to compensate for uncertainty of the edge pixel caused by digitisation errors.

In some situations, a series of stem runs is interrupted by a single leaf run, because of small objects or noise. A correction is needed to complete the stem runs and the single leaf run is changed into stem run. This backward checking through series of runs improved the performance of the segmentation.

The result of the raw segmentation is an image of stem and leaf runs. During the raw segmentation errors are made. These are caused by leaves which look very smooth and relatively thin to the camera. In the exact segmentation these errors are corrected.

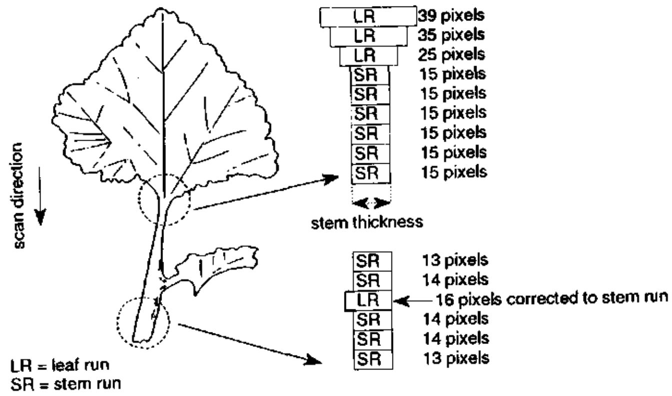

Figure 5.3 Classification of runs in the raw segmentation

In the exact segmentation the classification is based on the information from raw segmentation. The information is stored in segments which represent parts of leaves or stems. A segment contains the following information:

- segment identification number
- area of the segment (pixels)
- coordinate of the left most point
- coordinate of the right most point
- coordinate of the uppermost point
- coordinate of the lowest point
- parent segment, the segment identification number indicating where it has come from
- child segment, the segment identification number indicating where it goes to
- plant part identifier, stem or leaf
- grey value histogram of the runs to perform the corrected leaf area calculation

When a run is assigned to a certain segment, all data in the segment are updated. When the coordinates of a maximum in one of the four directions changes, the new maximum is stored.

The scanning of the image is done from bottom to top. For runs unconnected with runs in the previous lines, following rules are applied (see also Figure 5.4).

- If a run is the first run and the length is at least 6 pixels, it is considered to be a part of the basic stem because of the orientation of the cutting and the scanning direction. The length of the run has to be at least 6 pixels because irregularities occur at the cut plane. The value 6 has been determined experimentally.
- If a run is not the first one, it is part of a leaf. A cutting has only one basic stem, so the next run with no connected runs in the previous lines cannot be part of the basic stem. It is classified as a 'new leaf' run and stored in a 'new leaf' segment. Because of the orientation and scanning direction, leaves can only be connected to a stem. So leaves which begin from 'nothing' are called new leaves and merge into existing leaf segments later.

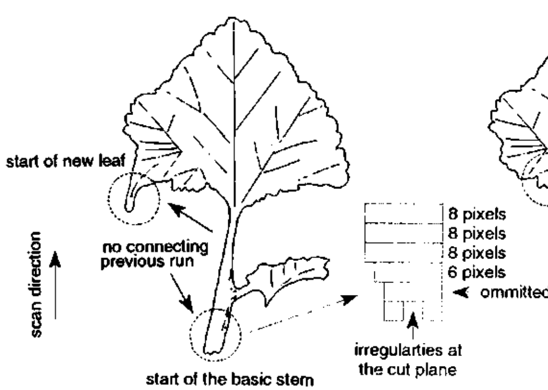

Figure 5.4 The classification of runs in the exact segmentation.

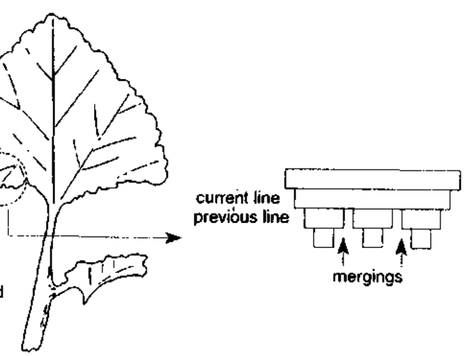

Figure 5.5 Definition of current and previous runs.

For runs with connected runs in the previous lines the following information is important:

- the classification during the raw segmentation (stem or leaf);
- the classification of the previous run in the exact segmentation (stem run (SR), leaf run (LR), new leaf run (NLR));
- the segment number of the previous, connecting run. Where the run is classified as a part of the same segment as the previous run, it is merged to the segment.

Before decisions are made about the classification of the run, tests are carried out. It is determined whether a run merges or splits and what kind of runs merge and split. The following tests (A, B, and C) are performed for all the runs on the current scan-line, run by run. In Figure 5.5, the current and previous runs are defined.

A- The number of merging runs in the previous line (previous runs) with the current run is determined.

B- If two or more previous runs merge into the current run, the following split and merge rules (R1, R2, and R3) are applied.

R1- Processing starts with the first pair of previous runs. If two different leaf runs (LR - LR) merge because of overlapping leaves (see Figure 5.6a), or two different stem runs (SR - SR) merge because of overlapping stems, or a leaf and a stem run (LR - SR) merge because of a leaf overlapping a stem (see Figure 5.6b), the current run is split-up into two runs. This procedure is discussed at the end of this section. 'Different' means that the segments, to which the previous runs belong, have different numbers. These segments are different parts of the plant during the segmentation. Splitting results in two current runs. The processing continues using the left current run (processing is done from the left to the right). The right current run is examined in the next step. If there are more than two merging runs, the processing continues by comparing the second previous run with the third previous run until all mergings into the current run have been checked.

R2- The next test is for the mergings of runs from the same origin. If two new leaf runs merge (NLR - NLR), the information of one segment is combined with information from the other segment. The merge point is deleted. This situation occurs when a leaf has an irregular shape and many NLR's have started (see Figure 5.7a), but some scan-lines later they merge into one run. Also two existing leaf runs (LR - LR) of the same origin can merge because, for example, a hole in the leaf (see Figure 5.7b). One of the two previous runs is deleted and no information has to be combined because the runs have the same origin. The merging of stems from the same origin is impossible due to the structure of the cutting. If the stem splits, the old stem segment is closed. Splitting is recorded and two new stem segments are created.

This step is repeated for all mergings belonging to the current run. If the first two previous runs are merged, the next test is again made on the first pair of previous runs, while the second previous run is the original third previous run. Otherwise the test is carried out on the second and third previous run and so on until all merging points are evaluated.

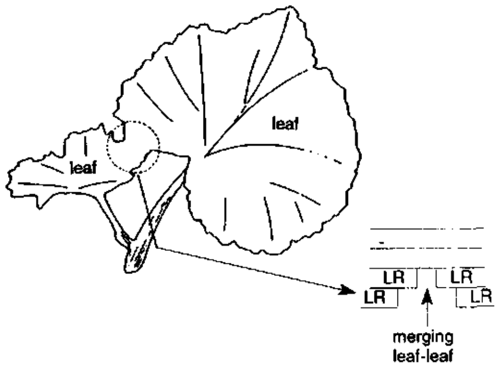

Figure 5.6a Merging of two different leaf runs.

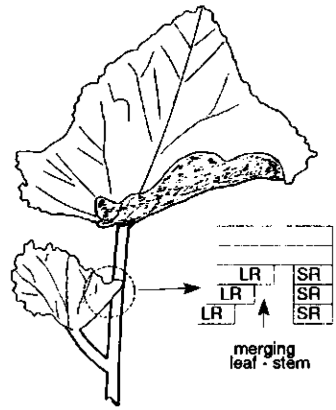

Figure 5.6b Merging of stem and leaf run.

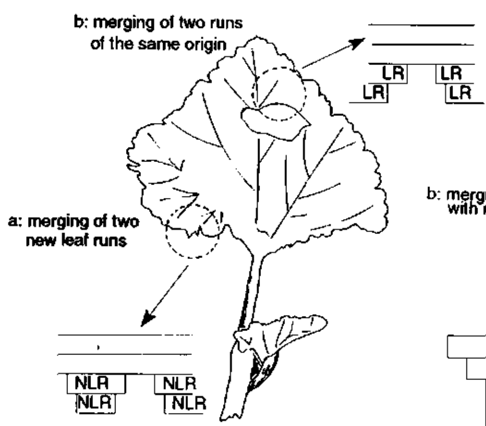

Figure 5.7 (a) Merging of two new leaf runs.
(b) Merging of runs from same origin.

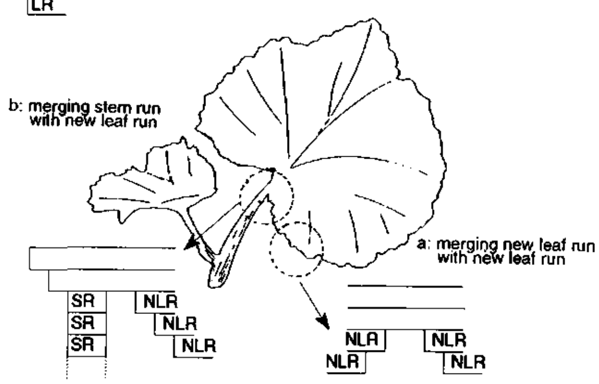

Figure 5.8 (a) Merging new leaf run with leaf run.
(b) Merging stem run with new leaf run.

R3- The last test is on the remaining connected runs in the previous scan-line. It determines whether a new leaf run (NLR) merges into a leaf or stem run. In the first situation (NLR - LR) (see Figure 5.8a), all the information of the new leaf segment is combined with the leaf segment, and the new leaf segment is destroyed. In the second situation (SR - NLR) (see Figure 5.8b), the stem segment is closed and the new leaf segment is turned into an existing leaf segment. An existing leaf segment can only be created when a stem is connected to it. The leaf segment is connected to the stem segment by a pointer. These pointers are used for analysing the cutting structure. This step is repeated for all the merging runs in the previous line.

When two or more merging runs exist in the previous line after R1, R2, and R3 have been applied, these rules are put into operation in reverse order.

The sequence SR - NLR - LR is analysed to illustrate the rules.

rule 1 :	nothing happens
rule 2 :	nothing happens
rule 3 :	SR is closed and NLR turns into an existing leaf run resulting in LR - LR with two different segment number
rule 2 :	nothing happens
rule 1 :	a division is made between the two different leaves resulting in two different LR's

<u>Summary of the rules</u>.
The segment number, indicating the number of the part, is listed in brackets.
- = merging to one segment
¦ = not merging to one segment

rule 1 :	LR(i) - LR(j)	= LR(i) ¦ LR(j)	if $i \neq j$
	SR(i) - SR(j)	= SR(i) ¦ SR(j)	if $i \neq j$
	LR(i) - SR(j)	= LR(i) ¦ SR(j)	if $i \neq j$
	SR(i) - LR(j)	= SR(i) ¦ LR(j)	if $i \neq j$
rule 2 :	NLR(i) - NLR(j)	= NLR(i)	
	LR(i) - LR(j)	= LR(i)	if $i = j$
rule 3 :	NLR(i) - LR(j)	= LR(j)	
	LR(i) - NLR(j)	= LR(i)	
	NLR(i) - SR(j)	= LR(k)	
	SR(i) - NLR(j)	= LR(k)	

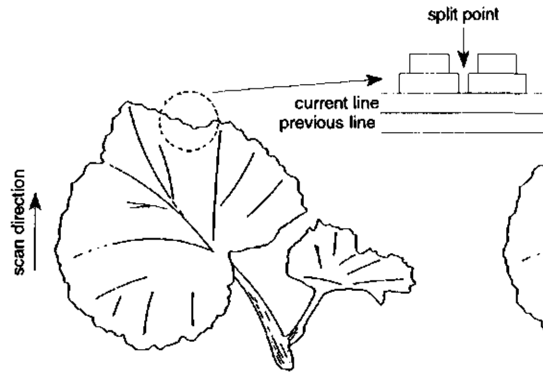

Figure 5.9 Connection between current and previous line.

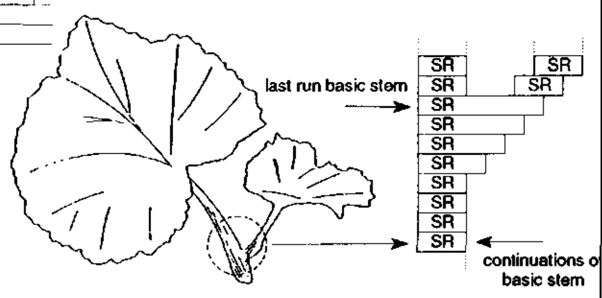

Figure 5.10 The continuation of the basic stem.

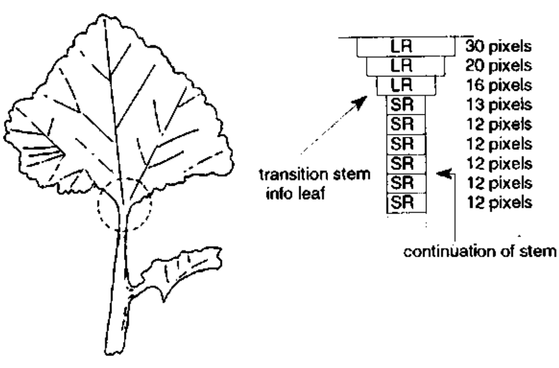

Figure 5.11 The continuation of a stem.

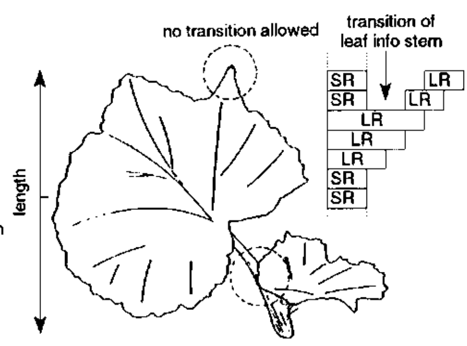

Figure 5.12 The transition of a leaf into a stem.

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Example          NLR(1) - NRL(2) - SR(3) - NRL(4) - LR(5) - NLR(6)
step 1 rule 2 :     NRL(1)      - SR(3) - NRL(4) - LR(5) - NRL(6)
step 2 rule 3 :            LR(7)        - NRL(4) - LR(5) - NRL(6)
step 3 rule 3 :                 LR(7)            - LR(5) - NRL(6)
step 4 rule 3 :                 LR(7)                LR(5)
step 5 rule 1 :                     LR(7)   ¦   LR(5)
```

At the end of the tests, only one previous run may be connected to the current run. By applying this set of split and merge rules, all situations can be deducted to one single run.

C- After the number of connecting runs in the previous line has been reduced to one, the number of connecting current runs to the previous line is counted. In Figure 5.9, the connection between current and previous runs is defined.

After the tests A, B, and C have been done, classification of the current run begins. The following situations are identified (a,b,c).

a - The continuation of the basic stem (see Figure 5.10).
A current run is classified as part of the basic stem if it meets the following criteria.
1 - The segment of the basic stem is still open.
2 - The previous connecting run is identified as a stem run.
3 - One and only one current run is connected to the previous run.
4 - The length of the run is at most 1.3 times the calculated stem thickness in the raw segmentation. This number has been chosen in order to allow the basic stem to be thicker than the other stems.
The basic stem segment closes if:
5 - More than one current run is connected to the previous run.
6 - The length of the run is more than 1.3 times the calculated stem thickness.
After the basic stem segment is closed new segments start which are connected to the basic stem by pointers. The type to which the new segment belongs depends on the situation.

b - The continuation of a stem (see Figure 5.11).
A current run is classified as stem run if it meets the following criteria.
1 - The previous run is a stem run.
2 - One and only one current run is connected to the previous run.
3 - The length of the run does not increase with two or more pixels when compared to the previous run. An increase of two or more pixels indicates a transition from a stem to a leaf run.
4 - The length of the run is less than the calculated stem width.
If Criteria 3 and 4 are not met, the stem segment is closed. The run is classified as leaf run. A new segment is created and identified as a leaf segment. This situation involves a transition from a stem into a leaf.

If more than one current run is connected to the previous run (splitting) Criterion 2 is not met. The stem segment is closed. If a current connected run was a stem run in the raw segmentation, the current run is classified as a stem run. A stem segment is created and connected to the previous stem segment. Otherwise the current run is classified as a leaf run and a leaf segment is created.

c - The transition of a leaf into a stem (see Figure 5.12). This situation occurs when the second leaf is very small and the splitting cannot be identified. If a current run meets the following criteria, a stem segment is created and the run is classified as a stem run.

1 - The previous run is a leaf run.

2 - One and only one current run is connected to the previous run.

3 - The current run was classified as a stem run in the raw segmentation. This means that the run already meets some criteria as far as the length and variation in length between the runs are concerned.

4 - The length of the run is smaller than the maximum stem thickness. This test is done again because the stem thickness calculated after the raw segmentation does not have to be the same as the stem thickness used in the raw segmentation for stem run classification.

5 - The position of the run in the cutting is below 0.6 times the length of the cutting from the tip of the basic stem. Stems are not allowed to start above a certain point in the cutting. Leaf tips at the top of the cutting are a particular cause of errors if this criterion is skipped.

6 - The previous run is not a NLR. A leaf run can only turn into a stem run if the stem starts somewhere above the basic stem. This situation can only occur with existing leaves.

If Criteria 3 till 6 are not met, the current run is classified as a leaf run and assigned to the current leaf segment. If more than one run is connected to the previous run, Criterion 2 is not met. If one of the connected runs meets Criteria 3 till 6, the run is classified as a stem run and a stem segment is created. This occurs when the second leaf and the connecting stem split-up into two runs. Otherwise the current run is classified as leaf run and the data is added to the current leaf segment.

If two different leaves or stems merge, the connected parts are separated by a split line. The start point of the split line is chosen just between the end point of the first, previous, connecting run and the start point of the second connecting, previous run (see Figure 5.13). Above this point an area is examined in order to find the end point of this split line. The search area is limited to a triangle which is determined by two lines through the start point of the split line having an angle of 60 degrees towards the vertical axis. The search in this area is done scan line by scan line in the scan direction starting with the same x-coordinate as the start point. Then a scan is done to the left and to the right direction. An angle of 60 degrees has been chosen because, if two leaves merge, the end point of the split line should be above the start point. This is because of the structure of the plant.

Points which are much more to the left or to the right cause the search routine to identify incorrect points. In this way, large parts of leaves could be attached to a wrong leaf. The scan stops as soon as a background point, located within this triangle and with the shortest distance to the start point has been found (see Figure 5.13).

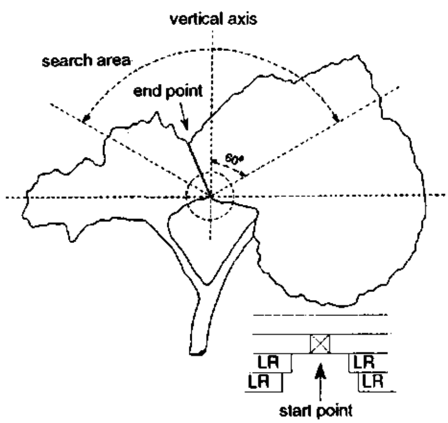


Figure 5.13 Separation of two different leaves.

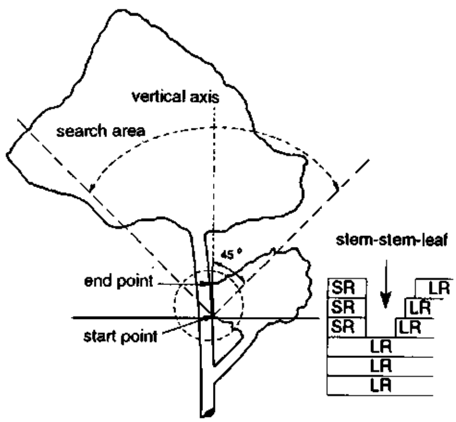


Figure 5.14 Separation of stem and leaf.

The merging of a stem and a leaf is evaluated in a similar way. The difference lies in the reconstruction of the stem. If a stem and a leaf overlap each other, it is sometimes possible to reconstruct the stem structure by looking for another stem structure with almost the same direction as the merging stem and which is located above the merging area. The Begonia has a straightforward structure so a reconstruction of the stem structure is possible.

If the stem run is the left one, the search area is limited to a triangle above the starting point determined by two lines through the starting point which both have an angle of 45 degrees towards the vertical axis. This angle has been chosen because the stems are at an angle of less than 45 degrees to the vertical axis. This is because of the structure of the plant. The routine looks for the sequence stem - stem - background (see Figure 5.14). In this way the right side of the stem is detected. When a stem comes from the right side, the opposite procedure will take place. The routine scans for the combination background - stem - stem. In this way the stem is reconstructed by drawing separation lines and replacing the runs in the raw segmented image by stem runs. When no stem runs are found in the triangle, the normal procedure for splitting leaves is applied.

The result of the exact segmentation is a set of segments connected by pointers containing information on leaves and stems, including the grey value histogram of each part. This set of segments is used to identify the basic stem, the first leaf, the connecting stem, and the second leaf. The identification is based on a model of the structure of the cutting (see Figure 5.15).

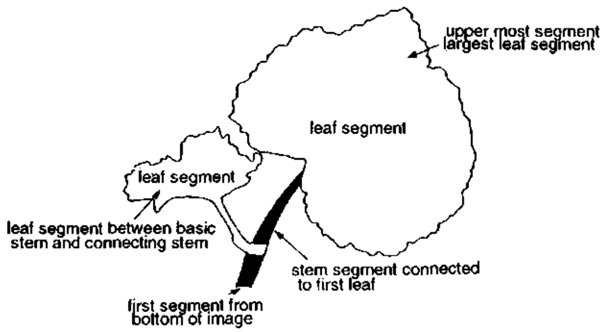


Figure 5.15 Identification of the parts of the Begonia cutting

- Basic stem : due to the orientation of the cutting, it is known that the first segment at the bottom of the image is the basic stem.

- First leaf : a segment is the first leaf if it meets the following criteria:
1. The segment is identified as a leaf segment.
2. The segment has the largest area. The first leaf is always larger than the second leaf.
3. The segment is the uppermost segment in the image.

If no segment meets these criteria, the image does not represent a normal cutting. The object is rejected.

- Connecting stem : a segment is the connecting stem if it meets the following criteria.
1. The segment is identified as a stem segment.
2. The segment has to be connected to the first leaf segment.
3. If more than one segment meet these criteria, the longest segment is selected.

If no segment meets these criteria, the image does not contain a cutting which can be described with a model. The cutting is rejected.

- Second leaf : a second leaf is found between the basic stem and the connecting stem. This part is identified on the basis of the connections between segments. The second leaf can consist of more segments because of splittings in the segment.

The features of each plant part are calculated after segmentation and identification,

1. Total corrected area of the cutting (pixels).
   Sum of pixels of all segments based on the grey value histograms and the weight factors.
2. Total corrected leaf area of the cutting (pixels).
   Sum of corrected leaf area of all leaf segments.
3. Total corrected leaf area of the second leaf (pixels).
   Sum of corrected leaf area of the segments identified as second leaf.
4. Total area of the cutting (pixels).
   Sum of pixels of all segments. This area represents the projected area.
5. Length of the cutting (pixels).
   The distance in a vertical direction between the uppermost and the lowest point on the cutting. This measurement is very sensitive to the orientation of the cutting. Therefore, it is important to orientate the cutting with the tip of the basic stem pointing downwards.
6. Width of the cutting (pixels).
   The distance in a horizontal direction between the left most and right most point of the cutting. This measurement is also sensitive to the orientation of the cutting.
7. Ratio between length and width. This measurement indicates the roundness of the cutting.
8. Ratio between length times width and total area. This measurement indicates the compactness of the cutting.
9. Length of the connecting stem defined as method 1 (pixels).
   The distance between the start point and end point of the connecting stem.
10. Length of the connecting stem defined as method 2 (pixels).
    The distance between the end point of the connecting stem and the start point of the second leaf.
11. Thickness of the stem (pixels).
    The area of the longest stem segment divided by the length of the longest stem segment. The length is calculated from the start and end point of the stem segment. This measurement gives the average thickness.
12. Distance from the tip of the basic stem of the cutting to the optical centre (pixels).
    This measurement indicates the compactness of the cutting. The distance in compact cuttings is relative short.
13. Mean distance of mass (pixels).
    The Euclidean distance of each plant pixel towards the optical centre is calculated. Compact cuttings have a relative smaller mass distance than extensive cuttings.

5.3.4 Consistency and range measurement of features of Begonia cuttings

The consistency test to determine the quantitative properties of features is discussed in Section 4.4. To perform this test, fifty Begonia cuttings were measured five times.

Table 5.1 Consistency and range measurements of unrooted Begonia cuttings.

feature	consistency in %	minimum	maximum	mean
Total corrected area	94.7	8382	40925	20399
Total corrected leaf area	94.1	7084	40813	19526
Total corr. 2-nd leaf area	86.1	0	13274	2884
Total projected area	94.6	8067	39487	19649
Length of cutting	95.8	109	266	172
Width of cutting	95.8	197	421	284
Ratio length/width	92.0	0.38	1.35	0.62
Ratio length*width/area	94.9	0.21	0.72	0.42
Length conn. stem method 1	77.0	2	176	71
Length conn. stem method 2	89.7	0	196	110
Thickness of stem	90.0	5.2	23.1	8.0
Distance optical centre to tip basic stem	97.7	102	263	176
Mean distance of mass	95.6	51	92	66

Minimum, maximum, and mean are expressed in number of units in which they have been measured.

It is stated that the consistency of a feature has to be at least 90 percent before it can be considered to be a potential grading feature. From Table 5.1 it can be seen that the measurement of the second leaf area and the length of the connecting stem do not meet this criterion. The consistency of the second leaf area is not very high because of its relatively small size and its orientation dependency. Small second leaves cause large relative errors. The length of the connecting stem gives the same problem. Sometimes the stem is occluded by the second leaf and perhaps the reconstruction is not done well. Therefore, the second method for length measurement shows better results.

The consistency of the corrected leaf area is similar to the projected leaf area. Both show good quantitative properties. The range of values is large enough to grade the plants into different groups. The fact that the projected and corrected leaf area have a similar consistency may possibly have been caused by the consistent natural rest position of the cutting. It has been observed that when a cutting is put on a flat surface, only a few positions of the cuttings are stable. The stable positions (natural rest position) show large similarities in the position of the cutting towards the camera. This is a disadvantage when calculating the weight factors for the corrected leaf area. There is not much difference between the grey value histograms of the cuttings. These differences however are used to determine the weight factors.

The weight factors and the grey value limits for calculating the corrected leaf area of the cutting are presented in Table 5.2.

Table 5.2 Results of the optimisation of the area of a cutting.

Grey value limits	85 - 95 - 110 - 130 - 150 - 180
Weight factor for this interval	2.0 1.8 1.4 1.1 1.0

From Table 5.2 it can be seen that the weight factors for the grey value show similarities with an exponential function. Considering the Lambert Beer law for transmission, this was to be expected.

Another test for the quantitative properties of features is to compare the values measured using DIP with values for the same features gained by using other methods. The procedure was discussed in Section 4.4. After measuring the features with DIP, the cuttings are cut into pieces. The length and thickness of the stem are measured manually. The area of the leaves is determined by putting the leaves between two glass plates, so they are totally spread out and the actual leaf area can be measured with DIP. The results of the comparison are presented in Table 5.3. The comparison is done by determining the Pearson correlation coefficients. All r's are 2-tailed significant with an uncertainty of $\leq$ 0.1%. Since fifty cuttings have been measured five times the total number of observations gave a total of 250.

Table 5.3 Pearson correlation coefficient between features measured with DIP and other measuring techniques of the Begonia cuttings.

DIP feature	Comparison with	Pearson r
Total corrected area	Area of flat cutting	0.87
Total corrected leaf area	Area of flat leaves	0.87
Total corr. 2-nd 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
Thickness of stem	Thickness of stem	0.50

As shown in Table 5.3, a small improvement is accomplished by using the corrected leaf area instead of the projected leaf area ($r=0.87$ respectively $r=0.82$). The problems with the second leaf area have already been discussed. The length of the connecting stem could be measured. Problems occur if the length of the stem is short. Information on the measurement problem associated with short stems can be included in a decision algorithm. E.g. the measurement is unreliable below a certain stem length. The thickness of the stem measured with DIP does not represent the actual thickness ($r=0.50$).

Sometimes the stem is partly occluded by leaves and, in some cases, a part of the second leaf is considered as stem. In these cases the calculated stem thickness differs considerably from the actual stem thickness.

5.3.5 Discussion and conclusions on measuring unrooted Begonia cuttings

The possibilities for measuring unrooted Begonia cuttings have been discussed. A method has been developed for a better estimation of the leaf area of the cutting. It can be concluded that the corrected leaf area measurement is a better estimation of the leaf area than the projected leaf area. The consistency is similar (94.7% to 94.6%) but the relationship to the flat area is better ($r = 0.87$ to $r = 0.82$). The influence of the stem (which is relatively dark so the pixels account for more than one) is not great because of its relatively small size.

The segmentation routines to identify the first and second leaf performed satisfactorily. In an older version of the program only the exact segmentation was performed. The classification of runs at splittings and the search for the end point of a split line was particularly difficult without the presence of a raw, segmented image.

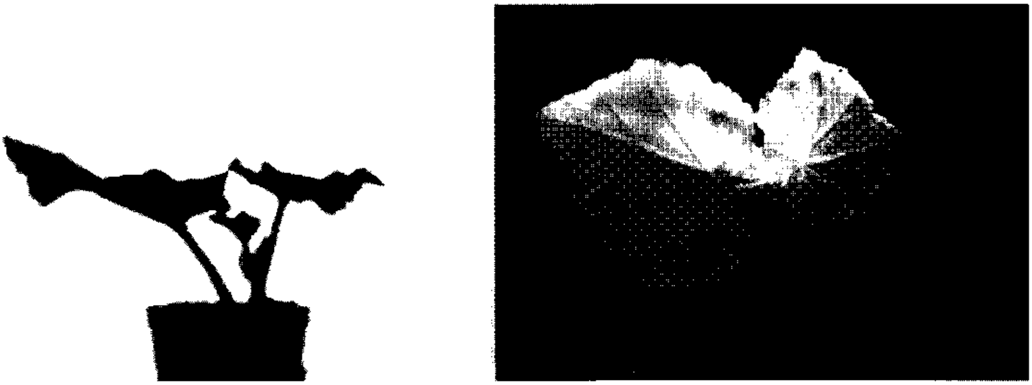
Considering the quantitative properties of area measurements, it can be concluded that these can be used as grading features. The length of the connecting stem - a feature mentioned by experts - has a lower consistency but can still be used as a grading feature.

5.4 The half-grown Begonia plant

5.4.1 Introduction

After a four week growth period, the cutting has developed into a plant with three leaves. This is called a half-grown plant. In Figure 5.16 a side- and top-view are given of a half-grown Begonia plant.

In this stage the first leaf, the second leaf, and the third leaf including the growth tip of the half-grown plant can be identified. The features which determine the quality of the plant in the half-grown stage are unknown. From visual inspections of the grading results produced by the human grader and discussions with experts, it appeared that the development of the second and third leaf is important. The first leaf does not seem to be important for the further development of the cutting. The second and third leaf indicate whether or not the half-grown plant will develop into a compact plant. Compact plants are considered to be better plants. If the second and third leaf are extended too much in the half-grown stage, the full-grown plant will not be compact. To measure the development individual leaves have to be identified. This identification is done by applying the knowledge which is available on the structure of the half-grown plant.



a b

Figure 5.16 Half-grown Begonia plant, side-view (a), top-view (b)

In this section the possibilities of measuring features of half-grown Begonia plants are investigated. These features are used to grade half-grown Begonia plants into groups of uniform quality and to evaluate growth experiments with unrooted Begonia cuttings.

5.4.2 Scene processing

A half-grown Begonia plant has a 3-dimensional structure. A plane can be constructed through the stem of the first and second leaf. The stem of the third leaf is located in this plane. The plant is positioned in front of the camera in such a way that the stem plane is parallel to the image plane. In this way the best information can be gathered on stem structure. A diffuse, uniform lighting system is used as background in order to provide the DIP system with a high quality image for the extraction of geometric features.

The plants are presented one by one in the experiments. The distance between the camera and the plant varies between 1.45 m and 1.55 m, so no correction is needed for the distance between the camera and the object (see Section 3.9). The plant is positioned in such a way that the upper side of the pot is just at the bottom of the image.

The side-view of the Begonia plant does not supply much information about the leaf area, because most of the leaves are perpendicular to the stem plane. Therefore, a top-view of the plant is taken. The plant is put on a dark, light absorbing, background. The front-light consists of incandescent light tubes providing uniform lighting. The light tubes emit both visible and near-infrared light. The leaves can be segmented easily from the background and soil because of the high reflectance of leaves in near-infrared light (see Section 3.3.3) and the sensitivity of the camera to near-infrared light.

5.4.3 Image processing

The identification of the individual parts of the plant is carried out using almost the same procedure as was used for unrooted Begonia cuttings. The raw segmentation is exactly the same. The first encountered runs from the top have to be leaf runs because of the orientation of the plant. The result of the raw segmentation is an image consisting of stem runs and leaf runs. Classification errors are made because some leaves look very similar to stems. In the exact segmentation this will be corrected.

The leaf area cannot be corrected on the basis of the grey values of the leaf. Unlike the case with Begonia cuttings, they are not representative for the amount of leaf mass between camera and background. The measured grey values are greatly affected by the direct reflectance of the leaves caused by the orientation of the leaves towards the camera.

In the exact segmentation, the data from the runs are stored in segments which represent leaves or stems. A segment contains the following information:

- segment identification number
- area of segment (pixels)
- coordinate of the left most point
- coordinate of the right most point
- coordinate of the uppermost point
- coordinate of the lowest point
- parent segment, the segment identification number indicating where it has come from
- child segment, the segment identification number indicating where it goes to
- plant part identifier, stem, leaf or pot
- structure identifier, which leaf or stem

Each time a run is assigned to a certain segment, all data in the segment are updated and if the coordinates of a maximum in one of the four directions changes, the new maximum is stored.

The exact segmentation is also very similar to the exact segmentation for the unrooted Begonia cutting. Scanning is from bottom to top. The first run in the bottom of the image has to be a 'pot' run (PR) because of its orientation towards the camera. The following classification rules are applied to the runs on the bottom line.

- The run has to meet the pot run criteria. This means that the run has to be in the middle of the image because of the position of the pot, the minimum run length is 25 pixels and the maximum run length is 150 pixels.
- If the bottom line contains one run and the run meets the criteria for a pot run, the run is classified as a pot run.

- If the bottom line contains one run and the run does not meet the criteria for a pot run, an unknown situation occurs. The plant is rejected. In the program the default situation is an error. The program only produces a decision if a valid solution has been found. In this way unusual situations are handled without errors being created.
- If the bottom line contains more than one run, the run which meets the criteria for a pot run is chosen as start for the pot. Other runs are classified as new leaf runs.

When the bottom line is finished, the procedure continues with the lines above the bottom line. Runs without a connecting run in the previous line are classified as new leaf runs. Stems are only allowed to start from the pot or from existing leaves. Existing leaves are only allowed to start from stems. In Figure 5.17, a schematic structure of the half-grown Begonia plant is shown.

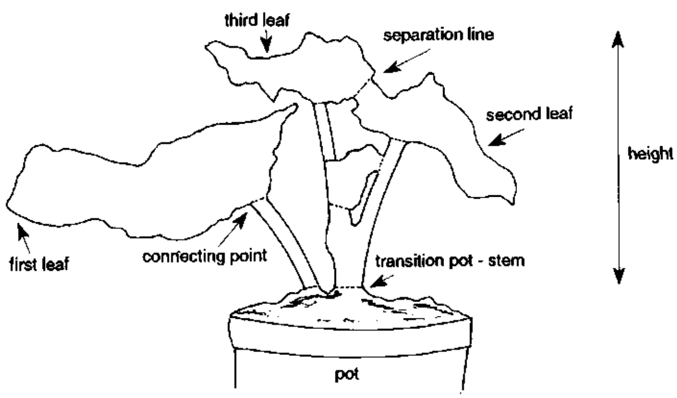


Figure 5.17 Schematic structure of a half-grown Begonia plant.

For runs with connected runs in the previous lines the following information is important;
- the classification during the raw segmentation (stem or leaf);
- the classification of the previous run in the exact segmentation (stem run, leaf run, new leaf run, or pot run);
- the segment number of the previous connecting run. If the run is classified as part of the same segment as the previous run, it is added to that segment.

Tests are carried out to determine whether runs merge or split in the same way as for unrooted Begonia cuttings. All split and merge rules discussed for the unrooted cuttings are applied again. Only an extension (R4) is discussed.

R4 - This rule is an extension of R3. A check is made on whether a new leaf run merges with a pot run or not. Merging only can occur as long as the scanning of the pot continues. Where merging occurs, the new leaf run is merged into the pot run. This situation occurs particularly when roots are extending beyond the pot (see Figure 5.18). Errors occur where a leaf merges with the pot. This situation can be recognised in an early stage and the image has to be recaptured by re-orientating the plant.

R4 is summarised as :

rule 4 :	NLR(i) - PR(j)	= PR(j)
	PR(i) - NLR(j)	= PR(i)

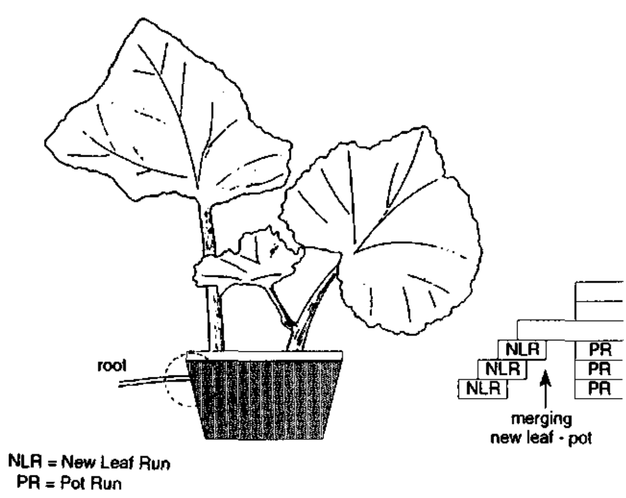


Figure 5.18 Merging of new leaf run and pot run.

The classification of the current run and its assignment to a segment shows similarities with the unrooted Begonia cutting classification. Because of this only the differences are discussed here.

a. The continuation of a pot (see Figure 5.19).
   A current run is classified as pot run and added to the pot segment if it meets the following criteria.
   1 - The previous run is a pot run.
   2 - The length of the run is above the minimum pot run length.
   If the length of the run is smaller than the minimum pot run length, the run is classified as a stem run. The data from the run are stored in a newly created stem segment. This transition of the pot to the stem works well. Only large ground particles, roots, and leaves which overlap the pot cause errors. The ground particles and roots are eliminated later on in the analysis. If a leaf overlaps the pot, the plant is generally small. This knowledge is used to analyse the structure.
b. The continuation of a stem.
   See unrooted Begonia cutting.
c. The transition of a leaf into a stem.
   See unrooted Begonia cutting. The only difference here is that the position of the run has to be below 0.8 times the height of the plant. The height of the plant is calculated in the raw segmentation. Above this point, stems are not allowed to start. Leaf tips at the top of the plant look particularly like stems.

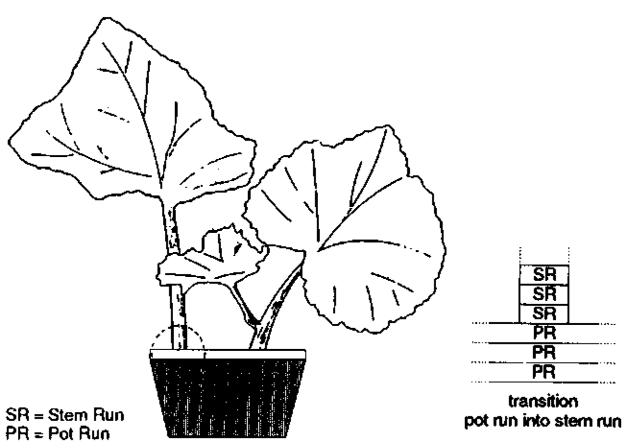


Figure 5.19 Transition of pot into stem.

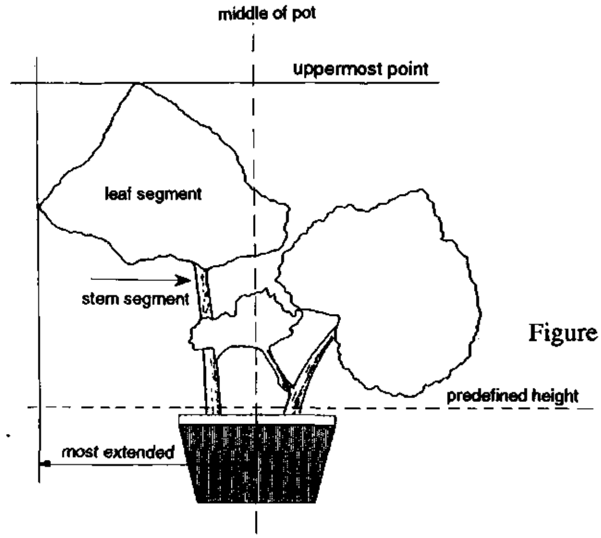


Figure 5.20 Identification of the first leaf.

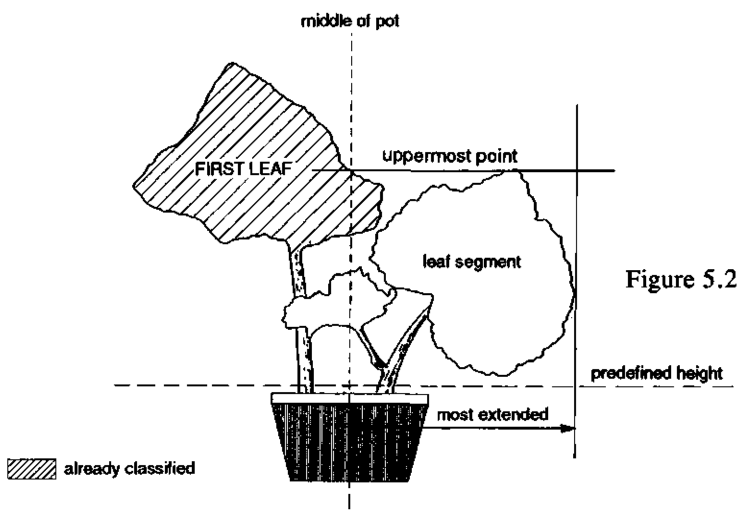


Figure 5.21 Identification of the second leaf.

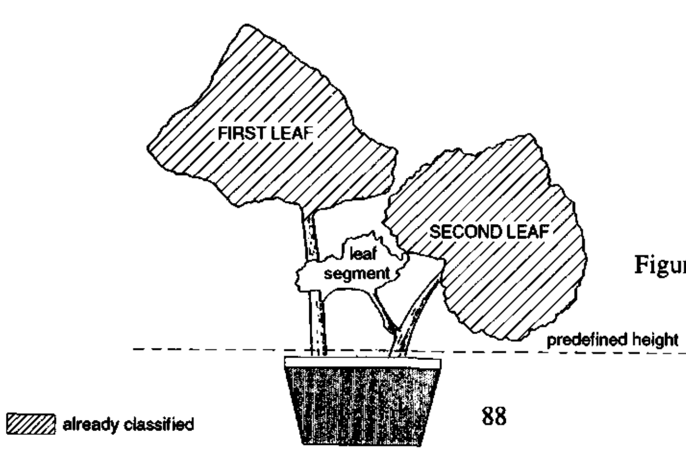


Figure 5.22 Identification of the third leaf.

The result of the exact segmentation is a set of segments containing information about the pot, stems, and leaves, including the coordinates of their extremes and pointers describing the connecting structure. The set of segments is used to identify the first, second and third leaf, including their features. The analysis is based on the model of the plant.

- First leaf : a segment is identified as first leaf if it meets the following criteria (see Figure 5.20).

1. The segment is the most extended segment of the plant calculated from the middle of the pot. The left most points and the right most points of the segments are used to determine this.
2. The segment is not the pot segment. The classification of the segments is stored in the part identifier of the segment.
3. The uppermost point of the segment is above a predefined height (30 pixels above pot) to avoid the selection of misclassified roots. In some situations, the roots are the most extended parts of the plants and have been classified as leaves. These roots do not meet the minimum height criterion.
4. The connecting previous segment is a stem.
5. The stem contains no splittings, so it is directly connected to the pot. If splittings occur, their number is determined and the height above the pot is recorded. The number of segments is easily determined by following the segments till a segment is connected to the pot. Meanwhile all segments belonging to this part are identified as first leaf so it is not possible to classify them a second time.

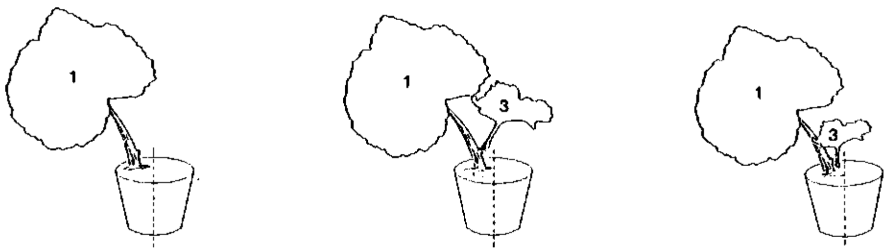
If no segment meets these criteria, the classification is wrong or the plant is misshaped. The image has to be recaptured with an other orientation of the plant or the object has to be rejected.

- Second leaf: a segment is identified as a second leaf if it meets the following criteria (see also Figure 5.21).

1. The segment is the most extended segment of the plant with respect to the middle of the pot. It is not classified as the first leaf and it is at the opposite side with respect to the first leaf.
2. The segment is not the pot segment.
3. The uppermost point of the segment is above a pre-defined height to avoid the selection of misclassified roots.
4. The connecting previous segment is a stem.

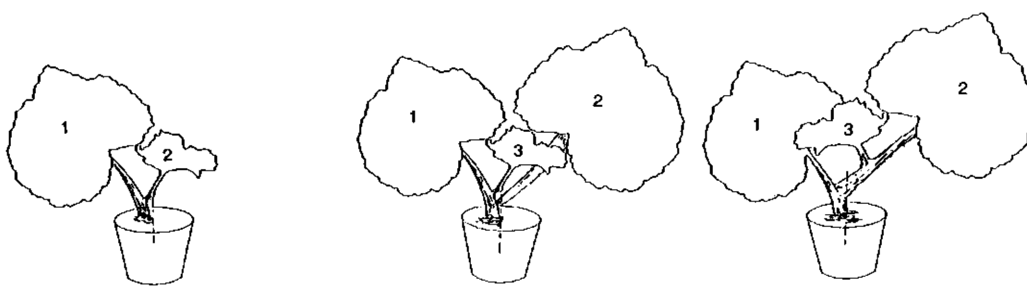
If no segment meets these criteria, the plant either has a shape that is not described or it has only one leaf.

The third leaf starts at the stem of the second leaf so the following classification is made. All the connecting segments between the second leaf segment and the pot segment are checked. If a segment is a stem segment, it is classified as part of the second leaf. If a segment is a leaf segment, it is classified as part of the third leaf.



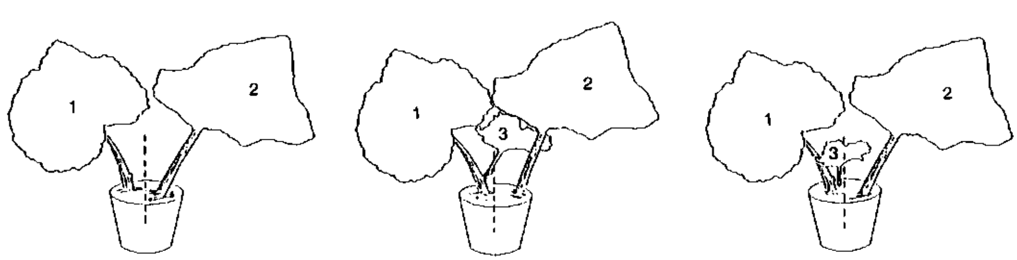
a b c

Figure 5.23 No second leaf found.



a b c

Figure 5.24 Second leaf is connected to the first leaf.



a b c

Figure 5.25 Second leaf is connected to the pot.

In some situations the most extended segment is not the complete leaf; the second leaf consists of more than one segment. If the second leaf segment has pointers connected to a next segment and this segment has not yet been classified, it is classified as being part of the second leaf.

- Third leaf : a segment is identified as third leaf if it meets the following criteria (see Figure 5.22).

1. The segment has not yet been classified.
2. The uppermost point of the segment is above a predefined height to avoid selection of misclassified roots.
3. The segment has no pointers to the next segments.
4. The segment has the largest area.

If no segment meets these criteria, the plant has no third leaf.

Finally all the segments connected to the third leaf and which have not yet been classified are classified as third leaf. Also a registration is made whether the third leaf is connected to the first leaf, second leaf, or pot.

The model assumes that the first leaf is the most extended one and that the third leaf is connected to the second leaf. However, this is not true in all cases, so a check has to be done. There may be a switch in the position of the first and second leaf because of the position of the third leaf. The check is based on the segment identifier from which the leaf structure starts.

The following situations are identified:

1. No first leaf found.
   The object is rejected.
2. No second leaf found.
   This situation occurs when the plant is very asymmetric. The plant is not correct and is hard to measure.
   Following sub-situations are defined.
   - No third leaf : only one leaf is seen (Figure 5.23a).
   - Third leaf is connected to the pot (Figure 5.23b): the third leaf is changed into the second leaf.
   - Third leaf is connected to the first leaf stem (Figure 5.23c): the third leaf is changed into the second leaf.
3. The second leaf is connected to the first leaf.
   One stem is connected to the pot. The splitting of the first and second leaf stem occurs above the pot.
   The following sub-situations are defined.
   - No third leaf (Figure 5.24a): the most extended leaf remains the first leaf.

- The third leaf is connected to the first leaf (Figure 5.24b): the first leaf is not the most extended leaf. The first leaf and second leaf are switched. The third leaf is only allowed to be connected with the second leaf. An indication for this situation is the number of splittings in the stem.
- The third leaf is connected to the second leaf (Figure 5.24c). The first leaf is the most extended as expected. Nothing changes.
- The third leaf is connected to the pot (Figure 5.24d). This is an unusual situation, but the classification is not changed.

4. The second leaf is connected to the pot.
   The splitting of the first and second leaf stem is hidden in the pot which is a normal situation. The following sub-situations are defined on basis of the number of splittings in the stem.
   - No third leaf (Figure 5.25a): the plant is not well developed or the third leaf cannot be seen. The classification of the first and second leaf may be changed depending on the number of splittings in the stem. If the number of splittings in the stem of the first leaf is greater than the number of splittings in the stem of the second leaf, the classification of the first and second leaf is switched. The stem of the second leaf contains more irregularities then the stem of the first leaf.
   - The third leaf is connected to the stem of the first leaf (Figure 5.25b). The first and second leaf are switched.
   - The third leaf is connected to the stem of the second leaf (Figure 5.25c). This is the most common situation and nothing changes.
   - The third leaf is connected to the pot (Figure 5.25d). The leaf with the most splittings in the stem is classified as second leaf, the other as first leaf. Where there are an equal number of splittings, the most extended leaf is the first leaf.

After this second classification, the segments which have not yet been classified are categorized as part of the segments they are connected to. In this way parts which are not connected to the plant, like noise and ground particles, are excluded.

The features of each plant part are calculated after segmentation and classification. The abbreviations between brackets are those used later on in the text. All units are measured in pixels.

First, second and third leaf.

- Area (Area 1, Area 2, Area 3): sum of pixels of the leaf segments classified as first leaf, second leaf, and third leaf respectively.
- Height (Height 1, Height 2, Height 3): uppermost point of the first leaf, second leaf, and third leaf respectively when measured from the pot.
- Junction (Junction 1, Junction 2, Junction 3): height of the point where the first leaf, second leaf, and third leaf are connected to their stem.

Second and third leaf combined (called main segment).

- Area (Area 2+3): sum of Area 2 and Area 3.
- Height (Height 2+3): uppermost point of Height 2 and Height 3.
- Junction (Junction 2+3): uppermost junction point of Junction 2 and Junction 3.

Total plant.

- Total projected area of the side-view (Area tot.): sum of all pixels classified as part of the plant.
- Uppermost point of the plant (Height tot.): uppermost point of Height 1, Height 2 and Height 3.
- Uppermost junction point (Junction tot.): uppermost junction of Junction 1, Junction 2, and Junction 3.
- Width of the plant (Width): the distance between the left most point and right most point of the plant.
- Height of the optical centre above the pot (Height centre).
- Total project area from the top-view (Area top-view): the top-view image is labelled and the area of the largest object is taken as the projected plant area. Small objects such as ground particles are not connected to the plant and therefore not included in the 'area top'.
- Volume determined by the total projected area from the top multiplied by the total height.

5.4.4 Consistency and range measurement of features of a half-grown Begonia plant

The consistency test to determine the quantitative properties of features is discussed in Section 4.4. Twenty half-grown Begonia plants have been measured five times to perform this test.

Table 5.4 Consistency and range measurement of a half-grown Begonia plant.

feature		consistency in %	minimum	maximum	mean
Area 1	first leaf	91.5	5457	41282	18365
Height 1		95.2	118	375	246
Junction 1		89.2	34	265	132
Area 2	second leaf	87.1	3600	39890	13223
Height 2		96.0	108	374	258
Junction 2		92.5	10	255	154
Area 3	third leaf	79.6	0	16486	6763
Height 3		91.4	0	455	245
Junction 3		88.1	0	331	171
Area 2+3	second +	91.9	6751	43529	19987
Height 2+3	third leaf	96.7	111	455	279
Junction 2+3		91.2	10	331	189
Area tot.		94.6	15882	64210	38987
Height tot.		97.9	148	455	294
Junction tot		93.0	52	331	194
Width		97.8	244	490	389
Height centre		96.8	49	222	143
Area top-view		98.5	27967	72585	44637
Volume		97.4	5964	27219	13465

Minimum, maximum, and mean are expressed in number of units in which they have been measured.

As can be seen from Table 5.4, the features of the third leaf are least consistent. Due to its position on the plant, much overlap with other leaves is possible. The largest relative errors occur with small third leaves. A third leaf which is just emerging, is close to the second leaf. In some orientations it is invisible to the camera. The measurement routine is able to distinguish between poorly developed third leaves and well-developed third leaves. The consistency of the area of the other leaves is affected by the position of the leaves in relation to the camera. According to the expert, the size of the first leaf is not important. However, to measure the second and third leaf it is important to identify the individual parts and this includes the first leaf. It was experienced that this could be done correctly in 99 percent of the cases. Only plants which were very misshaped caused classification errors. According to the expert the size of the second and third leaf together is important. This can be measured consistently (more than 90 percent).

Twenty half-grown Begonia plants have been measured five times to compare the DIP measurements with other measurement techniques. This procedure is discussed in Section 4.4. The actual leaf area has been measured by cutting the plants into parts and putting them between glass plates as it is explained in Section 5.3.4. The results of the different measurement techniques are compared by performing correlation analyses. Table 5.5 shows the results of the analyses. All values are 2-tailed significant with an uncertainty of ≤ 0.1%.

Table 5.5 Pearson correlation coefficients between features measured with DIP and other measuring techniques of the half-grown Begonia plant.

feature		comparison with	Pearson r
Area 1	first leaf	Area of flat first leaf	0.69
Height 1		Height of first leaf	0.76
Junction 1		Junction of first leaf	0.65
Area 2	second leaf	Area of flat second leaf	0.64
Height 2		Height of second leaf	0.39
Junction 2		Junction of second leaf	0.37
Area 3	third leaf	Area of flat third leaf	0.58
Height 3		Height of third leaf	0.60
Junction 3		Junction of third leaf	0.51
Area 2+3		Area of flat 2nd+3th leaf	0.83
Area tot.		Total flat leaf area	0.78
Area top-view		Total flat leaf area	0.90

From Table 5.5 it can be seen that the features of the individual leaves are not measured with a high degree of accuracy (correlation coefficients around 0.60). The area of the main segment (second + third leaf) is measured more accurately than the area of the individual parts. As mentioned before, the size of the first leaf is not important. The size of the main segment and the presence of the third leaf can be determined. The top-view provides a good estimation of the total leaf area (r = 0.90) despite overlapping leaves.

5.4.5 Discussion and conclusions about measuring half-grown Begonia plants

In this section the possibilities for measuring features of half-grown Begonia plants is discussed. The segmentation method is almost the same that is used for unrooted Begonia cuttings. Only a few modifications are needed for processing the pot. The quantitative properties of features measured from half-grown plants are less good than in the case of the unrooted Begonia cuttings (compare Table 5.3 with Table 5.5) but still the individual parts are identified. The difference can be explained by the orientation of the leaves in relation to the camera. In the half-grown stage this is less well defined. The presence of certain parts is more important then their individual size. The classification routines detect the individual parts correctly in 99 percent of the cases. The area of the main segment corresponds with the real area with an r of 0.83 and the consistency of 91.9 %. The measurement of the area of the main segment is accurate enough for these experiments. The routines described here can only be applied to plants with a clear stem-leaf structure. In more complex plants such as twelve week old Begonia plants, the individual leaves and stems cannot be distinguished.

5.5 Growth experiments with Begonia plants

5.5.1 Introduction

The objective of the growth experiments is to identify features of unrooted Begonia cuttings measured with DIP. These can be related to the size and development of the cutting after a growth period of four weeks (half-grown stage). Features which are strongly related to size and development in the half-grown stage have good qualitative properties and may be used as grading features. To determine the size and development of the plants in the half-grown stage, the plants are again measured with DIP and judged by experts. The relations between the features in both stages and the relation between the features and the expert judgement are investigated to identify grading features in both stages.

The plants have also been measured in the three week old stage. The objective of this measurement is to see whether the effect of grading is still present after a growth period of three weeks. At this stage the plants are not judged by experts. In normal processing no grading is performed at this stage.

5.5.2 Experimental set-up of the growth experiment

In Chapter 4, the set-up of the growth experiments is discussed. This section deals with the implementation of the Begonia experiment. The experiment include three blocks with the same area.

- Block 1 : the ordered experiment.
  360 unrooted Begonia cuttings are measured with DIP and labelled with a unique code so they can be traced. They are planted in a pot. From earlier experiments it was known that the corrected leaf area is an important feature for ascertaining the growth potential of cuttings. Therefore the corrected leaf area is used as ordering feature. Features of all the cuttings are stored together with the label number. A square of 20 by 18 plants is created by placing the pots in an ascending corrected-leaf-area order.
- Block 2 : the random experiment.
  Another 360 unrooted Begonia cuttings are measured with DIP, labelled with a unique code, and planted in a pot. The features of all the cuttings are stored together with the label number. In the random experiment, the pots are put in a square measuring 18 by 20 plants in the same order as used when the plants are presented to the DIP system. This order represents the random order in which the planters normally process the cuttings.
- Block 3 : the free spaced experiment.
  30 unrooted Begonia cuttings are measured with DIP, labelled with a unique code, and planted in a pot. The features of all the cuttings are stored. The plants are put in the greenhouse in a square of 5 by 6 plants. The area around each cutting is four times the normal area around a cutting in order to prevent competition between cuttings.

The blocks are put in the greenhouse close to each other to ensure a similar environment for all the blocks. Rows of un-measured cuttings are put between the blocks to avoid interaction between blocks.

After a period of three weeks, the blocks are measured again with DIP and put back in the greenhouse. The same measurement routines which are developed for the four weeks old stage are applied to the three week old stage. One week later, the blocks are measured again with DIP and judged by the expert. During normal processing the plants are also graded at the four week old stage. The judgement is made in the same way as in normal processing. Figure 5.26 shows the relationship between the measurements.

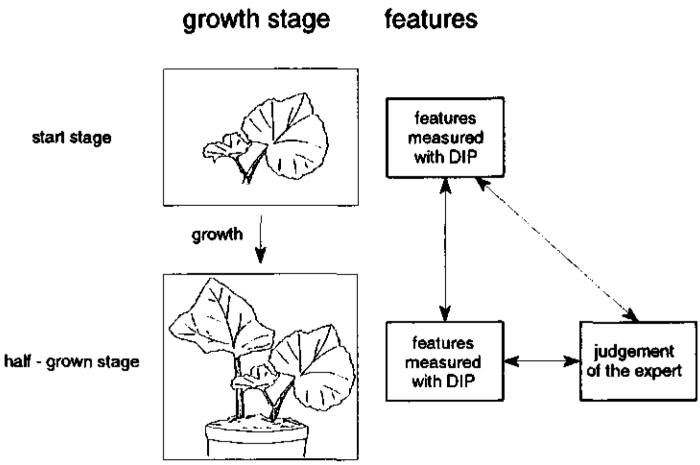


Figure 5.26 Relationships between measurements in the Begonia experiment.

5.5.3 Results of the Begonia growth experiment

5.5.3.1 Introduction

In Section 4.5.3, the analyses of the growth experiments are discussed. It is concluded that the best way to analyse the relationships is to start in the final stage (in this case the half-grown stage) because more knowledge on the Grading System Target Output is available for this stage. The analysis is done on the basis of the relationships set out in Figure 5.26. In the experimental set-up reference was made to a measurement which took place after three weeks. At this stage, Begonia plants are not very well developed and are very compact. Therefore the identification of the individual parts of the plant based on the DIP routines developed for the half-grown stage is difficult. Consistency at the three week old stage is low compared to the consistency of features in the half-grown stage. This consistency is important for statistical analyses. The three week old stage is not included in the analyses.

The results are analysed by first examining the correlation between expert judgement in the half-grown stage and the features measured by DIP during the same stage. These correlations provide information about the individual qualitative properties of features in the half-grown stage. The same is done for the features measured with DIP in the unrooted stage and the expert judgement in the half-grown stage. These correlations provide the individual qualitative properties of the features in the unrooted stage. Multiple linear regression analysis is applied in the half-grown and the unrooted stage to investigate whether combinations of features measured with DIP show a good relationship with the expert judgement. The correlation between features measured with DIP in the unrooted and half-grown stage is then calculated. On the basis of these analyses an interpretation is made of how plants in the half-grown stage are influenced by features in the unrooted stage. The analysis ends with a grading simulation in which the initial blocks are split-up into five growth groups in order to see whether there is a difference between the random-placed block and the ordered block.

The results of two experiments are discussed in this case study. Experiment 1 was carried out between May 23 and June 17 of 1991. Experiment 2 between June 7 and July 2 of 1991.

5.5.3.2 Correlation analysis between the expert judgement and features in half-grown stage

Correlation analysis between the expert judgement and features measured with DIP in the half-grown stage is performed to define features which have a strong relationship with the expert judgement. These features can be used to grade half-grown Begonia plants into uniform quality groups.

The values of the features have to meet certain criteria when correlation analysis is to be performed. They should be scalar and have a normal distribution. The features measured with DIP are already scalar. The judgement of the expert is not scalar, but is made scalar by defining numbers for the judgement. Small is replaced by 1, large is replaced by 3 and medium by 2. Whether the value 2 is correct or not, is investigated further in Section 5.5.3.3. The values of the features are assumed to be in a normal distribution, unless some of them have proportional errors such as those discussed in Chapter 3. The results of the analysis provide strong indicators for the strength of the relationship.

The results of the Pearson correlation analysis are presented in Table 5.6. A high value means a good relationship between the feature and the expert judgement. Only correlations with 2-tailed uncertainty of $\leq$ 0.1 % are presented.

Table 5.6 Pearson correlation coefficients (r) between features of half-grown plants measured using DIP and the expert judgement in the half-grown stage. Between brackets the ranking number of the five highest correlation coefficients in descending order is noted.

feature	experiment	1 - ord	1 - rand	2- ord	2 - rand
Area 1	first leaf	0.27	.	0.28	0.28
Height 1		.	0.29	0.42	0.36
Junction 1		.	0.23	0.34	0.35
Area 2	second leaf	.	.	0.27	0.28
Height 2		0.36	0.46	0.59	0.55
Junction 2		0.37	0.40	0.43	0.50
Area 3	third leaf	0.43	0.38	0.39	0.24
Height 3		0.60 (1)	0.59 (2)	0.60 (5)	0.44
Junction 3		0.54 (2)	0.53 (5)	0.54	0.45
Area 2+3	second +	0.40	0.39	0.48	0.37
Height 2+3	third leaf	0.53 (3)	0.60 (1)	0.68 (2)	0.60 (4)
Junction 2+3		0.54 (2)	0.57 (3)	0.63 (4)	0.59 (5)
Area tot.		0.53 (3)	0.39	0.54	0.45
Height tot.		0.48 (5)	0.55 (4)	0.74 (1)	0.65 (2)
Junction tot		0.52 (4)	0.55 (4)	0.64 (3)	0.62 (3)
Width		0.34	.	0.23	0.33
Height centre		0.42	0.48	0.68 (2)	0.66 (1)
Area top-view		0.36	0.33	0.53	0.38
Number of plants		359	359	346	336

1-ord = experiment 1 ordered block
1-rand = experiment 1 random placed block
2-ord = experiment 2 ordered block
2-rand = experiment 2 random placed block

The experiments were performed in a commercial greenhouse. Normally the same expert judges the plants. Unfortunately, the usual expert was not able to judge the second experiment. From the results of the correlation analysis it can be concluded that there is a difference between the experts. The expert who judged the first experiment shows the highest correlations with the development of the third leaf and the combination of second and third leaf. The correlation with height is less strong than with the third leaf. The expert who judged the second experiment shows the highest correlations with total height and height of optical centre. The correlation with the third leaf is less strong. In discussing of the results of the grading, the experts agreed on the difference. The expert who graded Experiment 1 thought that the development of the second and third leaf is important for uniformity whilst the expert who graded Experiment 2 thought that the height is more important. In the commercial greenhouse height is more often used as a grading criterion. The height of the container in which the plants are put during the harvest is used as grading criterion. Plants which are longer than the height of the container are considered large and the other plants are judged as being medium or small. The result of the grading looks uniform due to uniformity in height. No test has been made of which of the expert criteria were best for achieving the greatest degree of uniformity in the full-grown stage.

5.5.3.3 Multiple regression analysis with the expert judgement and features in the half-grown stage

In the correlation analysis, the relationship of the individual features with the expert judgement has been investigated. The size of a plant is not determined by one single feature but by a combination of features. Multiple linear regression analysis provides a combination of features which is related to the expert judgement.

The objective of this multiple regression analysis is to identify a set of features in the half-grown stage. This set provides a description of the size and development of a half-grown Begonia plant which corresponds with the expert judgement. The expert judgement in the half-grown stage is used as dependent and the features measured by DIP in the half-grown stage are used as independent.

In Table 5.7 the results of the multiple regression analysis are shown. The results are presented as a list of features which are in the regression equation. The values mentioned are the normalised weight factor for each feature. The expert judgement is used as dependent. To make the judgement scalar, the conversion already mentioned in Section 5.5.3.2. is carried out. The regression analysis has been done using the stepwise input selection method. The level of uncertainty was set at 5% to enter and 5.5% to exit a feature.

Table 5.7 Features in the multiple regression analysis using the features measured with DIP of the half-grown Begonia plants as independents and the expert judgement in the half-grown stage as dependent.

feature	experiment	1 - ord	1 - rand	2- ord	2 - rand
Multiple r		0.69	0.68	0.81	0.76
r square		0.48	0.46	0.67	0.58
Area 1	first leaf	.	.	.	0.16
Height 1		.	.	0.27	-0.18
Junction 1		.	-0.20	.	0.31
Area 2	second leaf	-0.11	.	0.11	0.18
Height 2		.	.	0.23	-0.17
Junction 2		0.12	.	.	0.40
Area 3	third leaf	-0.19	-0.16	0.46	.
Height 3		0.01	0.49	.	.
Junction 3		.	.	0.15	.
Area 2+3	second +	.	.	.	.
Height 2+3	third leaf	.	0.32	.	.
Junction 2+3		.	.	.	.
Area tot.		0.39	.	.	.
Height tot.		-0.01	.	1.30	1.18
Junction tot		.	.	.	.
Width		.	-0.01	.	.
Height 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

1-ord = experiment 1 ordered block
1-rand = experiment 1 random placed block
2-ord = experiment 2 ordered block
2-rand = experiment 2 random placed block

To check whether value 2 as scalar for the medium class is the correct choice, an additional test is performed. Different values are used for the medium class to see whether the strength of the relation between the expert judgement and the features will increase or decrease.

Table 5.8 Different values for the medium class used in the multiple regression.

class	experiment 1 - ordered		experiment 2 -ordered	
medium	multiple r	r square	multiple r	r square
1.7'	0.679	0.462	0.802	0.643
1.8	0.686	0.470	0.807	0.651
1.9	0.690	0.476	0.807	0.652
2.0	0.690	0.477	0.805	0.649
2.1	0.691	0.477	0.796	0.634
2.2	0.688	0.474		
2.3	0.685	0.469		

As can be concluded from Table 5.8, value 2 is a reasonable value for the medium class. It results in the highest multiple r so the classification is determined the best. In further analysis 2 is used as the scalar for the medium class.

From Table 5.7 it can be seen that the expert judgement in the second experiment has a higher multiple r than in the first experiment. The multiple regression analysis also shows different features included in the equation. In the equation of the second experiment, the feature height is more strongly present than in the first experiment. A higher multiple r for the second experiment is explained by the fact that the expert thought that height was important. The feature height is measured more accurately than the area of the third leaf, so there is a better relationship is to be expected.

The features measured with DIP are not independent so some features in the multiple regression equation can be replaced by others without affecting the multiple r too much.

Multiple regression analysis was also performed by introducing the square of the variables and by introducing the product of two variables. In the regression analysis all squares and products were excluded except the product of height and area top-view. This product was already defined as volume. A rank model provided no additional information, the multiple r was the same.

Some comment has to be made on why the multiple r does not reach 0.95 when the multiple r of the regression equation is being considered. The human grader makes some mistakes, so there can be misclassifications in the expert judgement. The judgement is 1, 2, or 3. The regression analysis assumes a classification which ranges from between 0.5 and 3.5. Thus a certain variation is introduced.

5.5.3.4 Correlation analysis between the expert judgement in the half-grown stage and features in the unrooted stage

Correlation analysis between expert judgement in the half-grown stage and features measured with DIP in the unrooted stage is performed to define features which have a strong relationship with the growth potential. These features can be used to grade unrooted cuttings in uniform growth groups. The results of the Pearson correlation analysis are presented in Table 5.9.

Table 5.9 Pearson correlation coefficients (r) between the features measured with DIP in the unrooted stage and the expert judgement in the half-grown stage.

experiment / feature	1-ord	1-rand	2-ord	2-rand
Total corrected area	0.44 **	0.28 **	0.45 **	0.08
Total corrected leaf area	0.45 **	0.28 **	0.45 **	0.08
Total corr. 2-nd leaf area	0.23 **	0.30 **	0.22 **	0.08
Total projected area	0.45 **	0.28 **	0.45 **	0.08
Length of cutting	0.32 **	0.30 **	0.38 **	0.05
Width of cutting	0.30 **	0.14 *	0.31 **	0.19 **
Ratio length/width	0.03	0.12	0.07	0.11
Ratio length*width/area	0.11	0.06	0.14 *	0.09
Length conn. stem method 1	0.08	0.09	0.09	0.09
Length conn. stem method 2	0.03	0.01	0.03	0.11
Thickness of stem	0.11	0.06	0.21 **	0.01
Distance optical centre to tip basic stem	0.16 *	0.08	0.24 **	0.13
Mean distance of mass	0.44 **	0.31 **	0.40 **	0.19 **
Number of plants	359	359	346	336

* = with 2-tailed uncertainty ≤ 1%
** = with 2-tailed uncertainty ≤ 0.1%
1-ord = experiment 1 ordered block
1-rand = experiment 1 random placed block
2-ord = experiment 2 ordered block
2-rand = experiment 2 random placed block

Table 5.9 indicates that there is a difference between the ordered blocks and the random placed blocks. The higher correlation between the features of the unrooted cuttings in the ordered blocks and the expert judgement means that the plants in the ordered blocks develop more uniformly. As a result size and development of plants in the ordered blocks in the half-grown stage can be predicted better on the basis of the features in the unrooted stage than of plants in the random blocks. A possible explanation for this is found in the homogeneity of the growth environment. In the ordered blocks, the cuttings experience more equal competition than in random placed blocks. During judgement the expert already mentioned a difference in shape between the ordered blocks and the random placed blocks. The ordered blocks contained more equally shaped plants, growing more uniformly in a horizontal direction than the random placed blocks. In the ordered blocks, the large plants in particular grow in height because the surrounding space is occupied by other cuttings. In the random placed blocks, some large cuttings were put next to small cuttings so they could grow horizontally. This was also observed in the free spaced block. Another difference between the ordered block and random placed block is possible variation in micro climate. The small cuttings are surrounded by a relatively large area, the large cuttings a relative small one. This difference in leaf mass per square meter may result a difference in humidity between the plants. However, the factor 'micro climate' is not investigated any further.

The leaf area is the feature that is best related ($r=0.45$) to the expert judgement. In the consistency tests the corrected leaf area was as consistent as the projected leaf area, but it showed a better correlation with the actual leaf area. There is not a better relationship between the corrected leaf area and the expert judgement in the half-grown stage. Accuracy gained because of the introduction of a correction for the leaf area measurement is lost because of other errors like edge pixels and scene set-up.

There is less relationship between the second leaf and the length of the connecting stem (respectively $r=0.23$ and $r=0.09$). This contrasts with the opinion of the expert during the interviews. An explanation for this is that the consistency of these features in the unrooted stage is smaller, so there is already more variation in the input data. It can be concluded that the leaf area, whether it is corrected or not, is the most important grading feature for the Begonia cutting in the unrooted stage to create uniform growth groups.

5.5.3.5 Multiple regression analyses with the expert judgement in the half-grown stage and the features in the unrooted stage

In the correlation analysis, the relationship between a single feature and the expert judgement was studied. Multiple linear regression analysis is performed to investigate whether combinations of features in the unrooted stage determine the size of the plant in the half-grown stage. The objective of this multiple regression analysis with the expert judgement in the half-grown stage as dependent and the features measured with DIP in the unrooted stage as independent is to identify a relationship by a set of features in the unrooted stage. This set should contain elements which are related to the size and development of a half-grown Begonia plant according to the expert judgement.

The results of the analysis are given in a Table 5.10 as a list of variables included in the regression equation after the stepwise selection method, using the level of uncertainty of 5.0% to enter and 5.5% to exit a feature. The values in Table 5.10 are normalised weight factors of each feature.

Table 5.10 Multiple regression analysis using the features measured with DIP in the unrooted stage as independents and the expert judgement in the half-grown stage as dependent.

experiment / feature	1-ord	1-rand	2-ord	2-rand
Multiple R	0.45	0.32	0.56	0.25
R square	0.20	0.10	0.32	0.06
Total corrected area	.	.	0.18	.
Total corrected leaf area	0.37	0.31	.	.
Total corr. 2-nd leaf area	0.12	.	0.11	.
Total projected area	.	.	.	.
Length of cutting	.	.	0.24	0.12
Width of cutting	.	.	.	.
Ratio length/width	.	.	.	.
Ratio length*width/area	.	.	.	.
Length conn. stem method 1	.	.	.	.
Length conn. stem method 2	.	0.32	.	.
Thickness of stem	.	.	0.24	.
Distance optical centre to tip basic stem	0.14	0.30	0.26	0.24
Mean distance of mass	.	.	.	.
Number of plants	359	359	346	336

1-ord = experiment 1 ordered block
1-rand = experiment 1 random placed block
2-ord = experiment 2 ordered block
2-rand = experiment 2 random placed block

The differences between Experiments 1 and 2 and the ordered blocks and the random placed blocks are also present in the multiple regression analysis as was explained in Section 5.5.3.4.

From the features included in the regression equation, it can be seen that the corrected leaf area together with the distance between the optical centre to the tip of the basis stem are important. These features together indicate the size and shape of the cutting.

5.5.3.6 Correlation analysis between features measured with DIP in the unrooted stage and the half-grown stage

The expert judgements in the half-grown stage show a relationship with features measured in the unrooted stage and with features measured in the half-grown stage. Correlation analysis is performed to quantify the relationship between features in the unrooted stage and the half-grown stage. The objective is to investigate how the height and size of the second and third leaf in the half-grown stage are related to features in the unrooted stage.

The results are presented in Table 5.11. The Pearson correlation is calculated for all features which are included in the regression analyses with the expert judgement. According to the expert judgement, these features are the most relevant ones for the development of the cutting. Features significantly related to each other are marked with **. The features in the unrooted stage which are best related to the features in the half-grown stage in the ordered blocks are: total area, length, and the area of the second leaf. In the random placed block these relations are less strong. The same results are found in the correlation analysis between the features in the unrooted stage and the expert judgement in the half-grown stage.

The results of the free spaced blocks are also included. The development of these plants is different: the plants are relatively low and wide. A possible explanation is a difference in micro climate and competition between the plants when they are compared to the other experimental blocks.

Factor analysis was done to see whether it was possible to make a model for the features in the half-grown and unrooted stage. They provided no additional information. The influence of the plants grown at the edge of the experimental blocks has also been investigated. The results did not change when these plants were excluded from the experiments.

Table 6.12a Pearson correlations between features in the unrooted and half-grown stage of experiment 1, ordened

Features in the rooted stage	Features in the unrooted stage Tot. area.	Length	Thickness stem	Area 2-nd leaf	Dist optical c.	Expert judgement
Area 3	0.17 *	0.18 **	0.03	0.22 **	0.04	0.42 **
Height 3	0.26 **	0.23 **	0.05	0.24 **	0.11	0.60 **
Area 2+3	0.13	0.15 *	0.07	0.21 **	0.03	0.40 **
Height 2+3	0.26 **	0.19 **	0.13	0.17 *	0.07	0.53 **
Area tot.	0.37 **	0.27 **	0.13	0.14 *	0.16 *	0.53 **
Height tot.	0.22 **	0.18 **	0.12	0.15 *	0.13	0.48 **
Area top view	0.23 **	0.25 **	0.12	0.13	0.18 **	0.36 **
Height centre	0.14 *	0.14 *	0.08	0.12	0.17 *	0.42 **
Expert judgement	0.44 **	0.33 **	0.11	0.23 **	0.16	1.00

number of plants = 359

Table 6.12b Pearson correlations between features in the unrooted and half-grown stage of experiment 1, random placed

Features in the rooted stage	Features in the unrooted stage Tot. area.	Length	Thickness stem	Area 2-nd leaf	Dist optical c.	Expert judgement
Area 3	0.17 *	0.15 *	0.01	0.10	0.21 **	0.38 **
Height 3	0.12	0.14 *	0.01	0.16 *	0.19 **	0.59 **
Area 2+3	0.11	0.13	0.02	0.15 *	0.13	0.39 **
Height 2+3	0.13	0.13	0.04	0.16 *	0.17 *	0.60 **
Area tot.	0.32 **	0.32 **	0.01	0.21 **	0.29 **	0.39 **
Height tot.	0.15 *	0.16 *	0.02	0.17 *	0.18 **	0.56 **
Area top view	0.39 **	0.32 **	0.14 *	0.17 *	0.35 **	0.33 **
Height centre	0.12	0.15 *	0.02	0.14 *	0.17 *	0.48 **
Expert judgement	0.28 **	0.30 **	0.06	0.30 **	0.31 **	1.00

number of plants = 359

Table 6.12c Pearson correlations between features in the unrooted and half-grown stage of experiment 1, free spaced

Features in the rooted stage	Features in the unrooted stage Tot. area.	Length	Thickness stem	Area 2-nd leaf	Dist optical c.	Expert judgement
Area 3	0.13	0.01	0.31	0.13	0.07	.
Height 3	0.02	0.17	0.41	0.01	0.09	.
Area 2+3	0.33	0.29	0.37	0.06	0.09	.
Height 2+3	0.30	0.49 *	0.32	0.10	0.13	.
Area tot.	0.49 *	0.44	0.29	0.12	0.16	.
Height tot.	0.25	0.31	0.19	0.11	0.07	.
Area top view	0.47 *	0.66 **	0.17	0.29	0.01	.
Height centre	0.17	0.40	0.16	0.13	0.05	.
Expert judgement	.	.	.	.	.	.

number of plants = 30

Table 6.12d Pearson correlations between features in the unrooted and half-grown stage of experiment 2, ordened

Features in the rooted stage	Features in the unrooted stage Tot. area.	Length	Thickness stem	Area 2-nd leaf	Dist optical c.	Expert judgement
Area 3	0.35 **	0.35 **	0.09	0.34 **	0.08	0.39 **
Height 3	0.45 **	0.42 **	0.14	0.34 **	0.12	0.60 **
Area 2+3	0.38 **	0.33 **	0.19 **	0.23 **	0.01	0.48 **
Height 2+3	0.39 **	0.37 **	0.23 **	0.26 **	0.08	0.68 **
Area tot.	0.52 **	0.37 **	0.20 **	0.22 **	0.17 *	0.54 **
Height tot.	0.40 **	0.36 **	0.16 *	0.25 **	0.22 **	0.74 **
Area top view	0.36 **	0.28 **	0.21 **	0.15 **	0.19 **	0.53 **
Height centre	0.37 **	0.29 **	0.15 *	0.23 **	0.27 **	0.68 **
Expert judgement	0.45 **	0.38 **	0.21 **	0.22 **	0.24 **	1.00

number of plants = 346

Table 6.12e Pearson correlations between features in the unrooted and half-grown stage of experiment 2, random placed

Features in the rooted stage	Features in the unrooted stage Tot. area.	Length	Thickness stem	Area 2-nd leaf	Dist optical c.	Expert judgement
Area 3	0.18 **	0.26 **	0.02	0.24 **	0.04	0.24 **
Height 3	0.16 *	0.26 **	0.01	0.20 **	0.03	0.44 **
Area 2+3	0.24 **	0.30 **	0.10	0.25 **	0.06	0.37 **
Height 2+3	0.05	0.10	0.05	0.12	0.06	0.60 **
Area tot.	0.44 **	0.40 **	0.12	0.30 **	0.12	0.45 **
Height tot.	0.08	0.12	0.01	0.09	0.19 **	0.65 **
Area top view	0.36 **	0.15 *	0.17 *	0.08	0.16 *	0.38 **
Height centre	0.11	0.11	0.01	0.07	0.23 **	0.67 **
Expert judgement	0.09	0.05	0.01	0.08	0.19 **	1.00

number of plants = 336

Table 6.12f Pearson correlations between features in the unrooted and half-grown stage of experiment 3, free spaced

Features in the rooted stage	Features in the unrooted stage Tot. area.	Length	Thickness stem	Area 2-nd leaf	Dist optical c.	Expert judgement
Area 3	0.30	0.19	0.03	0.09	0.38	0.18
Height 3	0.09	0.26	0.30	0.02	0.39	0.16
Area 2+3	0.23	0.38	0.05	0.09	0.25	0.28
Height 2+3	0.16	0.21	0.37	0.16	0.37	0.23
Area tot.	0.49 *	0.31	0.31	0.01	0.27	0.26
Height tot.	0.31	0.14	0.12	0.24	0.18	0.08
Area top view	0.45	0.43	0.07	0.02	0.24	0.29
Height centre	0.28	0.14	0.02	0.15	0.25	0.16
Expert judgement	0.29	0.29	0.12	0.16	0.17	1.00

number of plants = 30
* = significant with 2-tailed uncertainty < 1%
** = significant with 2-tailed uncertainty < 0.1%
. = coefficient could not be computed

5.5.3.7 Simulation of grading experiments

The objective of the simulation of the grading experiments is to test whether a difference exists between the ordered blocks and random placed blocks based on the expert judgement in the half-grown stage. The hypothesis is that in the half-grown stage the 'small' ordered group contains plants which are judged 'smaller' than plants in the 'large' ordered group. In the random placed groups all sizes are presented. The simulation involves the division of the experimental blocks into five groups. The ordered block is divided into groups of ascending corrected leaf area as used to order the block. The random block is organized on the basis of the rank number of the plants. This means that the ordered groups contain cuttings of almost the same size and the random groups contain cuttings of all sizes.

The 'size' of the blocks is expressed by the size ratio which is explained in Section 4.7. The size ratio is determined by the percentage of small, medium and large plants in a group. In the ordered block, Growth group 1 represents the cuttings with the smallest corrected leaf area, Growth group 5 represents the cuttings with the largest corrected leaf area. Table 5.12 gives the results of these grading simulations.

Table 5.12a Results of the expert grading. (Between brackets the number of plants which were judged in that particular class).
Ordered plants, experiment 1.

	Expert judgement : classes			
growth group	small	medium	large	size ratio
1	7% (5)	86% (62)	7% (5)	50
2	5% (4)	92% (66)	3% (2)	49
3	10% (7)	75% (54)	15% (11)	53
4	4% (3)	56% (40)	40% (29)	68
5	3% (2)	34% (25)	63% (45)	80

mean overall size ratio : 60

Table 5.12b Random placed plants, experiment 1.

	Expert judgement : classes			
growth group	small	medium	large	size ratio
1	4% (3)	49% (35)	47% (34)	72
2	8% (6)	71% (51)	21% (15)	57
3	6% (4)	71% (51)	23% (17)	59
4	4% (3)	71% (51)	25% (18)	61
5	4% (3)	73% (52)	23% (16)	60

mean overall size ratio : 62

Table 5.12c Ordered plants, experiment 2.

growth group	Expert judgement : classes			size ratio
	small	medium	large	
1	31% (22)	56% (40)	13% (9)	41
2	37% (26)	41% (29)	22% (15)	43
3	9% (6)	38% (26)	53% (36)	72
4	6% (4)	27% (19)	67% (46)	81
5	6% (4)	18% (13)	76% (54)	85

mean overall size ratio : 64

Table 5.12d Random placed plants, experiment 2.

growth group	Expert judgement : classes			size ratio
	small	medium	large	
1	18% (12)	23% (15)	59% (39)	71
2	12% (8)	29% (20)	59% (40)	74
3	1% (1)	43% (30)	56% (39)	78
4	13% (8)	36% (22)	51% (31)	69
5	3% (2)	28% (20)	69% (49)	83

mean overall size ratio : 75

From Table 5.12a and 5.12c it appears that there is a difference between growth groups. The size ratio increases for the 'larger' groups which means that these contain larger plants. From Table 5.12b and 5.12d it can be seen that the size ratio of the individual growth groups does not increase. It can be concluded that the effect of grading on the bases of the corrected leaf area in the unrooted stage is still present in the half-grown stage.

The total numbers of small, medium and large plants are not equally distributed in the expert judgement. This is possibly because of the time of the year and growth circumstances. The plants are graded in classes according their development and size.

The plants in the free spaced experiments were also judged. The stems were short and the leaves were spread out over a larger area. The expert was not able to judge these plants. Therefore no figures are presented for the free spaced experiments.

5.6 Expert judgement

5.6.1 Introduction

In Section 5.5, the expert judgement has already been discussed as a tool for identifying grading features. The objective of this section is to develop and to test decision models which are capable of grading four week old Begonia plants into uniform development groups. In Section 5.5.3.3, multiple linear regression analyses are performed using features measured with DIP in the half-grown stage. The resulting regression equations can also be used as a classifier. By comparing the classification of the regression equation as decision model with the expert judgement, its performance as classifier can be determined. In Chapter 3 it was explained that some relationships in the judgements made on the half-grown plants are not linear. The expectation is that a neural network will perform better. A neural network which was described in Chapter 3, is tested.

5.6.2 The performance of the regression equation as decision model

The equations with the highest multiple r have been chosen for the analyses. In the regression analyses of the different experiments the set of features with the highest multiple r change. The judgement of the experts in both experiments is different.

The computer judgement is calculated by entering the features in the regression equation. A score below 1.5 is interpreted as small, in the interval 1.5 to 2.5 as medium, and above 2.5 as large. The results are presented in Table 5.13. Section 4.7.2 explains the performance of a decision model.

Table 5.13a The judgement of the regression equation based on features measured using DIP compared with the judgement of the expert.
Experiment 1, ordered.

experiment 1 ordered		computer judgement		
		small	medium	large
expert judgement	small	8	13	0
	medium	13	228	16
	large	0	38	54

Total : 360
Correct : 290 = 81%
1st order error : 70 = 19%
2nd order error : 0 = 0%

Table 5.13b Experiment 1, random placed.

experiment 1 random placed		computer judgement		
		small	medium	large
expert judgement	small	6	13	0
	medium	4	218	19
	large	0	39	61

Total : 360
Correct : 285 = 79%
1st order error : 75 = 21%
2nd order error : 0 = 0%

Table 5.13c Experiment 2, ordered.

experiment 2 ordered		computer judgement		
		small	medium	large
expert judgement	small	38	24	0
	medium	10	104	13
	large	0	36	124

Total : 349
Correct : 266 = 76%
1st order error : 83 = 24%
2nd order error : 0 = 0%

Table 5.13d Experiment 2, random placed.

experiment 2 random placed		computer judgement		
		small	medium	large
expert judgement	small	13	18	0
	medium	3	87	17
	large	0	29	169

Total : 336
Correct : 269 = 80%
1st order error : 67 = 20%
2nd order error : 0 = 0%

As can be seen from the Tables 5.13, about 80 percent of the plants are graded as the grader did (defined as correct), while about 20 percent are graded with only one class difference. In Chapter 2, it was stated that the consistency of the human grader is about 80 percent when regrading a group of plants. Part of the remaining 20 percent involves the group of plants about which computer and the expert opinions sometimes differ.

The performances of the decision models for the ordered blocks in Experiment 1 and 2 are almost equal (81 % and 76 %). The multiple r of the best set of features were 0.69 and 0.81 respectively. The same effect is seen for the random placed blocks (performance 79% and 80% and multiple r 0.68 and 0.76 respectively). This means that the multiple r does not predict the performance of the decision model.

It can be concluded that the regression equation is able to serve as decision model.

5.6.3 The performance of a neural network as decision model

The decision model consists of a three-layer feed-forward neural network and is learned with the back-propagation generalised delta method (Rummelhart et al., 1986; Zhuang et al., 1992). This type of network and learning strategy is described in the literature as a robust method (Chang et al., 1992). The 18 features measured with DIP are used as input and this results in 18 input nodes. The output of the network can be small, medium, or large. This results in three output nodes, one for each class. The network was tested for different numbers of hidden nodes. A small number of nodes in the hidden layer gave a network which was unable to contain sufficient information. A large number of nodes in the hidden layer resulted in a network which learned too many specific situations from the training set. The optimum number of 12 nodes was chosen by iteration.

The training set which contained the measured features and the expert judgement is fed to the network. The values of the features are scaled between 0.0 and 1.0 and the training set is randomised. For this type of learning, random presentation is important. Where small plants are presented before the medium and large ones, the network forgets the small plants in the process of learning the large plants. The optimum set of weights found for the small plants is replaced during the training by an optimum set of weights for the large ones.

For optimal learning of the network all the grades should be equally distributed, otherwise the neural network will be less able to recognise the categories which are represented by a relative small number of plants. In the growth experiments not all classes were represented equally and this did lead to problems in the training of the network.

The expert score consists of a pattern of 0.1 and 0.9. For instance, if the judgement of the expert is small, the target pattern of the output nodes is 0.9 for small, 0.1 for medium, and 0.1 for large. The learning rate is set at 0.9 and the momentum at 0.25. These values proved to be good values during the tests.

In the recognition-mode of the network, the output nodes of the network are compared with each other. The node with the highest value is used to classify the plant. In some cases a plant falls between two categories (e.q. 0.4 for medium and 0.6 for large). In such cases, a plant will be classified as large.

Brons et al. (1991) did some preprocessing on the input of the neural network by excluding features which proved to be irrelevant in the statistical analysis. The performance of the network increased by presenting the relevant features. Instead of making a pre-selection, all features are used as input for the neural network. The statistical analyses resulted in different sets of features which are related to the size and development of the plant. The selection of inputs for the neural network should be changed for each different experiment. The network itself has to decide which features are important. The learning time increases because of the large number of weights which have to be determined. This is no problem in the context of this research.

The performance of the neural network is presented in Table 5.14. For each experiment and block, a new set of weights is determined because the system set-up, including the size and shape of the half-grown plants, was different.

Table 5.14a The judgement of the neural network based on features measured with DIP compared with the judgement of the expert. Experiment 1 : ordered.

experiment 1 ordered		computer judgement		
		small	medium	large
expert judgement	small	15	6	0
	medium	0	240	6
	large	0	35	57

Total : 359
Correct : 312 = 87%
1st order error : 47 = 13%
2nd order error : 0 = 0%

Table 5.14b Experiment 1 : random placed.

experiment 1 random placed		computer judgement		
		small	medium	large
expert judgement	small	10	9	0
	medium	2	223	16
	large	0	30	70

Total : 360
Correct : 303 = 84%
1st order error : 57 = 16%
2nd order error : 0 = 0%

Table 5.14c Experiment 2 : ordered.

experiment 2 ordered		computer judgement		
		small	medium	large
expert judgement	small	40	18	3
	medium	6	82	38
	large	0	6	153

Total : 346
Correct : 275 = 79%
1st order error : 81 = 20%
2nd order error : 3 = 1%

Table 5.14d Experiment 2 : random placed.

experiment 1 random placed		computer judgement		
		small	medium	large
expert judgement	small	29	2	0
	medium	4	91	12
	large	2	29	167

Total : 336
Correct : 287 = 85%
1st order error : 47 = 14%
2nd order error : 2 = 1%

The performance of the neural network should be compared with the performance of the regression equations in Table 5.13. A summary of both results is presented in Table 5.15. It can be concluded that the performance of the classification increased by 5% when a neural network is used as decision model. The small and large plants in particular are better classified by the neural network than by the regression equation. In Experiment 2, the neural network makes second order errors. The plants which cause the second order errors were investigated. Most of these plants were irregular in shape and the expert doubted about his classification. The expert could agree with changing the class for these plants. It can be concluded that the neural network is able to serve as decision model.

The reported performances are the classifications of the neural network after a limited number of iterations during the training. An iteration means that all plants in the training set are presented once. The performance of the network has not reached its maximum. It appeared that the performance of the network could be increased. However the performance of the neural network for the classification of the plants from the other experimental block decreases (test set) after a number of iterations. Longer training of the neural network leads to a situation in which it learns too many specific plants. The judgement errors of the expert are also learned. The training of the network can be divided into a generalisation stage - in which it learns the general decision rules - and a specialisation stage - in which it learns specific cases and errors (Knight, 1990). In Figure 5.27 the performances of a learn and a test set are shown. After each iteration the overall performances of the learn set (score learn set) and the test set (score test set) at that moment are determined. A good set of weights for the network are those for which the score of the test set reaches its maximum.

5.6.4 Comparison of the performances of the decision models

In Table 5.15 the performances of the regression equation and the neural network after 200 iterations and after 600 iterations are shown. The objective is to investigate the generalisation performances of the decision models. The performance is determined for each experiment and block. The plants from the same experiment in the other block are used as test set.

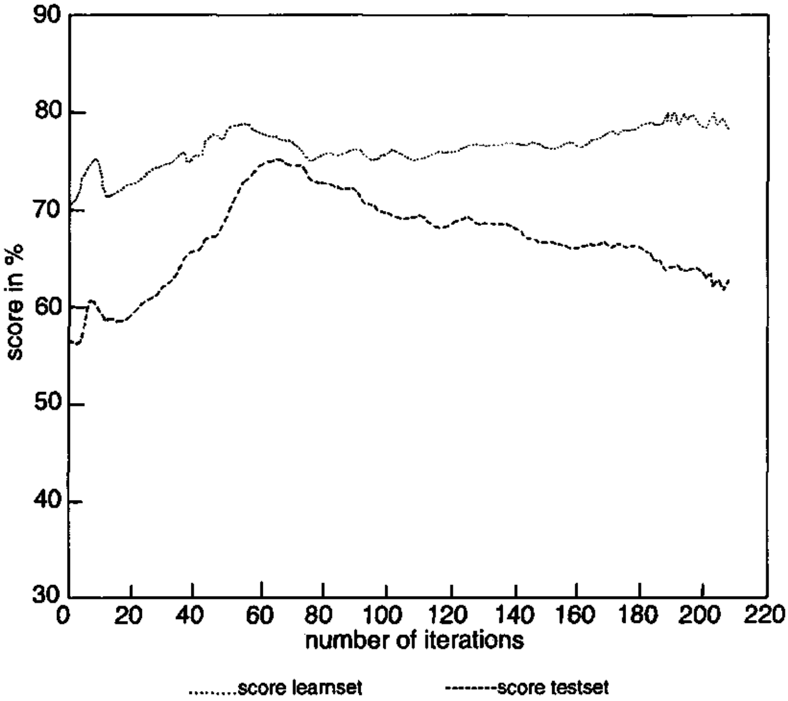


Figure 5.27 The performance of the learn and test set during the learning.

Table 5.15a Comparison of the performances of the regression equation with the neural network for both the training and the test set.

a : Experiment 1.

learn set for the decision model.	test set 1 - ord correct	1st	2nd	test set 1 - rand correct	1st	2nd
1-ord regression	81%	19%	0%	74%	26%	0%
1-ord neural 200 it	87%	13%	0%	76%	24%	0%
1-ord neural 600 it	91%	9%	0%	73%	27%	0%
1-rand regression	80%	20%	0%	79%	21%	0%
1-rand neural 200 it	76%	24%	0%	84%	16%	0%
1-rand neural 600 it	75%	25%	0%	89%	11%	0%

b : Experiment 2.

learn set for the decision model.	test set 2 - ord correct	1st	2nd	test set 2 - rand correct	1st	2nd
2-ord regression	76%	24%	0%	62%	37%	1%
2-ord neural 200 it	79%	20%	1%	72%	24%	2%
2-ord neural 600 it	88%	11%	1%	68%	29%	3%
2-rand regression	69%	29%	2%	80%	20%	0%
2-rand neural 200 it	65%	34%	1%	85%	14%	1%
2-rand neural 600 it	64%	33%	3%	90%	10%	0%

1-ord = experiment 1 ordered blocks
1-rand = experiment 1 random placed blocks
2-ord = experiment 2 ordered blocks
2-rand = experiment 2 random placed blocks
it = number of iterations
correct = percentage plants on which the decision model and expert agree
1st = percentage plants on which the decision model and expert differ 1 class
2nd = percentage plants on which the decision model and expert differ 2 classes

As can be seen from Table 5.15, the performance of the neural network and the regression equation decrease for the classification of the test set. (E.g. learn set Experiment 1 ordered block. The performance of the regression equation is 81 % for the plants for which it is learned. When the model is tested with the plants in the random block, the performance decrease to 74 %). Generally, the neural network can classify the test set better than the regression equation.

In all cases the performance for the training set improves after more iterations (Experiment 1 ordered : 87 % to 91 %, Experiment 1 random placed : 84 % to 89 %, Experiment 2 ordered : 79 % to 88 %, Experiment 2 random placed : 85 % to 90 %). The performance of the test set decreases when the performances after 200 and 600 iterations are compared (Experiment 1 ordered : 76 % to 75 %, Experiment 1 random placed : 76 % to 73 %, Experiment 2 ordered : 65 % to 64 %, Experiment 2 random placed : 72 % to 68 %). After 600 iterations the neural network is in the specialisation stage.

Both the regression equation and the neural network can be used as decision model. Both classify over 75 percent of the plants the same as the expert. It should be considered that the expert judgement contains classification errors as is explained in Chapter 2. The neural network shows a better performance - an average of 5 percent over the regression model.

5.7 General conclusions and discussion

The first objective of this case study was to identify and to test features of unrooted Begonia cuttings. These can be used to create uniform growth groups. Two methods are described. The first one is the estimation of the leaf area which is based on the grey values of the leaves. The corrected leaf area (the result of the estimation method) shows a better relationship with the real leaf area than the projected leaf area ($r=0.87$ respectively 0.82). Consistency did not improve (94.7 % and 94.6 % respectively). The second method is the knowledge-based segmentation of the stem-leaf structure of the Begonia cutting which is based on a general model of the cutting. With this method it is possible to identify the first and second leaf. This method can only be applied if a model of the stem-leaf structure can be defined.

Growth experiments are performed to identify features of unrooted Begonia cuttings which can be used to create uniform growth groups. Correlation analysis between the features in the unrooted stage and the expert judgement in the half-grown stage shows that both the leaf area and the corrected leaf area are features that relate best to the expert judgement (maximum achieved $r=0.45$). Multiple regression analysis shows that a combination of the corrected leaf area, the area of the second leaf and the distance of the optical centre to base point of the stem relate best to the development of the half-grown Begonia plant (maximum achieved multiple $r= 0.56$). A possible explanation for this set of features can be found in the growth potential of the plant. The growth potential of a young plant is determined by its assimilating area. The distance from the optical centre to the base point of the stem partly describes the shape of the cutting. Cuttings with longer stems, resulting in a greater distance, have more overlap with their neighbours. This results in difference in competition. The size of the second leaf area indicates the development of the cutting. The measurement of the area of the second leaf (consistency = 86.1 %) causes errors, especially in cases of small second leaves and short stems. The expert mentioned that the length of the connecting stem is also important. The measurement of this feature is not sufficiently consistent (89.7 %) but the distance of the optical centre to the tip of the basic stem provides similar information (consistency = 97.7 %).

The grading simulations show that the size ratio's of the five growth groups of the ordered blocks increase with the 'size' of the unrooted cutting. This means that the average size of the plants in the 'small' growth groups is smaller than in the 'large' ones. In the random placed growth groups all sizes are present and the average size of the plants in the growth groups is equal. It is concluded that grading based on the corrected leaf area results in more uniform growth groups after a growth period of four weeks.

Analyses of the results of the growth experiments show a difference in response between the ordered and random placed blocks. In the ordered blocks, development after four weeks is better determined by the features in the unrooted stage. The difference in plant interaction is a possible explanation for this effect. In the random placed blocks a cutting is bordered to cuttings with different size. Therefore the competition of the individual cutting in the random placed block is heterogeneous when compared to the ordered block. The uniformity in the growth group is determined by two factors: the uniformity of the starting plants, and the uniformity of the plant interaction.

The second objective was to identify and to test features of half-grown Begonia plants which describe size and development. These features are used to evaluate the uniformity of the growth groups after a growth period of four weeks and they are used to grade the plants into uniform development groups. The features of the half-grown Begonia plant are measured with knowledge-based segmentation. At this stage, the stem-leaf structure is well visible in the side-view of the plant. The segmentation technique is almost the same as for the Begonia cuttings only the rules for the relationship between the stems and the leaves are modified for the half-grown stage. The identification of the individual leaves is important because the first leaf has to be excluded. This could be done over 99 percent. The area of the main segment (second + third leaf) shows a correlation of 0.83 with the real area and a consistency of 91.9 %.

Judgement experiments are performed to identify features of the half-grown Begonia plant. Analyses of the results of two of the experiments show that different experts have different opinions on grading features. One expert appreciated the development of the second and third leaf together with the height (multiple r=0.45). The other expert only appreciated the height (multiple r=0.56).

A regression equation and a neural network have been tested as a decision model. Both are able to grade the half-grown plants with a performance of at least 75 percent. The neural network performs better (improvement of about 5 percent) than the regression equation, especially for the small and large plants.

It should be remarked that the relationship between the unrooted stage and the four weeks old stage in these experiments may be stronger under normal circumstances. The plants were also measured after a growth period of three weeks. The roots and leaves may have been damaged during the handling.

6 Case study on Dieffenbachia plants

6.1 Introduction

The second case study deals with Dieffenbachia plants. Dieffenbachia plants are chosen because the structure of the plant is different to that of Begonia plants which involves the application of other DIP measurement techniques. The leaves of the shoots are reasonably transparent like the leaves of the Begonia cutting but the stem structure cannot be described in the same way as is done for Begonia cuttings. The shoots consist out of four or more leaves which overlap each other so it is difficult to distinguish the individual leaves. Therefore global features are identified and measured. In the older stage the stem structure and the individual leaves cannot be distinguished so also here global features are measured.

The Dieffenbachia plant is a 'green' pot plant and the plant's spotted leaves determine it's ornamental value. It is propagated by splitting shoots off from the mother plant. In the unrooted stage some grading is done during the separation. The shoots are graded into size groups and the smallest shoots are removed. In Section 2.5 it is explained how the human expert grades the unrooted Dieffenbachia shoots. The expert makes errors during the grading and so the groups are not uniform.

The first objective in this case study is to identify and to test features with respect to their quantitative and qualitative properties of unrooted Dieffenbachia shoots which are measured with DIP. These features are used to create uniform growth groups which still have a high degree of uniformity after a growth period of eleven weeks. The second objective is to identify and to test features of six and nine week old Dieffenbachia plants (half-grown plants) which are measured with DIP. These features are used to evaluate the uniformity of the growth groups after a certain growth period. They also can be used for regrading the plants into uniform growth groups. The third objective is to identify and to test features which describe the size and development of eleven week old Dieffenbachia plants (the full-grown stage). These features are used to evaluate the uniformity of the growth groups and to grade the plants into uniform size and development groups according to the expert's standards.

The growth and judgement experiments were carried out at a company where the Dieffenbachia plants are grown for an eleven week period.

6.2 Flow chart of the growth and processing points

After separation from the mother plant, the shoots are put in a pot. In order to develop the roots they are placed in an environment with high humidity and temperature for a period of two weeks. Then they are placed into a greenhouse for a period of nine weeks. After a total growth period of eleven weeks they are judged by experts. In normal processing these plants are harvested in a number of cycles. Each time the largest plants are removed. Figure 6.1 gives a flow chart of the growth of Dieffenbachia plants.

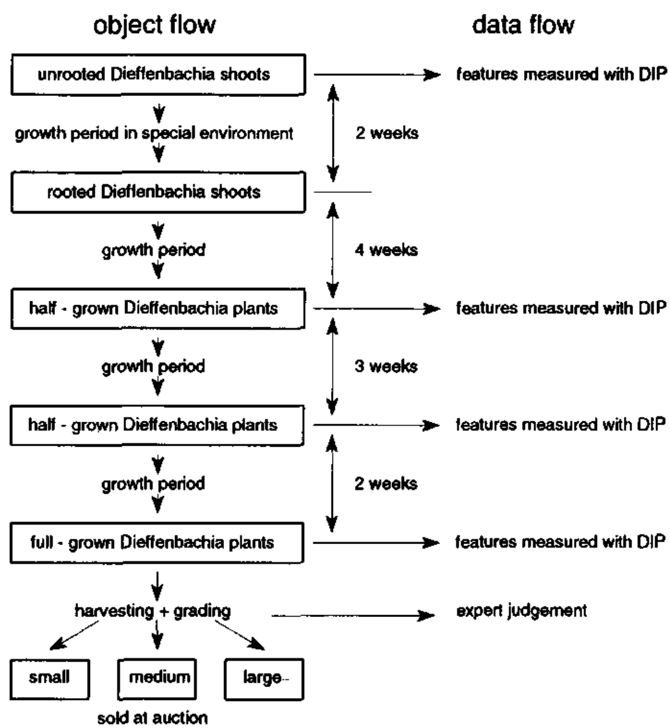


Figure 6.1 Flow chart of Dieffenbachia cultivation.

In the growth experiments the plants are measured four times: in the unrooted stage, after six weeks of growth, after nine weeks of growth, and after eleven weeks of growth. In the eleven week old stage they were also judged by the expert.

6.3 Unrooted Dieffenbachia shoots

6.3.1 Introduction

According to Jansen (1979) the ideal length of a shoot is between five and seven centimetres and it should have about four leaves. He also stated that the size of the stem is important for the growth potential. In the stem the reserve energy is located. The number of leaves is not important for the growth potential. The size of the stem which is indicated by its diameter, was also mentioned by expert at the experimental location.

The choice is made to measure the leaf area and stem diameter. Other features such as length, width and location of optical centre have been measured based on experience gained in former experiments with Dieffenbachia's.

Figure 6.2 Unrooted Dieffenbachia shoot on a diffuse back-lighted transparent plate

In this section the possibilities of measuring features of unrooted Dieffenbachia shoots and their quantitative properties are investigated.

6.3.2 Scene processing

The Dieffenbachia shoot has a three-dimensional structure. As it is noted for Begonia cuttings, the projected leaf area differs from the real leaf area because of tilting and overlapping leaves. The shoot may not be flattened because the leaf area must be measured in a non-destructive way. Therefore the shoot is placed in the natural rest position on a diffuse back-lighted transparent plate (Figure 6.2). The leaves of the shoot are 'sufficiently transparent' to apply the estimation method for the area as described for the Begonia cutting. 'Sufficiently transparent' means that differences in grey values occur, related to the leaf configuration.

The back-lighting system provides sharp images so no additional processing is needed. The shoots are presented singularised and orientated with the basic stem pointing downwards in the image to reduce the calculation time of the computer system. The distance between the camera and the shoot is between 0.97 m and 1.03 m. The error due to this difference in distance between camera and object is negligible (Section 3.9). The largest shoot just fits into the camera's viewing area (512*512 pixels).

In order to measure the thickness of the stem an additional camera is used to zoom in on the stem. In the main image the thickness of the stem is about 17 pixels. Due to digitising, the thickness measurement is 17 +/- 1 pixel, which is a relatively large error. In the zoomed image, the stem thickness is about 100 +/- 1 pixels. This measurement is less affected by edge pixels.

6.3.3 Image processing

The leaf area is estimated in the same way as is done for the unrooted Begonia cuttings. The stem thickness is measured by determining the average length of the pixel runs of the stem in the zoomed image. The average length is used because the shape of the stem can change. Some stems are equally thick at all points while other stems are more trapezium shaped.

The tip of the stem is just at the bottom of the image. The image is scanned from bottom to top. Segmentation is done with run length coding. The first run at the bottom is a stem run. When this run is found a number of lines is skipped to avoid the irregular edge at the bottom of the stem. Then the length of the runs is determined every tenth line. The scanning stops if:

- the stem is out of the view area,
- a splitting occurs in the stem,
- the scanning reaches the top of the image.

To determine the orientation of the stem, the middle points of the runs are calculated. A line is constructed through these points. This line (centre line) is used to determine the angle towards the vertical axis. If the stem is not parallel to the vertical axis of the image, the measured run length is corrected by multiplying it with the cosine of the angle between the centre line and the vertical axis (see Figure 6.3).

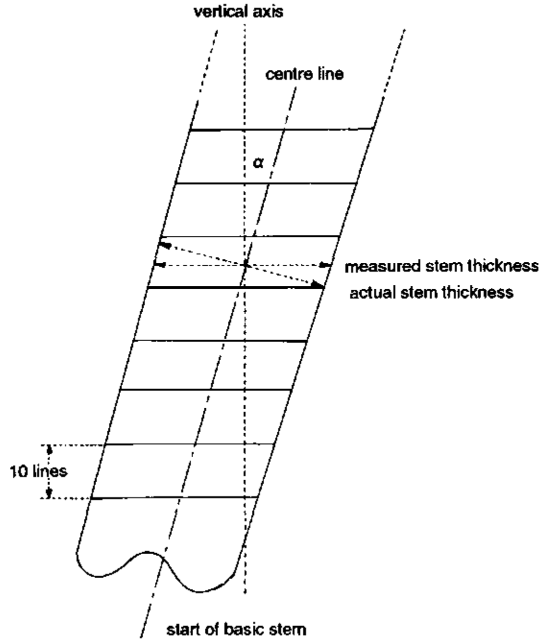


Figure 6.3 Calculating stem thickness

As is already mentioned, the structure of the unrooted Dieffenbachia shoot is difficult to describe in terms of individual stems and leaves, but it is possible to distinguish stem parts from leaf parts. The routines used to analyse the structure of the unrooted Begonia cuttings are also applied to the unrooted Dieffenbachia shoots, except for the classification of the first and second leaf. The results of the raw and exact segmentation are a set of stem and leaf segments. This set is used to calculate the following shoot features:

1. Total corrected leaf area of the shoot (pixels).
   Sum of pixels of all segments identified as leaf based on the grey value histograms and weight values.
2. Total corrected area of the shoot (pixels).
   Sum of pixels of all segments based on the grey value histograms and weight values.
3. Total projected area of the shoot (pixels).
   Sum of pixels of all segments.
4. Length of shoot (pixels).
   The distance in a vertical direction between the uppermost and the lowest point of the shoot.
5. Width of the shoot (pixels).
   The distance in a horizontal direction between the left most and right most point of the shoot.
6. Ratio between length and width. This measurement indicates the roundness of the shoot.
7. Ratio between length times width and total projected area. This ratio indicates the compactness of the cutting. When the cutting is extended with long stems its compactness is relatively small.
8. Thickness of the stem defined as method 1 (pixels).
   The average thickness of the base stem measured from the overall image.
9. Thickness of the stem defined as method 2 (pixels).
   The average thickness of the stem measured from the zoomed image.
10. Distance between the optical centre and the tip of the basic stem of the shoot (pixels).
    This measurement indicates the compactness of the shoot.

6.3.4 Consistency and range measurement of features of Dieffenbachia shoots

The consistency test to determine the quantitative properties of features is discussed in Section 4.4. Twenty-five unrooted Dieffenbachia shoots were measured five times to perform this test.

Table 6.1 Consistency and range measurements of unrooted Dieffenbachia shoots.

feature	consistency in %	minimum	maximum	mean
Total corrected leaf area	96.7	23751	65769	45769
Total corrected area	97.1	27659	70701	49088
Total projected area	97.0	20299	46720	32711
Length of shoot	98.1	309	491	430
Width of shoot	98.1	78	409	303
Ratio length/width	97.0	0.37	1.00	0.72
Ratio (length*width)/area	96.1	0.26	0.62	0.39
Thickness of stem method 1	93.8	11	28	17
Thickness of stem method 2	95.8	54	142	93
Distance optical centre to bottom	98.4	193	316	265

Minimum, maximum, and mean are expressed in number of units in which they have been measured.

It is already stated that the consistency of a feature should be at least 90 percent. From Table 6.1 it can be seen that all features meet this criterion. There is little difference between the consistency concerning the corrected leaf area and the projected area (97.1% and 97.0%). Similar as was found for the unrooted Begonia cuttings (corrected leaf area 94.1% and projected area 94.6%). As has been mentioned for the unrooted Begonia cuttings the cause of the similar consistency may be the consistent natural rest position. It has been observed that a Dieffenbachia shoot is rather flat. If the shoot is put on a flat surface it orients itself most of the times in the same orientation (natural rest position). This involves a low variation in the grey value histogram. This variation is needed for the determination of the weights (Section 5.3.3). The stem thickness measurement based on the zoomed image shows a better consistency than the measurement in the overall image (95.8% to 93.8%). This is explained by the higher resolution which involves a smaller influence of the edge pixels. The shape of the stem is irregular. This also causes errors even in the zoomed image.

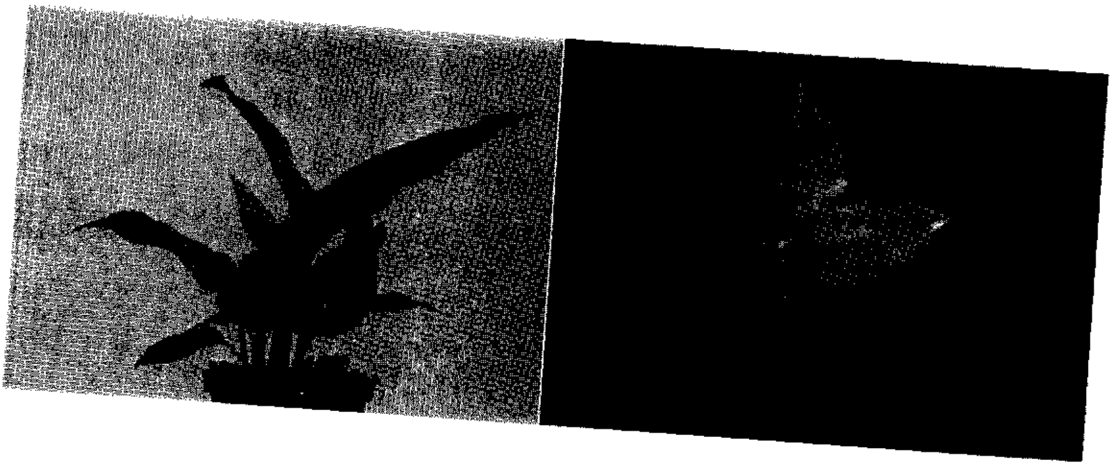
The real values of the features of the unrooted Dieffenbachia shoots are not determined. The results of the unrooted Begonia cuttings (Table 5.3) showed satisfactory results. The results for the unrooted Dieffenbachia shoots are expected to be similar.

It can be concluded that features of the unrooted Dieffenbachia shoots can be measured using DIP. The stem thickness, which is considered by the experts to be an essential feature, is measured with a satisfactory consistency (95.8%).

6.4 The full-grown Dieffenbachia plant

6.4.1 Introduction

A normally developed, full-grown Dieffenbachia plant consists of several leaves and shoots. According to the experts the number of shoots, representing the thickness of the plant, is an important features for its quality. In Figure 6.4 a full-grown Dieffenbachia plant is shown. The number of shoots is hard to determine. The thickness of the plant cannot be defined objectively. It is chosen to measure global features of the plant such as height and projected leaf area from top- and side-view.



a b

Figure 6.4 Full-grown Dieffenbachia plant, side-view (a), top-view (b).

In this section the possibilities of measuring features of full-grown Dieffenbachia plants and their quantitative properties are investigated.

6.4.2 Scene processing

The features extracted from the side-view are geometrical. A diffuse, uniform lighting system is used as background. This provides sharp images for the extraction of geometrical features (see Section 3.3.2). One by one, the plants are presented in front of the camera. The distance between the camera and the plant varies between 1.35 m and 1.65 m. Therefore corrections have to be made for this variation in distance (see Section 3.9). Three side-views are taken. For each side-view the plant is rotated a further 90 degrees in the horizontal plane. The initial orientation is not important. A top-view image is captured to get the projected leaf area from the top. The plant is positioned on a dark, light absorbing background. The front-lighting is supplied by incandescent light tubes which produce near-infrared light as well as visible light. The difference in reflectance in the near-infrared region for the leaves and soil is used to segment the image (see Section 3.3.3).

6.4.3 Image processing

The height of the plant is defined by the distance between the predefined pot height and the highest visible point of the plant. The calculated height of the plants depends on the orientation of the plant because of the difference in distance between the camera and the highest point of the plant. To improve its consistency the height of the plant is determined by calculating the average height from two images. For each side-view image the plant is rotated 180 degrees in the horizontal plane. The errors in the height measurement compensate each other when the images are taken from opposite sides of the plants.

The plant is not symmetrical. Therefore the projected leaf area from side-view is calculated from two images. The second image is captured after the plant has been rotated 90 degrees in the horizontal plane. The two projections are perpendicular and are representative for the shape of the plant.

The plants are positioned in the front of the camera in such a way that the pot is just visible. The transition pot - plant is hard to determine because of the ground particles above the pot and the leaves which overlap the pot. Therefore the pot height is predefined.

The abbreviation which is used further on in the text is mentioned in brackets. All units are measured in pixels.

1. Total projected area from top-view (Area top).
   In the top-view image the total number of pixels connected to the plant is determined. The routine which has been developed for the half-grown Begonia plants is applied.
2. Total projected area from side-views (Area side).
   The projected areas of two side-view images which are captured 90 degrees apart in the horizontal plane are cumulated.

3. Height of the plant (Average height).
   The average height calculated from two side-view images which are captured 180 degrees apart in the horizontal plane.
4. Deviation of the x-position of the optical centre above the middle of the pot (X-dev.).
   In the side-view images the location of the middle of the pot and the location of the optical centre is determined. The deviation of the x-coordinate of the optical centre from the x-coordinate of the middle of the pot indicates the asymmetry of the plant. After two images have been captured following a 90 degree rotation in the horizontal plane, the value of this deviation is determined by adding the two absolute values of the x-deviation in each image.
5. Height of the optical centre above the pot (Height centre).
   The height of the optical centre combined with the height of the plant indicates whether the leaf mass is at the top of the plant or at the bottom of the plant.
6. Volume (Volume).
   Total projected area from top-view multiplied by the average height.

6.4.4 Consistency and range measurement of features of full-grown Dieffenbachia plants

The consistency test to determine the quantitative properties of features was discussed in Section 4.4. Twenty full-grown Dieffenbachia plants were measured five times. The values for the single image measurement are also presented to determine whether combining the measurements of two images influences consistency.

Table 6.2 Consistency and range measurement of full-grown Dieffenbachia plants.

feature	consistency in %	minimum	maximum	mean
Area top	97.7	46413	101880	73493
Area side 2 images	96.3	36653	109378	73829
Area side 1 image	93.7	17479	59517	37151
Average height 2 images	97.4	270	449	355
Average height 1 image	97.1	270	459	355
X - dev optical centre	79.4	4	218	50
Height optical centre	97.2	123	221	177
Volume	97.1	13877	40344	26210

Minimum, maximum, and mean are expressed in number of units in which they have been measured.

From Table 6.2 it can be seen that all features can be measured with a consistency better than 90 percent except the deviation of the optical centre in the horizontal direction. Combining the features from two images improves the consistency. In particular the consistency for the side area improves (93.7% for the single image and 96.3% for two images). Hardly no improvement in the consistency of the height measurement (97.1% for single and 97.4% for two images) is found. In some experiments a larger difference was measured. The differences can be reduced by choosing the correct camera-object set-up. In this case the centre of the lens is chosen at the same height as the average height of the plant. The deviation of the x-coordinate of the optical centre is very sensitive to the orientation. Therefore this feature is not useful as a grading feature.

6.5 Growth experiments with Dieffenbachia plants

6.5.1 Introduction

The objective of the Dieffenbachia growth experiments is to identify features of unrooted shoots, half-grown plants, and full-grown plants measured with DIP. Features which have a strong relation to size and development in the full-grown stage have good qualitative properties and can be used as grading feature. The objective of the measurements after six and nine weeks (half-grown stage) is to investigate whether the effect of grading is still present after a particular growth period.

6.5.2 Experimental set-up of the growth experiments

In Chapter 4 the set-up of the growth experiments is discussed. Here the implementation for the Dieffenbachia experiments is explained. The ordering feature for the ordered blocks is the corrected leaf area which is the same as for the Begonia cuttings. In former experiments this feature showed a strong relationship with growth potential. The same methodology used for Begonia experiments is used for the Dieffenbachia experiments (Section 5.5.2). The total number of shoots per block was 288 (arranged in 16 x 18 pots). This was determined by the lay-out of the greenhouse.
Following blocks were created :

- Block 1 : The ordered experiment.
- Block 2 : The random experiment.
- Block 3 : The free-spaced experiment (30 plants).

After a period of six and nine weeks, the blocks were measured again with DIP. No expert judgements were made during these measurements. In normal processing, plants are not graded at these points so no standards are available.

The same routines which were developed for the full-grown stage of the Dieffenbachia plant are applied at the six and nine week old stage. The consistencies of the features in these stages are similar as for the full-grown stage. In Figure 6.5 the relationships between the measurements are shown.

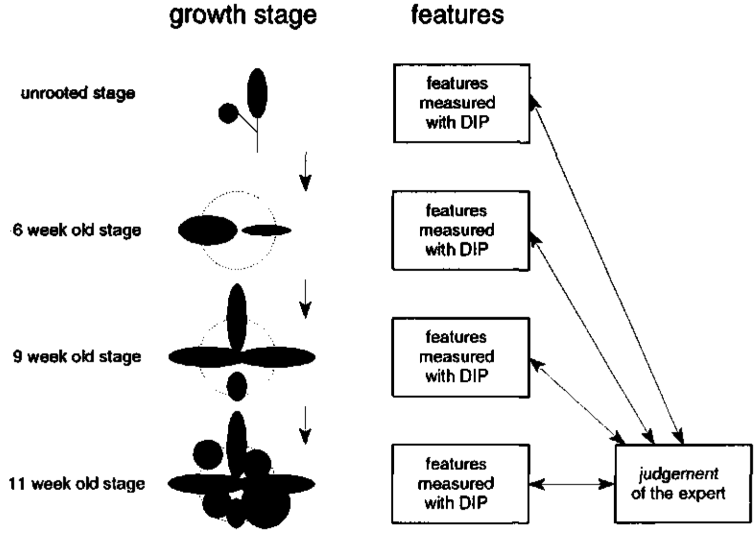


Figure 6.5 Relationships between measurements in the Dieffenbachia experiment.

6.5.3 Results of the Dieffenbachia experiments

6.5.3.1 Introduction

In Section 4.5.3 the analyses of the growth experiment are discussed. The analyses are performed on the basis of the relationships in Figure 6.5. The discussion of the results starts by analysing the correlation between the expert's judgement in the full-grown stage and the features measured with DIP in the four different stages. The correlation coefficients provide information about the individual qualitative properties of the features in relation to size and development in the full-grown stage. Multiple linear regression analysis is applied to investigate whether a combination of features in the different stages measured with DIP relate to expert judgement in the full-grown stage. The analysis ends with a grading simulation in which the initial blocks are split-up into five growth groups in order to investigate the difference in homogeneity between the random placed blocks and the ordered blocks. Grading simulations at the six and nine week old stage are performed to establish whether or not regrading in these stages produce a higher uniformity in the full-grown stage.

Over a two year period (from 1989 to 1991) several growth experiments with Dieffenbachia shoots were performed. The test period ended with a series of four experiments using 'Compacta' shoots. In this case study the results of two experiments are discussed.

Experiment 1 was carried out between February 1 and April 16 of 1991. Experiment 2 was carried out between April 26 and July 11 of 1991.

6.5.3.2 Correlation analysis of the growth experiments

The objective in making a correlation analysis between the features of the Dieffenbachia plant in different growth stages measured by DIP and the expert judgement in the full-grown stage is to define features in these growth stages which have a strong relationship with expert judgements. These features can be used to grade the plants into uniform growth- and quality groups. The conditions for the correlation analysis have already been discussed in Section 5.5.3.3.

The results of the Pearson correlation analysis are presented in Table 6.3. Only features which have a correlation (r) with a 2-tailed uncertainty of $\leq$ 0.1 % are presented.

The plants in the free standing blocks were judged too. The expert was not able to classify these plants. The plants were able to spread out over a large area which resulted in unusual shapes.

Some plants did not survive the experiment. Dieffenbachia shoots sometimes have problems in rooting. The dead plants were replaced by plants of the same size to avoid undesirable plant interaction.

From Table 6.3 it can be seen that the Pearson correlation coefficients between most features and the expert judgement decrease if the period between measurement by DIP and judgement by the expert in the full-grown stage increases. This means that the uniformity of the growth groups decreases during growth due to possible differences in climate and plant interactions. The greatest difference in correlation coefficients is found between the unrooted stage and the six week old stage. In the first two weeks the shoots get roots. The developing speed of roots can be very different for the same sized shoots and so the moment when the shoots start to develop may vary.

Table 6.3 Pearson correlation coefficients between the expert judgement in the full-grown stage and the features measured using DIP in different growth stages of the Dieffenbachia plant. The rank numbers of the two highest correlation coefficients per stage are noted in descending order in brackets.

experiment / feature	1 - rand	1 - ord	2 - rand	2 - ord
Unrooted :				
Corrected leaf area	0.38 (1)	0.43 (1)	0.32 (1)	0.45 (1)
Length of the shoot	0.31 (2)	0.23	0.07	0.27 (2)
Stem thickness method 2	0.28	0.28 (2)	0.25 (2)	0.22
6 week old stage :				
Area top	0.54 (1)	0.66 (1)	0.49	0.69 (2)
Area side	0.54 (1)	0.58 (2)	0.54 (1)	0.67
Tot. height	0.39	0.49	0.35	0.60
Height centre	0.40	0.53	0.34	0.54
Volume	0.53 (2)	0.66 (1)	0.51 (2)	0.73 (1)
9 week old stage :				
Area top	0.62 (2)	0.65 (1)	0.53	0.71
Area side	0.65 (1)	0.65 (1)	0.63 (1)	0.75 (2)
Tot. height	0.53	0.57	0.46	0.61
Height centre	0.47	0.55	0.43	0.54
Volume	0.65 (1)	0.63 (2)	0.60 (2)	0.78 (1)
11 week old stage :				
Area top	0.62	0.70 (2)	0.56	0.69
Area side	0.70 (1)	0.73 (1)	0.68 (1)	0.76 (1)
Tot. height	0.47	0.53	0.33	0.52
Height centre	0.56	0.54	0.43	0.54
Volume	0.66 (2)	0.69	0.62 (2)	0.75 (2)
Number of plants	285	284	279	278

1 - ord = experiment 1 ordered block
1 - rand = experiment 1 random placed block
2 - ord = experiment 2 ordered block
2 - rand = experiment 2 random placed block

The difference between random placed and ordered blocks found for the Begonia cuttings can also be seen for Dieffenbachia shoots. This difference between the correlation coefficient of the features with the expert judgement in the full-grown stage is the largest in the unrooted stage. In the ordered block the best correlated feature to the expert judgement, the corrected leaf area, has a correlation of 0.43 and 0.45 for experiment 1 and 2 respectively. In the random placed blocks the correlation of this feature is lower (0.38 and 0.32 respectively). An explanation may be found in the differences in plant interaction. In the random placed blocks the plants endure much more heterogeneous plant interaction effects. The difference in correlation coefficient between the features and the expert judgement for the random placed and ordered blocks becomes smaller when the growth period between measurement and judgement becomes smaller. The disturbing effect of the difference in plant interaction is smaller.

At all stages, the leaf area showed the strongest correlation with the expert judgement in the full-grown stage. The volume in the older stage proved to be a relevant feature as well. This means that the height (included in the volume) of the plants is also important.

6.5.3.3 Multiple linear regression analysis of the growth experiments

The correlation analysis determines the relationship between the individual features and the expert judgements. However the size of the plant may not be determined by a single feature but by a combination of features. Therefore multiple linear regression analysis has been performed to identify combinations of features for the different growth stages. These combinations should have a good relationship with the size and development of the full-grown plants according to expert's judgement. The expert judgement in the full-grown stage is used as dependent and the features measured by DIP in different growth stages are used as independent variables.

Table 6.4 gives the results of the multiple linear regression analysis. The regression analysis has been performed using the stepwise selection method. The level of uncertainty has been chosen at 5.0% to enter and 5.5% to exit a feature. The values mentioned in Table 6.4 are the normalised weight factors for each feature. In Chapter 5 the conditions for performing regression analysis are discussed.

Table 6.4 Multiple linear regression analysis with expert judgement in the full-grown stage as dependent and the features measured with DIP in different growth stages as independent.

feature / experiment		1-rand	1-ord	2-rand	2-ord
unrooted stage	multiple r	0.43	0.47	0.35	0.53
Corrected leaf area		0.67	1.12	0.24	0.26
Length of the shoot		0.20	.	.	.
Ratio length*width/area		.	-0.13	.	.
Stem thickness method 2		.	.	0.16	.
Ratio length/width		.	.	.	0.28
6-week old stage	multiple r	0.58	0.69	0.56	0.74
Area top		0.32	0.56	0.21	.
Area side		0.31	.	0.40	0.20
Tot. height		.	0.21	.	.
Volume		.	.	.	0.56
9-week old stage	multiple r	0.68	0.69	0.64	0.80
Area top		.	0.39	.	.
Area side		0.33	0.35	0.41	0.36
Volume		0.37	.	0.25	0.49
11-week old stage	multiple r	0.73	0.76	0.71	0.79
Area top		0.27	0.47	0.26	.
Area side		0.52	0.35	0.53	0.43
Volume		.	.	.	0.38
Number of plants		285	284	279	278

1 - ord = experiment 1 ordered block
1 - rand = experiment 1 random placed block
2 - ord = experiment 2 ordered block
2 - rand = experiment 2 random placed block

From Table 6.4 it can be seen that the multiple r of the ordered blocks does not change much between the six week old stage and the full-grown stage (0.69, 0.69 and 0.76 for experiment 1, 0.74, 0.80, and 0.79 for experiment 2). The multiple r for the random placed blocks increases during this period (0.58, 0.68 and 0.76 for experiment 1, and 0.56, 0.64, and 0.71 for experiment 2). Growth of the plants in the random placed blocks is probably affected by the plant interaction which is already noticed in the correlation analysis. The multiple r's for the ordered blocks in all cases are higher than for the random placed blocks in comparable stages. Also in the full-grown stage, the multiple r of the combination of features with the expert judgement is higher for the ordered blocks than for the random placed blocks (0.76 and 0.79 versus 0.73 and 0.71). According to the expert the shape of the plants in the ordered blocks was more consistent and better to be judged.

It can be concluded that, in the unrooted stage, the corrected leaf area is the most important feature for grading into uniform growth groups. In the older stages a combination of top- and side-view area is the best combination for grading into uniform growth groups.

6.5.3.4 Simulation of grading experiments

In Section 5.5.3.7 a simulation of the grading experiment is discussed for Begonia cuttings. The same simulations are performed for Dieffenbachia shoots. The objective is to test whether a difference in uniformity exists between the ordered and random placed blocks based on expert judgement in the full-grown stage.

Grading of shoots in the unrooted stage is based on the corrected leaf area which proved to have the best relationship with the expert judgement in the full-grown stage. The description of uniformity in the full-grown stage is based upon the size ratio of each growth group as discussed in Section 4.7. Table 6.5 presents the results of the grading simulation based on five growth groups per block. In the ordered block growth group 1 represents the shoots with the smallest corrected leaf area and growth group 5 the largest ones.

Table 6.5a Results of the expert grading. (Between brackets the number of plants which were judged in that particular class).
Ordered plants, experiment 1.

	Expert judgement : classes			
growth group	small	medium	large	size ratio
1	37% (21)	54% (31)	9% (5)	36
2	28% (16)	56% (32)	16% (9)	44
3	23% (13)	56% (32)	21% (12)	49
4	12% (7)	42% (24)	46% (26)	67
5	4% (2)	32% (18)	64% (36)	80

Average size ratio : 55

Table 6.5b Random placed plants, experiment 1.

growth group	Expert judgement : classes			size ratio
	small	medium	large	
1	25% (14)	72% (41)	3% (2)	39
2	39% (22)	58% (33)	3% (2)	32
3	25% (14)	68% (39)	7% (4)	41
4	28% (16)	68% (39)	4% (2)	38
5	19% (11)	68% (39)	13% (7)	47

Average size ratio : 40

Table 6.5c Ordered plants, experiment 2.

growth group	Expert judgement : classes			size ratio
	small	medium	large	
1	50% (28)	43% (24)	7% (4)	29
2	39% (22)	52% (29)	9% (5)	35
3	34% (19)	48% (27)	18% (10)	42
4	20% (11)	57% (32)	23% (13)	52
5	4% (2)	39% (21)	57% (31)	77

Average size ratio : 47

Table 6.5d Random placed plants, experiment 2.

growth group	Expert judgement : classes			size ratio
	small	medium	large	
1	21% (12)	45% (25)	34% (19)	57
2	25% (14)	34% (19)	41% (23)	58
3	20% (11)	43% (24)	37% (21)	59
4	21% (12)	37% (21)	42% (23)	61
5	11% (6)	47% (25)	42% (22)	66

Average size ratio : 60

From Table 6.5a and 6.5c it can be seen that the size ratio of the ordered blocks increases for the 'larger' growth groups (36 to 80 for Experiment 1, and 29 to 77 for Experiment 2). This means that the plants in the 'smaller' growth groups are smaller in the full-grown stage than the plants in the 'larger' growth groups. In the random placed blocks the size ratio's of the growth groups are similar. Also the distribution of small, medium and large plants in the different growth groups (Table 6.5b and Table 6.5d) is similar. This means that all plant sizes are present in the growth groups in the full-grown stage. It can be concluded that grading of unrooted shoots based on the corrected leaf area increases the uniformity in the full-grown stage.

The average size ratio's for the ordered and random placed blocks are different. The average size of the unrooted shoots proofed to be the same. In the first experiment the average size ratio for the ordered block is higher (55) than for the random placed block (40). The average values of the features in the full-grown stage of the ordered block are higher (area top: 66119 pixels, area side: 75170 pixels) than for the random placed block (area top: 60577 pixels, area side: 70418 pixels). It can be concluded that the plants in the ordered block developed into larger plants than those in the random placed block in the same time.

In the second experiment the values for the ordered block are 81281 and 87367 pixels respectively and for the random placed blocks 80374 and 88076 pixels respectively. The difference in values for the second experiment is smaller but the difference in size ratio is about the same as for the first experiment (47 for the ordered and 60 for random placed). This difference can be explained by possible changes in the standards of the expert during different judgement moments. This difference does not necessary affect the range of size ratio which is used to investigate the homogeneity. It only affects the average size ratio.

As is already mentioned, the unrooted Dieffenbachia shoots have problems in rooting. Therefore a regrading is simulated after a growth period of six weeks. The objective is to test whether or not regrading after a growth period of six weeks improves the uniformity in the full-grown stage. The plants are regraded on the bases of the projected leaf area from the top-view. This feature in the six week old stage shows a strong relationship with expert judgement in the full-grown stage (see Table 6.3 and 6.4). The same procedure used for the unrooted shoots is also applied by creating five growth groups in each block. Table 6.5e and 6.5f present these results. Again growth group 1 represents the half-grown plants with the smallest leaf area in top-view and growth group 5 the largest. This simulation is only performed for the ordered blocks because the random placed blocks contain heterogeneous plant interactions.

Table 6.5e Results of the expert grading of the ordered placed plants, experiment 1, regrading after 6 weeks.

	Expert judgement : classes			
growth group	small	medium	large	size ratio
1	56% (32)	40% (23)	4% (2)	24
2	26% (15)	63% (36)	11% (6)	43
3	18% (10)	46% (26)	36% (21)	59
4	4% (2)	53% (30)	43% (25)	70
5	0% (0)	39% (22)	61% (34)	81

Average size ratio : 55

Table 6.5f experiment 2.

growth group	Expert judgement : classes			size ratio
	small	medium	large	
1	79% (44)	20% (11)	1% (1)	11
2	32% (18)	57% (32)	11% (6)	40
3	27% (15)	57% (32)	16% (9)	45
4	9% (5)	62% (35)	29% (16)	60
5	0% (0)	43% (23)	57% (31)	79

Average size ratio : 47

The results in Table 6.5e and 6.5f should be compared to the results in Table 6.5a and 6.5c. It can be concluded that regrading in the six week old stage results in a larger range of size ratio's than grading in the unrooted stage. This means that regrading at the six week old stage results in larger differences between the growth groups in the full-grown stage than grading in the unrooted stage. Excluding uncertainty about the rooting process improves the uniformity of the growth groups.

It is also expected that regrading in the nine week old stage would result in even more uniform growth groups in the full-grown stage. Growth is disturbed for a shorter period. The results of the grading simulation of nine week old Dieffenbachia plants are presented in Table 6.5g and 6.5h.

Table 6.5g Results of the expert grading of the ordered placed plants, experiment 1, regrading after 9 weeks.

growth group	Expert judgement : classes			size ratio
	small	medium	large	
1	61% (35)	35% (20)	4% (2)	22
2	21% (12)	72% (41)	7% (4)	43
3	18% (10)	56% (32)	26% (15)	54
4	4% (2)	51% (29)	45% (26)	71
5	0% (0)	27% (15)	73% (41)	87

Average size ratio : 55

Table 6.5h experiment 2.

growth group	Expert judgement : classes			size ratio
	small	medium	large	
1	84% (47)	16% (9)	0% (0)	8
2	38% (21)	59% (33)	3% (2)	33
3	25% (14)	57% (32)	18% (10)	47
4	0% (0)	68% (38)	32% (18)	66
5	0% (0)	39% (21)	61% (33)	81

Average size ratio : 47

Comparison of the results of Table 6.5g and 6.5h with Table 6.5e and 6.5f shows that the uniformity in the growth groups in the full-grown stage is higher when regrading is carried out after nine weeks. The size ratio range for the regrading simulation is larger after nine weeks than for the regrading after six weeks (22 to 87 and 8 to 81 compared with 24 to 81 and 11 to 79). The growth process is disturbed in the growth period from six to nine weeks and this affects the homogeneity of the growth groups.

The regrading carried out in the six and nine week old stage were simulations. The plants grew in a more heterogeneous environment than they would have had when regraded in reality. Considering the plant interaction effect in a heterogeneous environment and the results of the grading simulations, it might be expected that the regrading would result in even more uniform growth groups.

6.6 Expert judgement

6.6.1 Introduction

The objective of the expert judgement is to test whether decision models are able to grade full-grown Dieffenbachia plants into uniform development groups. The performance of a decision model based on a regression equation has been compared to the performance of a decision model based on a neural network. The procedure for the Dieffenbachia judgement experiments is the same as for the Begonia experiments. The conditions and set-up of the regression equation and neural network have already been discussed in Section 5.6.

6.6.2 The performance of the computer as grader

In Table 6.6 the results of the grading of the two experiments in the full-grown stage for both the decision models based on a regression equation and on a neural network are presented. The performance of a decision model is explained in Section 4.7.2.

Table 6.6a The judgement of the decision model using features measured with DIP compared with the judgement of the expert. Experiment 1 ordered.

experiment 1 ordered		computer judgement regression equation			computer judgement neural network		
		small	medium	large	small	medium	large
expert judgement	small	27	32	0	41	18	0
	medium	3	129	4	12	100	24
	large	0	35	53	0	9	79

Total	: 283	Total	: 283
Correct	: 209 = 74%	Correct	: 220 = 78%
1st order error	: 74 = 26%	1st order error	: 63 = 22%
2nd order error	: 0 = 0%	2nd order error	: 0 = 0%

Table 6.6b Experiment 1 random placed.

experiment 1 random placed		computer judgement regression equation			computer judgement neural network		
		small	medium	large	small	medium	large
expert judgement	small	55	22	0	57	20	0
	medium	8	179	4	4	185	2
	large	0	12	5	0	10	7

Total	: 285	Total	: 285
Correct	: 239 = 84%	Correct	: 249 = 87%
1st order error	: 46 = 16%	1st order error	: 36 = 13%
2nd order error	: 0 = 0%	2nd order error	: 0 = 0%

Table 6.6c Experiment 2 ordered.

experiment 2 ordered		computer judgement regression equation			computer judgement neural network		
		small	medium	large	small	medium	large
expert judge-ment	small	50	29	0	64	15	0
	medium	20	104	12	25	98	13
	large	0	26	37	0	26	37

Total : 278	Total : 278
Correct : 191 = 69%	Correct : 199 = 71%
1st order error : 87 = 31%	1st order error : 79 = 29%
2nd order error : 0 = 0%	2nd order error : 0 = 0%

Table 6.6d Experiment 2 random placed.

experiment 2 random placed		computer judgement regression equation			computer judgement neural network		
		small	medium	large	small	medium	large
expert judge-ment	small	31	23	1	25	26	4
	medium	7	91	17	0	83	32
	large	0	49	60	0	20	89

Total : 279	Total : 279
Correct : 182 = 65%	Correct : 197 = 71%
1st order error : 96 = 34%	1st order error : 78 = 27%
2nd order error : 1 = 1%	2nd order error : 4 = 2%

Table 6.6 shows that the performances of the decision model changes for the different experiments. Performances for the full-grown Dieffenbachia plants are lower than for the half-grown Begonia plants (compare the performance of the regression equation for the full-grown Dieffenbachia plants: 74%, 84%, 69%, and 65% to the performance of the regression equation for the half-grown Begonia plants: 81%, 79%, 76%, and 80%, and compare the performance of the neural network for the full-grown Dieffenbachia plants: 78%, 87% 71%, and 71% to the performance of the neural network for the half-grown Begonia plants: 87%, 84%, 79%, and 85%).

A problem is the consistency of the expert judgement. In Section 2.7 it is pointed out that the reproducibility of the expert is lower for full-grown Dieffenbachia plants (66% of the plants classified the same in a second judgement) than for the half-grown Begonia plants (87% of the plants classified the same in a second judgement). The judgement in the consistency experiments and the growth experiments for each specie were performed by the same experts. Judgement of the different experimental blocks was not made at the same moment. This difference in time probably caused a difference in the standards which were used by the expert.

The neural network scores between 2 and 6 percent better than the regression equation. The same effect is found for the Begonia experiments. It can be concluded that the full-grown Dieffenbachia plants can be graded with DIP and decision models. The consistency of the judgement of the expert should be improved in order to achieve a better performance of the decision models.

6.7 Conclusions and discussions

The first objective of this case study was to identify and test features of unrooted Dieffenbachia shoots. These can be used to create uniform growth groups. From the growth experiments the corrected leaf area proved to be the feature which is best related to expert judgement in the full-grown stage (maximum achieved r is 0.45). Growth potential is mainly determined by a plant's leaf area. The consistency of the corrected leaf area is 96.7%. It can be concluded that the corrected leaf area can be used as grading feature.

Special techniques are developed to measure the stem thickness which was mentioned by the expert as an important feature. No strong correlations ($r \leq 0.28$) were found between the stem thickness in the unrooted stage and the expert judgement in the full-grown stage. The regression analysis also did not include the stem thickness in the set of features which was related to expert judgement in the full-grown stage.

The plants in the ordered blocks show a better relation with expert judgement in the full-grown stage than those in the random placed blocks. The growth of the plants in the random placed blocks probably is affected by the heterogeneity of plant interaction. From the correlation and regression analysis it is found that the relationship between the features and expert judgement in the full-grown stage becomes stronger during the growth cycle. The greatest change is seen during the first six weeks. In the first two weeks the shoots get roots. This process is not uniform for the different shoots and introduces heterogeneity in the growth groups.

The second objective was to identify features of six and nine week old Dieffenbachia plants measured with DIP. These can be used to evaluate the uniformity of the growth groups after a certain growth period and to grade the plants into uniform growth groups. From the growth experiments the volume and the projected area from top- and side-view show to be the features which relate best to expert judgement (maximum achieved multiple r is 0.74 for the six week old stage and r is 0.80 for the nine week old stage).

The consistencies of the side-view area (96.3%) and the top-view area (97.7%) are satisfactorily. It can be concluded that these features can be used as grading feature.

From the grading simulations it was seen that the uniformity in the full-grown stage in the ordered blocks is higher than in the random placed blocks. This uniformity can be higher if regrading in the six week old stage or the nine week old stage is applied. Regrading after six and nine weeks was based on the projected leaf area from the top. The regrading excludes the effect of heterogeneity which is introduced during the rooting period.

The third objective was to identify and to test features which describe the size and development of full-grown Dieffenbachia plants. These can be used to evaluate the uniformity of the growth groups and to grade the plants into uniform development groups. From the judgement experiments it can be seen that the projected area from top- and side-view prove to be the features which best related to expert judgement (maximum achieved multiple r is 0.79). It can be concluded that these features can be used for grading.

The decision model based on a regression equation grades between 65% and 84% of the plants correctly. A neural network grades between the 71% and 87% correctly. On average the neural networks scores better than the regression equations. Considering the low consistency of the human grader, it can be concluded that it is possible to use DIP in combination with a decision model to grade full-grown Dieffenbachia plants. A problem is that the learn set, which is used to train the decision models, contains errors. These are caused by misclassifications on the part of the expert so high performances cannot be achieved by the decision models. By revising the plants about which the decision model and the expert did not agree, the expert could agree with the decision model.

7 Case study on Saintpaulia plants

7.1 Introduction

The third case study focuses on Saintpaulia plants. Saintpaulia plants are chosen because of the different structure of the plant and the different growth cycle compared to that of the Begonia and Dieffenbachia plant. The leaves of the Saintpaulia cuttings are not transparent enough to apply the leaf area correction method. The leaves are also sometimes not parallel to the image plane in the natural rest position. The structure of the cutting is well visible, so individual structures can be identified. In the half-grown and full-grown stage the leaves of the Saintpaulia plant are almost in the same horizontal plane, so the leaves are well visible.

The Saintpaulia plant is a flowering plant which is available in a wide variety of colours. It is propagated by planting 'mother leaves' in trays with pot soil. After a few weeks, cuttings will grow from this mother leaf. After about nine weeks, the mother leaves are taken away from the tray to allow the cuttings to get more light and space. Then follows another period of growth. When the cuttings are large enough (two to four leaves have been developed) they are separated and the roots are removed. A group of cuttings contains a variety of different sizes because they grow from a mother leaf and are all harvested at once. Therefore the separation process results in cuttings of different sizes. At present cuttings are graded manually into the following classes: small, medium and large. The cuttings in these classes are put into separate trays to reduce the difference in plant interaction.

The first objective of this case study is to identify and to test features of unrooted Saintpaulia cuttings measured with DIP. These features are used to create uniform growth groups which can be marketed at the same time. The second objective is to identify and to test features of half-grown Saintpaulia plants measured with DIP. These features are used to evaluate the uniformity of the growth groups in the half-grown stage and to create uniform growth and development groups. The third objective is to investigate the relationships between the features in the different growth stages and the length of the growth period needed by the plants to reach the marketable stage (the full-grown stage).

The growth experiments were carried out at a company where the plants were grown to a marketable stage. The period between planting of the unrooted cuttings and picking the marketable plants is about 15 weeks.

7.2 Flow chart of the growth and processing points

After separation, the cuttings are put in a tray to root for a growth period of six weeks. After this period they are transplanted into pots. Five weeks later they are respaced. Between 12 and 19 weeks after the unrooted cuttings have been planted in a tray, the Saintpaulia plants reach the marketable stage. Figure 7.1 shows the flow chart of the growth of Saintpaulia plants.

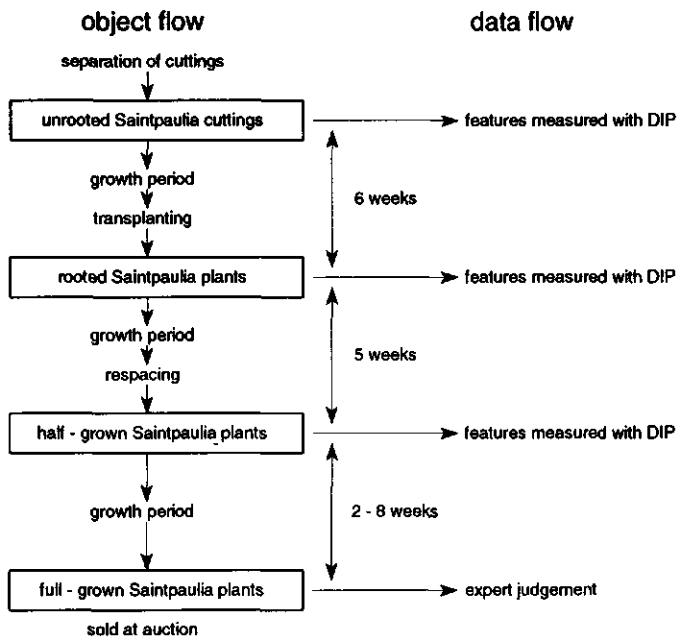


Figure 7.1 Flow chart of the Saintpaulia cultivation

The plants were measured three times during the growth experiments: at the unrooted stage when the cuttings were planted, after six weeks when the plants were transplanted, and after eleven weeks when the plants were respaced.

7.3 Unrooted Saintpaulia cuttings

7.3.1 Introduction

According to the expert, the development of the 'heart' of the Saintpaulia cutting is important for its growth potential. The 'heart' of the cutting represents the growth tip and the leaves 'just starting to develop'. The number of leaves can vary. Some cuttings have only two leaves while others have four. Figure 7.2 shows an unrooted Saintpaulia cutting on a diffuse back-lighted transparent plate.

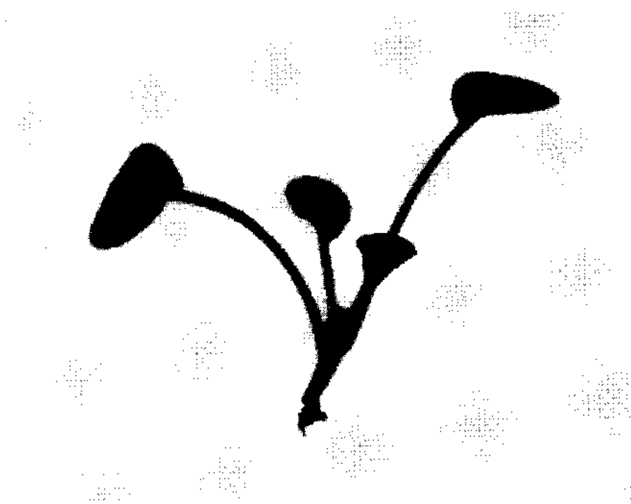


Figure 7.2 Unrooted Saintpaulia cutting

In this section the possibilities of measuring features of unrooted Saintpaulia cuttings and the their quantitative properties are investigated.

7.3.2 Scene processing

The Saintpaulia cutting has a three-dimensional structure. The back-lighting system does not produce enough light to use the difference in grey values to correct the projected leaf area for overlapping and tilting leaves. The use of stronger light sources would damage the cuttings because of heat production. The leaves do not show much overlap so this will not be a source of error. The cutting has a stiff structure. In the natural rest position, some leaves are not parallel to the image plane. Therefore the projected leaf area will be different from the actual leaf area.

The back-lighting system provides sharp images so no additional processing is needed when the structure is analysed. The cuttings are presented singularised in their natural rest position. The basic stem is oriented with the tip downwards in the image. The distance between the camera and the shoot is between 0.98 m and 1.02 m. The error due to this difference in distance between camera and object is negligible (Section 3.9). The largest cutting just fits into the camera's view area (512*512 pixels).

7.3.3 Image processing

The heart of the Saintpaulia cutting cannot be determined with DIP. Therefore other features of the cutting have been measured. The cutting is segmented into stem and leaf segments using the same method as for the Begonia cuttings. However, the leaves are not classified as first leaf, second leaf, etc. The following features of the cutting are determined. The abbreviations used in the text are noted in brackets.

1. Total projected area of the cutting (pixels) (Total area).
   Sum of pixels of all segments.
2. Total leaf area of the cutting (pixels) (Total leaf area).
   Sum of pixels of the segments which are identified as leaf segment during the exact segmentation.
3. Total stem area of the cutting (pixels) (Total stem area).
   Sum of pixels of the segments which are identified as stem segment during the exact segmentation.
4. Total area of the end parts of the cutting (pixels) (Total area end parts).
   Sum of pixels of segments which meet the following criteria; the segment is identified as leaf segment; the segment is a top segment which means that it is not connected to a next segment.
5. Total area of central parts of the cutting (pixels) (Total area central parts).
   The area of the central part represents the 'heart' of the cutting. Due to the structure of the cutting, its 'heart' is classified as leaf segment. This segment is connected to other segments such as the stem segments and therefore not classified as an end part. The area of the central parts is calculated by subtracting the area of the end parts from the total leaf area.
6. Length of the cutting (pixels) (Length).
   The distance in a vertical direction between the uppermost and lowest point of the cutting.
7. Width of the cutting (pixels) (Width),
   The distance in a horizontal direction between the left most and the right most point of the cutting.
8. Distance between the tip of the basic stem of the cutting and the optical centre (pixels) (Distance optical centre).
   This measurement indicates the compactness of the cutting.

9. Number of stems of the cutting (Number of stems).
   The number of stem segments which are connected to the end parts.
10. Length of cutting stems (Length of stems).
    The length of the segments which are connected to the end parts.
11. Average distance between the object points and the optical centre (Mass distance).
    The summation of the Euclidean distance between the object pixels and the optical centre divided by the total area. This feature indicates the compactness of the cuttings.
12. Average square distance between the object pixels and the optical centre (Square mass distance).
    The same feature as 11 but extended pixels have more influence on this feature.

The consistency test to determine the quantitative properties of features is discussed in Section 4.4. Twenty-five unrooted Saintpaulia cuttings were measured five times in order to perform this test. The results are presented in Table 7.1.

Table 7.1 Consistency and range measurement of unrooted Saintpaulia cutting.

feature	consistency in %	minimum	maximum	mean
Total area	98.1	4444	25852	11669
Total leaf area	96.4	2387	22949	9655
Total stem area	90.5	462	4016	2014
Total area end parts	90.0	1727	19609	7083
Total area central parts	67.5	0	15987	2572
Length	97.5	149	335	230
Width	97.0	59	322	156
Distance optical centre	98.5	99	216	141
Number of stems	85.8	1	4	2
Length of stems	83.1	19	320	116
Mass distance	98.8	42	88	63
Square mass distance	96.9	2580	9416	5310

Minimum, maximum and mean are expressed in number of units in which they have been measured.

From Table 7.1 it can be seen that the total area and total leaf area can be measured with a consistency of 98.1% and 96.4% respectively. This is above the required 90 percent for a grading feature. The stem area has a consistency of 90.5 % which indicates that there are problems with identifying the stem segments. In some orientations the stems are overlapped by other stems which affects the calculated stem area. This overlapping also determines the error in the calculation of the number of stems (consistency of 85.8%) and the stem length (consistency of 83.1%). In some cases a stem is classified as a leaf belonging to the central part. This partly explains the error in the central leaf measurement (consistency of 67.5%). It can be concluded that the features related to the stem measurement are not consistent enough. These cannot be used as grading feature. The global features like length, width, distance optical centre, mass distance, and square mass distance all have consistencies of more than 90 percent and therefore can be used as grading features.

7.3.4 Comparison of the variation between human grading and computer grading

At the moment the unrooted Saintpaulia cuttings are graded by man because the size of the cuttings differ considerably. Cuttings are graded into three groups; small, medium, and large. More groups would slow down the work rate because the cuttings would then have to be compared to certain standards (Dijkstra et al., 1990).
An experiment has been done to investigate the variation within the groups created by human graders and DIP.

The total area of each cutting in each group was measured with DIP to establish the variation in the groups created by the human graders. Another group of Saintpaulia cuttings was graded into three groups with DIP on the bases of total area. From former experiments it appeared that the total area is a good grading feature. Table 7.2 gives the results of this comparison.

Table 7.2 Computer graded (comp.) compared with human graded (human) Saintpaulia cuttings graded in three groups

group		mean total area	Coefficient of variation
group 1	(comp.)	3965	0.093 = 9.3%
small	(human)	3903	0.109
group 2	(comp.)	8185	0.034
medium	(human)	6704	0.069
group 3	(comp.)	15015	0.039
large	(human)	12238	0.069

As can be seen from Table 7.2, the variation within the groups graded with DIP is smaller than within groups graded by man. The mean values of the groups differ because of the overall difference in cutting size. The group from which the cuttings were drawn was different in each experiment.

The cuttings used for the comparison experiment were also graded into five growth groups using the DIP system. According to the grower, five growth groups would be suitable for the greenhouse operation. The objective of this experiment is to investigate the variation within the groups when there are five growth groups. In Table 7.3 the mean total area and the variation in these growth groups are presented.

Table 7.3 The mean total area and the variation of the five growth groups created with DIP

group	mean total area	coefficient of variation
group 1	3112	0.067 = 6.7%
group 2	5302	0.012
group 3	7818	0.014
group 4	11844	0.012
group 5	16918	0.024

From Table 7.3 it can be seen that the variation of the individual growth groups is smaller than in Table 7.2 because the cuttings have been divided into 5 growth groups. The coefficient of variation is significantly lower than within the groups created by the human graders.

It can be concluded that the DIP creates groups of unrooted Saintpaulia cuttings which are more uniform than the groups created by human graders even if the number of growth groups remains constant.

7.4 Half-grown Saintpaulia plant

7.4.1 Introduction

A half-grown Saintpaulia plant has its leaves in one horizontal plane. According to the experts the leaf area and the compactness are important grading features in the half-grown stage. These are global features which describe size and development. The choice was made to measure the projected leaf area, length, width and convex-hull from the top-view. A side-view does not provide information about the plant because the leaves are in one plane, so the height as almost the same for all plants and the leaves are perpendicular to the image plane. The half-grown Saintpaulia plant does not contain flowers. Figure 7.3 shows a half-grown Saintpaulia plant.

The objective of this section is to investigate the possibilities of measuring features of half-grown Saintpaulia plants and to determine the quantitative properties of these features.

Figure 7.3 Half-grown Saintpaulia plant (top-view).

7.4.2 Scene processing

In order to measure the projected leaf area from the top, the pot is positioned on a dark, light absorbing background. The front-light is supplied by incandescent light tubes. (The same set-up was used for the top-view images of the half-grown Begonia plants and the top-view images of the half-grown and full-grown Dieffenbachia plants).

The difference in reflection in the near-infrared wavelengths for the leaves and soil is used to segment the image. However, the plastic pot reflects the near-infrared light in the same way as the leaves. Small plants, which do not cover the whole pot area, cause problems. A part of the pot is connected to the leaves during segmentation.

The plants are presented singularised to the camera system. The orientation of the plant is not important. The distance between the camera and the plant varies between 1.47 m and 1.53 m. The error because of the variation in distance is negligible (see Section 3.9). The largest plants just fits into the camera's viewing area (512*512 pixels).

7.4.3 Image processing

As has been explained in Section 7.4.2, parts of the pot are identified as parts of a leaf. The pot is removed by applying an 7 * 7-minimum filter and then a 7 * 7-maximum filter (7 * 7 opening). This is sufficient to remove the pot or to disconnect parts of the pot from the leaves. The pot is a relatively thin structure in the image which disappears after the minimum/maximum filter has been applied. The objects which are connected to the main leaf clusters are included for the measurement of the projected area. The leaf area measurement is done using the method employed for getting a top-view image of the half-grown Begonia plants.

The measurement of the half-grown Saintpaulia plant is based on five features. The abbreviation used in the text is noted in brackets. With except for the ratio, all units are measured in pixels.

1. Total projected leaf area from top view (Leaf area).
   Total number of pixels of the segments connected to the main leaf cluster.
2. Width of the plant in vertical direction (Length).
   The distance in vertical direction between the uppermost and the lowest point of the segments which are classified as plant.
3. Width of the plant in horizontal direction (Width).
   The distance in horizontal direction between the left most and right most point of the segments which are classified as plant.
4. Convex hull area (Convex area).
   The area included in the convex hull which is constructed around the segments classified as plants. The measurement also includes the holes in the plant.
5. Ratio between leaf area and convex hull (Leaf area/convex hull).
   This ratio describes the density of the canopy.

Table 7.4 gives the consistency and range measurements of the features. The consistency tests are discussed in Section 4.4. Twenty half-grown Saintpaulia plants have been measured five times to perform this test.

Table 7.4 Consistency and range measurements of half-grown Saintpaulia plants.

feature	consistency in %	minimum	maximum	mean
Leaf area	99.1	19447	62002	40328
Length	95.2	224	389	320
Width	95.3	154	297	242
Convex area	99.2	31675	82844	56202
Leaf area/convex area	99.3	0.57	0.8	0.71

Minimum, maximum, and mean are expressed in number of units in which they have been measured.

From Table 7.4 it can be seen that the leaf area and convex area are measured with a high consistency (99.1% for the leaf area and 99.2% for the convex area) and a large range. Length and width measurements are sensitive to the orientation of the plant but they can still be used as grading features.

7.5 Growth experiments

7.5.1 Introduction

The objective of the Saintpaulia growth experiments is to identify features of unrooted cuttings and half-grown plants measured with DIP. They can be related to size and development in different growth stages and to the length of the growth period which the plant needs in order to develop to a marketable plant.

The experimental set-up of the Saintpaulia experiments differs from those of the Begonia and Dieffenbachia. In the Saintpaulia experiment only ordered blocks were created. It is already known that random placed Saintpaulia cuttings grow very heterogeneously.

First the cuttings are graded on the basis of total area. Former experiments showed that total area is a good grading feature and that it has a high consistency (98.1 %). After ordering the cuttings, five groups are created each of which contains 208 cuttings. Each group is graded again on the basis of mass distance. In this way compact cuttings are put together in one tray of 104 plants and extended cuttings are put together in another tray of 104 plants. Each tray is filled up according to the increase of total area. In this way the variation in plant interaction within the tray is minimised and the variation between the trays is maximised. During the measurements all cuttings are labelled so they can be traced individually during the growth experiments. The trays are put in the greenhouse between other cuttings of almost the same size. The large and small cuttings receive different treatment. This is also done in normal processing of the cuttings.

After six weeks the plants are transplanted into a pot and measured with DIP. After eleven weeks the plants are respaced and measured again with DIP. No expert judgements have been made at this point. In normal processing they are also not judged and so no standards are available. The expert checks the plants twice a week to determine whether a plant is marketable. When a plant has four open flowers it is judged as marketable. The plant's label is registered and the plant is removed from the greenhouse. In this way the time needed by each plant to reach the marketable stage can be determined. Figure 7.4 shows the relationships between the measurements.

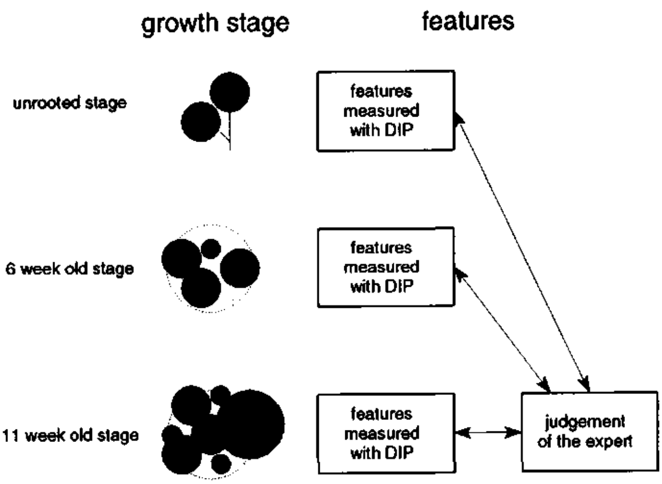


Figure 7.4 Relationships between measurements in the Saintpaulia experiment.

7.5.2 Results of the Saintpaulia experiments

7.5.2.1 Introduction

Section 4.5.3 indicates how the growth experiments are analysed. This analysis is performed on basis of the relationships given in Figure 7.4. The discussion of the results starts by analysing the correlations between the length of period that a plant needs to reach the marketable stage and the features measured with DIP in the different growth stages. The same relations have been investigated with multiple linear regression analysis to see whether combinations of features in the different stages show a stronger relationship with the length of the growth period.

During a period of two years, between 1989 and 1991, several growth experiments with Saintpaulia cuttings were carried out. The test period ended with a series of three experiments. In this case study the results of two experiments are discussed. Experiment 1 was carried out in the period 23 April 23 to September 9 in 1991 using the variety 'Ramona'. Experiment 2 was carried out in the period May 21 to September 26 in 1991 using the variety 'Vivian'. The reason why two different varieties were used was simply because of their availability. These two varieties show large similarities.

7.5.2.2 Correlation analysis of the growth experiment

A correlation analysis is made between the length of the period the Saintpaulia cuttings needs in order to reach the marketable stage and the features measured with DIP in the various stages of growth. This is done to identify those features which have a strong correlation with the length of time the plant needs to reach the marketable stage. These features can be used to grade the Saintpaulia plants into uniform growth groups suitable for harvesting at the same time. The conditions for performing correlation analysis are discussed in Section 5.5.3.3.
The results of the correlation analysis are presented in Table 7.5. A high negative value means a good relationship with the length of the growth period needed for the plant to reach the marketable stage. The length of the growth period is expressed in number of days. It is to be expected that larger plants will reach the marketable stage earlier than smaller plants. Only features which had a Pearson correlation coefficient (r) with a 2-tailed uncertainty of $\leq 0.1\%$ are presented.

From Table 7.5 it can be seen that in the unrooted stage the total area and the total leaf area are the features which relate best with the length of time needed to reach the marketable stage. It is possible to measure these features consistently (98.1% for total area and 96.4% for total leaf area) so they can be used as grading features. There is a difference in the strength of correlations between Experiment 1 and Experiment 2 (-0.27 respectively -0.56 for the total area in the unrooted stage). In Experiment 1 the early stages of growth may have been affected by dehydration of the cuttings as they were being measured. In addition, the cuttings were not treated with a fungicide immediately after planting. This was an accident and was only discovered after the experiments were completed.

The mass distance, which has been used to separate the compact cuttings from the extended cuttings, does not show a strong correlation with the length of the growth period (-0.18 respectively -0.35). The effect of putting compact and extended cuttings of the same total area in the same growth group has not been tested. It is possible that the uniformity of the growth groups will be affected because of overlapping.

At the six week and eleven week old stage, the leaf area show to have the best correlation with the length of the growth period (0.59 respectively 0.74 in the six week old stage and 0.62 for the eleven week old stage for Experiment 1). This is also a feature which can be measured consistently (99.1%). From Table 7.5 it can be seen that the correlation is higher when the period between the measurement and the marketable stage is shorter. The same effect has been noticed for the Dieffenbachia plants and is possibly caused by disturbance during growth (in case of the Dieffenbachia particularly the rooting process).

Table 7.5 Pearson correlation coefficients between the number of days needed for the Saintpaulia plants to reach the marketable stage and the features measured using DIP in different growth stages. The rank numbers of the two highest correlation coefficients per growth stage are noted in descending order in brackets.

feature	experiment 1	experiment 2
Unrooted stage :		
Total area	-0.27 (1)	-0.56 (2)
Total leaf area	-0.26 (2)	-0.57 (1)
Total stem area	-0.18	-0.07
Total area central part	-0.19	-0.42
Length	-0.17	-0.31
Width	-0.24	-0.45
Mass distance	-0.18	-0.35
Square mass distance	-0.17	-0.31
6 week old stage :		
Leaf area	-0.59 (1)	-0.74 (1)
Length	-0.52	-0.59
Width	-0.54 (2)	-0.62 (2)
11 week old stage :		
Leaf area	-0.62 (1)	
Length	-0.56	
Width	-0.58 (2)	
Convex area	-0.57	
Number of plants	1017	1002

7.5.2.3 Multiple regression analysis of the growth experiments

The objective of the multiple linear regression analysis is to find combination of features in different growth stages measured with DIP which show a good relationship with the length of the growth period until the plant becomes marketable. As dependent the length of growth period needed for the Saintpaulia cuttings to reach the marketable stage is used. As independent combinations of features measured with DIP are used. The analysis is repeated for different growth stages. Table 7.6 shows the results of the multiple linear regression analysis. The conditions for performing multiple linear regression analysis are discussed in Chapter 5. The values which are mentioned are normalised weight factors for each feature. The regression analysis has been performed using the stepwise selection method with a level of uncertainty of 5.0% to enter and 5.5% to exit a feature.

Table 7.6 Multiple linear regression analysis with the days needed to reach the marketable stage as dependent and the features measured with DIP as independent in different growth stages of the Saintpaulia plant.

feature		experiment 1	experiment 2
Unrooted stage	multiple r	0.31	0.58
Total area		-0.91	.
Total leaf area		0.71	-0.54
Total area end parts		.	0.13
Length		.	-0.37
Width		-0.14	-0.21
Length of stems		0.13	.
Mass distance		.	0.18
Distance optical centre		.	0.20
6 - week old stage	multiple r	0.60	0.74
Leaf area		-0.46	-0.74
Width		-0.15	.
11 - week old stage	multiple r	0.63	
Leaf area		-0.42	
Length		-0.42	
Width		-0.07	
Number of plants		1017	1002

In Table 7.6 the differences in the strength of the relationships between the two experiments already mentioned in the correlation analysis can be seen. This difference in strength is still present at the six week old stage (0.60 respectively 0.74). In can be concluded that the difference in treatment also affected growth between the six week old stage and the marketable stage. This may have been caused by a larger heterogeneity in plant interactions.

In the unrooted stage, the total area and leaf area are important features. In the half-grown stage the projected leaf area is the only feature which is important for the growth period needed for the plant to become marketable. The convex hull area (compactness), length and width do not add information to the strength of the relationship.

The total area of the central part of the cutting which is used as a replacement for the development of 'the heart' of the cutting, is not to be found an important feature in the regression analysis. The low consistency of the feature (67.5%) is an explanation for this. Figure 7.5 shows the relationship between the total leaf area in the unrooted stage and the number of days needed to reach the marketable stage.

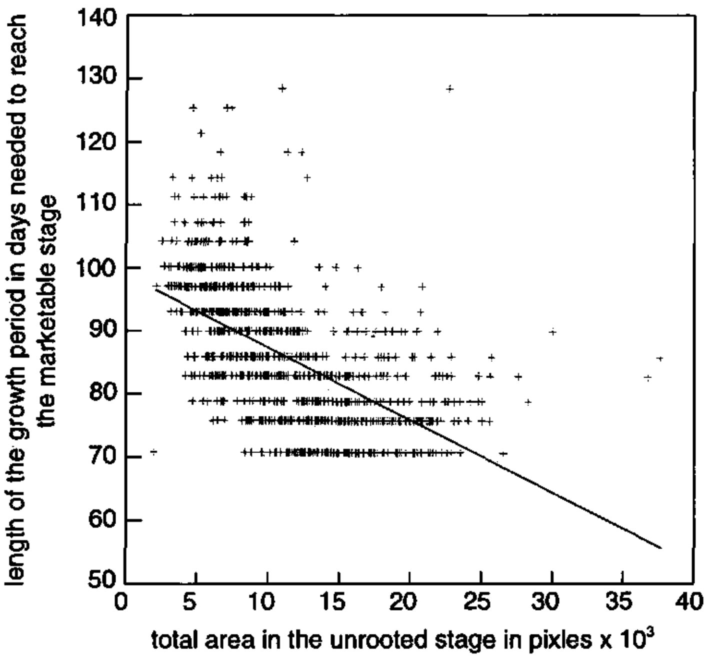


Figure 7.5 The relation between the total area in the unrooted stage and the length of the growth period in days needed to reach the marketable stage.

7.6 Conclusions and discussion

The first objective of this case study was to identify and to test features of unrooted Saintpaulia cuttings in order to create uniform growth groups. The correlation and regression analyses show that the total area and the leaf area of the cuttings give the best relationship with the length of the growth period needed for the plant to reach the marketable stage. These features have a high consistency (98.1% and 96.4%) so they can be used as grading features.

When the consistencies of the leaf area measurements are compared (unrooted Begonia cutting corrected leaf area: 94.1%, unrooted Dieffenbachia cutting corrected leaf area: 96.6%, unrooted Saintpaulia cutting projected leaf area 96.4%) it can be concluded that the consistency of the projected leaf area measurement of the Saintpaulia cutting is similar to that of the corrected leaf area of the other cuttings.

Detailed features of the cuttings such as the number of stems and the length of stems are difficult to measure consistently (85.8% respectively 83.1%) because of overlapping stems.

According to the expert the 'heart' of the cutting is an important feature in describing its growth potential. The 'heart' of the cutting is difficult to measure with DIP. Therefore the area of the central part of the cutting has been measured as replacement. In the correlation and regression analyses this features does not show up as important for growth potential. Its low consistency (67.5%) is a possible explanation for the weak relationship.

The mass distance, which is used as a grading criterion in the unrooted stage in order to separate the compact cuttings from the extended ones, does not show a strong relationship with the length of the growth period (r is -0.18 and r is -0.35 for Experiment 1 and Experiment 2 respectively).

By comparing the variation in the grading results produced by a DIP system and the human graders, it can be concluded that the coefficient of variation in the groups created by DIP is lower that in groups created by human graders.

The second objective was to identify and to test features of half-grown Saintpaulia plants. These features can be used to evaluate the uniformity of the growth groups in the half-grown stage and they can also be used to create uniform growth and development groups in the half-grown stage. The growth experiments show that the projected leaf area from the top-view is the feature which related best to the length of the growth period needed for the plant to reach the marketable stage. The compactness, expressed in the ratio between projected leaf area and convex hull, which was mentioned by the expert as an important feature, does not show a strong relationship with the length of the growth period.

The projected leaf area measurement of the half-grown Saintpaulia plant is affected by parts of the plastic pot. These show a large similarity in reflectance with the leaves. A minimum/maximum filter of 7 * 7 removed the relatively thin parts of the pot adequately so the leaf area can be measured with high consistency (99.1%).

The experiments show that the way the cuttings are treated is very important. Poor treatment at the unrooted stage affects growth for a long period and the effect of grading disappears.

8 Conclusions, discussion and recommendations

8.1 General conclusions

The main research hypothesis in this study is that 'Grading pot plants by means of digital image processing in (a) certain growth stage(s) results in more homogeneous groups of plants'. Growth and judgement experiments have been performed to substantiate this hypothesis. The research uses Begonia, Dieffenbachia, and Saintpaulia plants. These species are chosen as representatives of a wider range of plants on the basis of differences in plant structure and growth.

The following research questions have been identified:

A. Why should plants be graded?
   It is expected that grading plants at different stages of growth has many advantages (Chapter 2).
   - In the young stage weak plants can be excluded. If the plants that are unlikely to develop into marketable plants are excluded from the growth cycle, they will not occupy greenhouse space and will not use energy and nutrients. Furthermore, during the growth cycle and at the end it will not be necessary to remove these weak plants which means a saving on labour costs.
   - During the growth cycle, plant growth can be optimised. The interaction between plants is more uniform if plants of the same size are put together. They will develop in a more uniform way and this will increase the quality of the plants in the full-grown stage. Plants are able to receive treatments when they need it, for example, larger plants should be treated earlier with growth regulators.
   - In the full-grown stage, the amount of labour needed to harvest the plants can be reduced. Manual picking of individual plants in the greenhouse is labour intensive. Uniform growth groups mean that a whole group of plants can be harvested at one time and this means a reduction of the required labour. There is also a better utilisation of greenhouse space after harvest. No plants are left behind in the compartment and so it can be filled again. Rearranging of plants which are left in the compartment after manual harvesting is labour intensive. In many cases plants are not rearranged because the labour costs are too high.
     For the automation of the harvesting process it is important that the plants are uniform. If there are many unmarketable plants at the harvest time, a large number of plants have to be put back into the greenhouse and this involves additional transportation and handling.
   - The production of pot plants can be managed in a more efficient way. If uniform growth groups are created, the grower has information about both the number of plant and their development. In the marketable stage, for example, he knows how many plants are available.

Grading also has disadvantages. Additional handling is required and the speed of operation is slowed down. Grading also involves a redistribution of plants over groups, which involves additional transport.

B. At which stage of growth should plants be graded?
It is concluded that from an economical and logistical point of view the number of operations in the growth cycle should be minimised (Chapter 2). Therefore, grading can be performed best at those points in the growth cycle where physical actions are already taking place, like planting, respacing, transplanting, and harvesting.

C. Why should grading be done automatically?
At the moment grading is carried out by man and it is based on a complex set of features most of which are determined visually. Grading is a labour intensive operation which requires constant concentration. The human grader is not able to grade plants according to the same standards during a whole day. His performance depends on experience, physical and mental condition, work rate and motivation. The grading criteria are based on specific and personal experience which is difficult to transfer from one person to another. Due to the lack of objective criteria, each grader tends to use his own criteria.

The changing standards of the human grader are tested by performing consistency experiments in which the same plants have to be graded several times while three groups are created (small, medium, and large). Experiments with unrooted Begonia cuttings show that when a human grades the cuttings for a second time, 66 percent get the same classification. In the case of the half-grown Begonia plants 87 percent are graded into the same group after the second judgement. After five judgements the score for the unrooted cuttings is 48 percent and for the half-grown plants 68 percent.

Similar tests have been performed for Dieffenbachia plants. After a second judgement 76 percent of the Dieffenbachia shoots and 66 percent of the half-grown Dieffenbachia plants are graded into the same group. After five judgements these percentages are 29 percent for the shoots and 47 percent for the half-grown plants. It is concluded that the grading standards which are used by the graders do change during a day. Grading standards are better known for the half-grown plants than for the cuttings (Chapter 2).

Nowadays, pot plant cultivation demands uniformity throughout the growth cycle in order to profit from the advantages of automation. From a commercial point of view there is a greater demand for more uniform and standardised full-grown plants. Therefore an automatic system with objective standards is needed to improve uniformity and to standardise quality. Furthermore, labour costs in the Netherlands are very high and moreover it is difficult to employ qualified people for the grading operation. Digital Image Processing (DIP) is expected to emerge as an interesting alternative to the human eye-brain combination. The strong point of DIP is its ability to measure (combinations of) relevant features in an objective way (Chapter 3).

D. Is it possible to measure the features of plants using DIP?

In Chapter 3, the application of DIP in an agricultural environment has been discussed. It is concluded that an important part of the development of a grading system concerns identifying the plant features which have to be measured. Grading features are identified on the basis of literature, by interviewing growers, and by performing growth and judgement experiments (Chapter 4).

A grading feature has a quantitative and a qualitative property. The quantitative property describes the consistency and range of a feature. A feature can be measured consistently if the value of the feature is the same after measuring the same plant several times. A feature is defined as a useful grading feature if it has a consistency of at least 90 percent (Section 4.4). The qualitative property describes the influence of that feature on the classification of the plant. A strong influence means a good qualitative property.

It is important to determine the quantitative properties of a feature measured with DIP first. If the quantitative properties of a feature are bad, its qualitative properties will also be bad. In such cases it means that the feature mentioned may be a good grading feature, but it can not be measured with DIP and therefore it is not useful in a grading system. Alternative features, which can be measured better by DIP and which are related to the features mentioned have to be found then.

At the young stage, the features which have to be measured are quite detailed such as the size of individual leaves and stems. Therefore knowledge-based segmentation is used. Knowledge-based segmentation means that objects in the image are identified on the basis of a model or rules (Ballard and Brown, 1982). In the case of the unrooted Begonia cutting, it was possible to develop a model of the plant's stem-leaf structure because the cuttings have a well-defined structure and only two leaves.

A same knowledge-based segmentation has been applied to the Dieffenbachia shoots. The Dieffenbachia shoot has more leaves than the Begonia cutting and the leaves overlap. Therefore, it is difficult to develop a model for the Dieffenbachia shoot. The segmentation method identifies stem and leaf parts on the basis of geometrical properties (for example, long thin segments are stems).

The Saintpaulia cuttings have been measured with the same knowledge-based segmentation. Leaves of this cutting do not overlap very much, but the number of leaves varies considerably. Even so the segmentation of stem and leaf parts can be applied to the Saintpaulia cutting.

For all these young plants knowledge-based segmentation can be applied to identify stem and leaf parts. A detailed model is needed to identify specific parts of the plant, as developed for the unrooted Begonia cutting.

Literature and experts confirm that the leaf area is an important feature in the young stage. The leaf area of the unrooted Begonia and Dieffenbachia cuttings is estimated by correcting the projected leaf area. This correction method is based on the transparency of the leaves and is determined by presenting the same cutting to the camera several times in a random, natural rest position. By minimising the variation in area measurement of the same cutting, correction factors for the grey values are determined. The consistency of the corrected leaf area does not show better results than the projected leaf area (unrooted Begonia cutting corrected leaf area 94.1%, projected leaf area 94.6%, unrooted Dieffenbachia shoot corrected leaf area 96.7%, projected leaf area 97.0%). The correlation with the actual leaf area is higher when the corrected leaf area is used instead of the projected leaf area. (Begonia: r is 0.87 and 0.82 respectively). It is concluded that the correction method produces a better estimation of the actual leaf area but does not result in a more consistent grading feature (Chapter 5). The growth experiments have to indicate which feature describing the leaf area has a better quantitative property. The leaf area correction method cannot be applied to the Saintpaulia cuttings because of the low transparency of the leaves. The consistency of the projected leaf area measurement is the same as for the Begonia cuttings and Dieffenbachia shoots (96.4%).

In the half-grown stage, the type of feature to be measured is less detailed than in the young stage. This is due to the structure of the plant and the number of parts. A model of the four-week old Begonia plants has been developed in order to identify the individual parts of the plant. The feature measurements of these parts are less consistent. The leaves are perpendicular to the image plane and stems are not always completely visible. The six-week old Dieffenbachia plants and the six-week old Saintpaulia plants are measured using global features like the projected leaf area from top- and side-view. These feature measurements do not use knowledge-based segmentation.

The literature and the experts agree that an important feature in the final stage is the projected leaf area from the top-view (global feature). This feature can be measured consistently (Begonia 98.5%, Dieffenbachia 97.7%, Saintpaulia 99.1%) since the measurement is not affected by the orientation of the plant. The measurement of features in side-view images is affected by the plant's orientation. This effect can be reduced by the use of multiple images. The consistency of the measurement of the projected leaf area of the Dieffenbachia plant taken from the side-view is found to increase from 93.7% to 96.3% when two images are used which are captured 90 degrees apart in the horizontal plane. Similar effect is achieved for the height measurement of the plant if two opposite images are taken in the horizontal plane.

It is concluded that plant features can be measured with DIP. The growth stage and the complexity of the plant determine the level of detail of the features.

E. Which features should be measured in order to grade plants into uniform groups? Both growth and judgement experiments were performed in order to identify grading features. The way these experiments were arranged has been described in Chapter 4. Two different blocks were created to test plant interaction effects. In one block the plants grow among plants of almost the same size (ordered block: homogeneous plant interaction), and in the other in which normal greenhouse conditions are represented, i.e. plants grow among plants of different sizes (random placed block: heterogeneous plant interaction).

The growth experiments with Begonia plants show that the corrected leaf area in the unrooted stage correlates best with expert judgement in the four week old stage (Table 5.11). In the multiple regression analyses, multiple r values of 0.45 to 0.56 between expert judgement and the features are achieved for the ordered blocks.

The growth experiments with Dieffenbachia plants show that the corrected leaf area in the unrooted stage has the best correlation with expert judgement in the eleven week old stage (Table 6.3). In the regression analyses multiple r values of 0.47 to 0.53 between the expert judgement and the features are achieved for the ordered blocks.

For the six and nine week old stages the projected leaf area from side- and top-view and the volume demonstrate the strongest correlation with expert judgement in the eleven week old stage (Table 6.3). The correlation of expert judgement with the individual features and with combinations of features (multiple r) increases for plants in an older stage of development. Disturbance to growth decreases when the period of time between the measurement and the judgement is small. This effect is stronger for the random placed blocks than for the ordered blocks (Table 6.4).

The growth experiments with Saintpaulia plants show that the leaf area and total area in the unrooted stage do have the best correlation with the total number of days needed for the plant to reach the marketable stage (Table 7.5). In the regression analyses, multiple r values of 0.31 and 0.58 between the features and the time needed to reach the marketable stage are found (Table 7.6). In the six and eleven week old stage, the projected leaf area from top-view demonstrates the strongest correlation with the length of this period (Table 7.5).

Sometimes features which are mentioned by the experts do not relate to development at a later stage. According to the expert, the length of the connecting stem, between the first and second leaf of the unrooted Begonia cutting, is important. However, in the analyses this feature was not shown to be important.

The thickness of the stem of the unrooted Dieffenbachia shoot is also mentioned by the expert. Special techniques have been developed to measure the thickness of the stem but no strong relationships with the development in an older stage are found.

The Saintpaulia expert indicated that the development of 'the heart' is important for the unrooted Saintpaulia cutting. The development of 'the heart' cannot be determined using DIP. Therefore, as a substitute the leaf mass in the central part of the cutting is measured. The consistency of this feature is low (68%) and no strong relationship is found with the development at an older stage. Other features (total area, leaf area) can be used better as substitutes for the development of the heart. It is concluded that sometimes other features have to be used than those mentioned by the experts.

The judgement experiments with the half-grown Begonia plants show that the development of the second and third leaf, as well as the total height, are the features which correlate best with the expert judgement (Table 5.7). In the regression analyses multiple r values of 0.68 to 0.81 between the features and the expert judgement are achieved (Table 5.8). For the eleven week old Dieffenbachia plants, the projected leaf area from top- and side-view and the volume of the plant are the features which correlate best with expert judgement (Table 6.3). In the regression analyses multiple r values of 0.71 and 0.79 between the features and the expert judgement are achieved (Table 6.4). The correlation coefficients and the multiple r change, depending on the expert, the time between the judgements, and the group of plants. The multiple r values between features and expert judgement are higher for the ordered blocks than for the random placed blocks (Begonia ordered: 0.69 versus random 0.68 and ordered 0.81 versus random 0.76, Dieffenbachia: ordered 0.76 versus random 0.73 and ordered 0.79 versus random 0.71; Experiment 1 and 2 respectively). The experts mentioned that the plants in the ordered blocks develop more homogeneously. Therefore, they could be judged better.

When considering the grading features which are identified, it is concluded that in the young stage the leaf area is the most important feature. In the full-grown stage the projected leaf area from side- and top-view and the height are the most important features. In the half-grown stage the features that have to be measured depend on the development of the plant itself. For half-grown Begonia plants, detailed features like the development of the second and third leaf are important. The features of a six week old Dieffenbachia plant cannot be measured in such detail. Therefore the projected leaf area from side- and top-view are used. As mentioned in Chapter 4, the type of grading features depends on the stage of growth.

F. What is the effect of grading plants in different growth stages?
Growth experiments were also performed to test whether a grading system based on DIP is capable to grade plants into uniform growth groups. Uniformity is determined by calculating the size ratios of the growth groups (Section 4.7.2). The size ratio indicates the average size and the distribution of the plants in a growth group. It is determined for each growth group by the percentage of small, medium and large plants. A large difference in size ratio between two growth groups indicates a large difference between the growth groups. The differences in size ratios between the growth groups are used to evaluate the effect of grading.

The ordered Begonia plants show an increase of the size ratio in 'larger' (larger projected leaf area in the unrooted stage) growth groups (50 to 80, and 41 to 85 for Experiment 1 and 2 respectively). The size ratios of the random placed plants do not differ very much. The same effect can be observed in Dieffenbachia plants. The size ratios for the ordered blocks agree well with the size of the starting plants (36 to 80, and 29 to 77 for Experiment 1 and 2 respectively). Considering the range of values, it is concluded that grading plants at a young stage produces groups of plants of a similar size at an older stage.

Simulating the grading of the Dieffenbachia plants after six weeks or after nine weeks shows that the uniformity of the growth groups in the eleven week stage has been improved. The range of the size ratios of the growth groups is larger than when grading takes place only at the unrooted stage (six week stage 24 to 81 and 11 to 79; nine week stage 22 to 87 and 8 to 81 for Experiment 1 and 2 respectively). The greatest loss of uniformity occurs during the rooting stage because of the uncertainty of the rooting process (Chapter 6).

The Begonia and Dieffenbachia growth experiments show a difference in response for the ordered blocks as well as for the random placed blocks. Correlation coefficients between the expert judgement in the final stage and the leaf area in the start stage (which have proven to be the best related feature for both young plants) are higher for the ordered blocks (Begonia r is 0.45 for the ordered blocks and 0.28 and 0.08 for the random placed blocks; Dieffenbachia r is 0.43 and 0.45 for the ordered blocks and 0.38 and 0.32 for the random placed blocks for Experiment 1 and 2 respectively). This means that the development of the plants in the ordered blocks is better determined by features in a young stage than the development of plants in the random placed blocks. Besides, putting plants of the same size into one group, grading leads to the development of more uniform plants. The differences between the random placed blocks and the ordered blocks are possibly caused by differences in micro-climate and differences in the interaction between plants.

The Saintpaulia growth experiments are only performed for the ordered blocks. The correlation between the leaf area of the unrooted cutting and the number of days a plant needs to reach the marketable stage is of the same strength as for the Begonia cuttings and the Dieffenbachia shoots (r is 0.26 for Experiment 1 and 0.57 for Experiment 2).

G. Are plants graded as well using DIP as when they are graded by a human grader? Judgement experiments were done to test whether a grading system based on DIP is able to grade plants in groups in the same way as a human grader does. The performance of the grading system is determined by looking at the percentage of plants where both the computer decision model and the human expert agree about the grade.

For the Begonia judgement experiments with four week old plants, the maximum achieved agreement with a regression equation model is 81 percent. Dieffenbachia judgement experiments with eleven week old plants show a maximum agreement of 84 percent. For both case studies, a neural network decision model gives a better performance than the regression equation model (Begonia 87 percent, Dieffenbachia 87 percent). An explanation for this is that the neural network can handle the non-linear relationships between the features and the expert judgement (Chapter 4). One problem with the neural network is 'specialisation'. This means that the performance of the neural network can be improved by increasing the number of presentations of a learn set. The performance of a test set also increases during the generalisation stage. As soon as the neural network reaches the specialisation stage, the performance for the learn set goes on increasing, but at the same time it decreases for the test set. When the network is trained to classify 100 percent of the plants from the learn set correctly, the network also has learned the classification of human errors in the learn set. Considering the consistency of the human grader and the performance of the grading system, it is concluded that it is possible to grade plants at least as well with DIP as with a human grader (Chapter 5).

A problem with expert judgements is the possible difference in opinion between experts. The judgement experiments with four week old Begonia plants show that one expert uses the development of the second and third leaf as grading features while the other expert uses the total height of the plant. The judgement experiments with eleven weeks old Dieffenbachia plants show that the expert changed the standards during judgement.

8.2 Discussion

It can be concluded that the grading of pot plants results in more homogeneous groups. In Chapter 2, the advantages of grading and the potential grading points are discussed. However, to profit from the advantages of grading with DIP, the following remarks should be taken into consideration.

- Grading has to be effective. When the growth of a group of plants is heterogeneous, the effect of grading disappears during the growth cycle. For the Dieffenbachia shoots it is found that in the rooting stage heterogeneity is introduced because the rooting process does not depend on the size of the cuttings only. For these plants the grading should be done in a later growth stage. The uniformity of the growth environment and treatments are also important for the development of the plants. Introduction of differences in treatment for the same growth group results in heterogeneity. In this way the effect of grading may even be eliminated. The Saintpaulia experiments show that the grading results can be affected by a treatment during the planting of cuttings (in Experiment 1, a weaker relationship between the total area and the number of days needed for a plant to reach a marketable stage is found because of possible dehydration and fungicide treatment being omitted).

  How effective grading at a certain point in the growth process is in ensuring uniformity of the growth group at the full-grown stage, is related to the period between grading and the full-grown stage. Grading at the end of the growth process results in the highest degree of uniformity in the full-grown growth groups. Here, growth is least affected by disturbances such as differences in temperature and water supply. The Dieffenbachia and the Saintpaulia experiments show this effect: the relationship with the full-grown stage becomes stronger when measurements are performed at later stages of growth.

- The possibility of controlling the growth of the uniform growth groups. In Section 2.2, the advantages of grading are discussed. If the various growth groups can be treated in different ways, it is possible to produce better plants in a more efficient way. For this reason the smaller Saintpaulia cuttings receive a different type of treatment to the large Saintpaulia cuttings.

- The complexity of the grading operation. In Chapter 4, an explanation is given of the nature of feature change in different growth stages. In the full-grown stage, the plant structure is complex and therefore only global features can be measured. However, a judgement on the full-grown plant is known. Therefore complex decision systems (consisting out of several features which are used in linear or non-linear combinations) can be developed. In the young stage, the plant structure is simple and therefore detailed features can be measured. However, the expert judgement on the young plant is generally not well-known. Thus, only simple decision models (one to three features in a linear model or rule system) can be developed. The result of grading is only known after a period of growth. It is difficult to develop absolute standards because they change with the size and origin of the young plant.

- The decision where to grade and how to grade depends upon the processing of the plants in the greenhouse. When many of the greenhouse processes have been automated, grading can also be automated. When many of the processes are done manually, the introduction of automatic grading implies the need for an additional action (transport of the plants to and from the grading system). Whether automatic grading in such cases will result in a better product which will justify investments, has to be tested.

It is not to be expected that an automatic grading system will replace all the human labour in the grading process because of the complexity of the handling at the full-grown stage. Automatic grading, however, can help the grower to standardise the size of his plants.

Hines et al. (1986) proposed to establish features for all species and growth stages. In this way a system can be built which is able to grade all plants. When grading a certain type of plant, only the weight for each feature has to be determined. It is possible to include in one system all the features which can be measured. However each specie and growth stage have their own specific set of features and only a few features can be used in common. If a neural network is used as decision model, it results in a network with a large number of input neurons (each feature results in a neuron). In such cases a large training set is needed (Rummelhart et al., 1986). The number of input neurons is large compared to the number of relevant input neurons. To avoid this it is better to identify a relevant set of features for each type of plant and growth stage.

8.3 Suggestions for further research

Consistency tests on features show that some cannot be measured with a high degree of accuracy. It is possible to detect stem and leaf structures using knowledge-based segmentation. However, the reconstruction of these structures is not always correct. The feature measurement can be improved by reconstructing the stem structure first. Therefore, stem regions have to be identified in the image. This can be based on the geometrical features of the regions (for example thin structures). The leaf regions can be segmented and identified then on the basis of irregular shape and leaf position in relation to the stem structure.

The classification of regions in the image follows many rules. These rules are used to describe the geometrical and spectral properties of the regions. A neural network should be able to learn these rules by presenting parts of the image to the network (Nikhil et al, 1993). A part of the segmentation and feature extraction can be skipped in this way. Research has to be done on how to represent the image to the network. Research into the human vision system can be a useful source of information to see how the human recognises an object (Cornsweet, 1971). Maybe some processing done by the human brain like rotating an object can be applied to the image before presenting it to a neural network.

The neural network assisted image segmentation can be applied to unrooted cuttings but also to images of full-grown plants. It should be investigated whether the network is able to measure global features or not.

The decision system for the full-grown plants may be based on different models. In this research, regression equations and neural networks are used. The neural network which is used consisted of three layers and was learned with generalised delta back propagation. Although this method is able to find global minima in the set of weights, other methods are described in the literature like the conjugate gradient method, which claim to be better and faster (Knight, 1990; Johansson, 1992; Chang et al, 1992). The methods should be compared.

Brons (1992) tested a neural network with only a few relevant features selected by statistical methods. In this research all features have been presented to the network. It is recommended to evaluate methods which claim to reduce the size of the network without negative influence on the performance. This can be accomplished by reducing the number of inputs (like Brons did), by varying the number of hidden neurons, or by removing connections from the network (pruning).

The classification of the plant sometimes consists out of a well described part like the height and a poorly described part like the shape. In such cases the classification about the height can be done by a rule system and the classification about the shape by a neural network. Then these classifications are combined for the final classification of the plant. This combination is called expert networks.

It is not necessary that all features have to be processed by just one network. A rule system can decide which network has to be activated for the classification.

In the growth experiments, regrading after a certain growth period was not applied actually. The consequences of regrading after a certain period of growth should be tested. The advantage is that homogeneity in the growth environment increases. The growth experiments show that uniformity in the growth environment is important for the development of the plants. The growth experiments should be repeated at different places and in different seasons to get more information about variation in growth. The whole growth cycle should be covered to obtain more information about grading in different growth stages. So an analysis can be made of the most effective growth stage for grading.

The judgements have been made by one expert. It is noticed that an expert can make mistakes and different experts have different opinions. To obtain a more general judgement about the plants and to avoid judgement errors, more experts can be consulted.

When for instance ten experts are consulted, the score of the majority of the panel can be used (for example, at least seven of the ten judgements about the same plant have to be similar). A problem arises when experts have completely different opinions. It is useful to register the plants about which experts have doubts. These plants should be excluded from the learn set. They may cause inconsistencies in the learn set. If the grading system assigns during testing a doubtful plant to another group then the one chosen by the experts, the misclassification of the decision model is not a serious problem.

Another method is to grade a group of plants after a set of features has been identified and a decision system has been developed. Then a panel of experts inspects the groups which are created by the grading system. The experts have to identify plants which have been graded into the wrong group. In this way the errors in the grading system can be identified. An advantage is that the experts do not have to grade all plants. They only have to compare plants and this may possibly enable the expert to grade more consistently because there is some standard available.

Decision systems can be developed in two different ways. The first method is by presenting plants to the grading system together with the expert judgements. A problem is the changing standards of the expert. In this case the system learns to grade according to a particular expert or a group of experts. The classification is based on subjective judgements.

The second method is to the develop standards which are set by external institutions. These standards can be translated into rules in the grading system. The advantage of this system is that the decision to grade into a certain group is based on an objective standard. Research should be done to the most useful method.

In this thesis, potential grading points have been mentioned. In the Dieffenbachia case study, it was found that grading at certain points is more efficient. An economic analysis may determine whether and when to grade in the growth cycle.

The automatic grading system is not considered to be an isolated machine in the greenhouse. It interacts with other machines and it provides information about the number of plants in each growth group and their development. This information can be integrated into a Management Information System as described by Hofstede (1992). The effect of implementation of automatic grading on management should be investigated.

Summary

The main research objective in this thesis is the possibility of grading pot plants in homogeneous groups using Digital Image Processing (DIP). The general objective in pot plant cultivation is to produce full-grown plants of a desired quality. This involves grading operations.

Grading of plants in different growth stages has many advantages.

- In the young stage weak plants can be excluded. As a result they do not occupy greenhouse space and energy and nutrients can be saved. During and at the end of the growth cycle these plants do not have to be removed.
- Plant growth can be optimised during the growth cycle. Plant-plant interactions are more even when plants of the same size are grouped together.
- In the full-grown stage the amount of labour for harvesting can be reduced. This also results in a better use greenhouse space.
  For the automation of the harvesting process it is important that plants are uniform.
- The production of pot plants can be managed in a more efficient way. The grower has information about the number of plants and their development.

Grading also has disadvantages. It causes additional handlings and it slows down the speed of operation. Grading involves a redistribution of plants over groups which leads to additional transport. From an economic and logistic point of view the best points to perform grading coincide with other physical operations like planting, re-spacing, transplanting, and harvesting.

At the moment, grading is done by man and based on a complex set of features which are mostly visually determined. Grading is a labour intensive operation which requires constant concentration. The human grader is not able to grade plants according to the same standards during the whole day. His performance depends on experience, physical and mental condition, work rate and motivation. Grading criteria are based on specific and personal experience and it is difficult to transfer these to other graders. Due to the lack of objective criteria each grader tends to develop and use his own criteria.

Experiments with unrooted Begonia cuttings show that when a human grades cuttings into three groups a second time, 66 percent get the same classification. Classifying half-grown Begonia plants a second time results in a score of 87. After five judgements the score for the unrooted cuttings is 48 percent and for the half-grown plants 68 percent. For Dieffenbachia shoots it is found that after a second judgement, 76 percent of the Dieffenbachia shoots and 66 percent of the half-grown plants are graded into the same group. After five judgements these figures are 29 percent for the shoots and 47 percent for the half-grown plants. It is concluded that the grading standards which are used by the graders do change during the day. Grading standards are better known for the half-grown plants than for the cuttings.

Nowadays pot plant cultivation demands uniformity during the growth cycle in order to be able to profit from automation. From a commercial point of view, there is a growing demand for more uniformity and standardisation of full-grown plants. An automatic system with objective standards is needed to improve uniformity and to standardise quality. Furthermore, labour costs in the Netherlands are very high and it is difficult to employ qualified people for the grading operation. DIP is expected to offer an interesting alternative to the human eye-brain combination.

An important part of the development of a grading system is the information about the features that have to be measured and their processing in a decision model which can be used to come to a classification of the plant. Grading features are identified from literature, by interviewing growers, and by performing growth and judgement experiments.

The type of feature that has to be measured depends on the growth stage. In the young stage, the features which have to be measured are detailed ones like the size of individual leaves and stems. Therefore knowledge-based segmentation is used which is based on a model of the plant. Knowledge-based segmentation means that objects in the image are identified on the basis of a model or rules.

The literature and the experts agree that the leaf area is an important feature in the young stage. The leaf area of the unrooted Begonia and Dieffenbachia cuttings is estimated by correcting the projected leaf area. The correction method is based on the transparency of the leaves and is determined by presenting the same cutting to the camera several times in a random, natural rest position. The consistency of the corrected leaf area does not show better results than the projected leaf area (unrooted Begonia cutting corrected leaf area 94.1%, projected leaf area 94.6%, unrooted Dieffenbachia shoot corrected leaf area 96.7%, projected leaf area 97.0%). The correlation with the actual leaf area is higher when using the corrected leaf area instead of the projected leaf area. (Begonia: r is 0.87 and 0.82 respectively).

In the half-grown stage, the type of feature that has to be measured is less detailed than in the young stage. This is caused by the structure of the plant and the number of parts. To identify the individual parts of the plant, a model has been developed of the stem-leaf structure of the four week old Begonia plant. The feature measurements of these parts are not as consistent as in the young stage. The leaves are perpendicular to the image plane and stems are not always completely visible. The six week old Dieffenbachia plants and the six week old Saintpaulia plants are measured with global features such as the projected leaf area from top- and side-view. These feature measurements do not use knowledge-based segmentation.

In the final stage, both literature and experts agree that the projected leaf area from the top-view (global feature) is an important feature. This feature can be measured consistently (Begonia 98.5%, Dieffenbachia 97.7%, Saintpaulia 99.1%) since the measurement is not affected by the orientation of the plant. On the contrary measurements of features in the side-view images are affected by the orientation. This effect can be reduced by using multiple images. It is found that the consistency of the measurement of the projected leaf area from the side-view of the Dieffenbachia plant increases from 93.7% to 96.3% when two images are used which are captured 90 degrees apart in the horizontal plane. The same is found for the height measurement of the plant if two opposite images are taken in the horizontal plane.

In the growth experiments, two blocks were created. One block in which the plants grow among plants of almost the same size (ordered block: homogeneous plant interaction), and another block in which normal circumstances are represented meaning that plants grow amongst plants of varying sizes (random placed block: heterogeneous plant interaction).

The growth experiments with Begonia plants show that the corrected leaf area in the unrooted stage has the best correlation with expert judgement in the four week old stage. The corrected leaf area in the unrooted stage of the Dieffenbachia shoot shows the best correlation with the expert judgement in the eleven week old stage. For the six and nine week old stage the projected leaf area from side- and top-view and the volume demonstrate the strongest correlation with expert judgement in the eleven week old stage. The growth experiments with the Saintpaulia plants show that the leaf area and total area in the unrooted stage have the best correlation with the total number of days required for the plant to reach the marketable stage. In the six and eleven week old stage, the projected leaf area from the top-view has the strongest correlation with the length of this period.

It has been observed that features which are sometimes mentioned by the experts do not relate to development at a later stage. It is possible that these features cannot be measured with DIP. In such cases related features have to be found.

The judgement experiments with the half-grown Begonia plants show that the development of the second and third leaf, as well as total height, are features which correlate best with expert judgement. For the eleven week old Dieffenbachia plants, the projected leaf area from top- and side-view together with the volume are the features which correlate best with expert judgement. The correlation coefficients and the multiple r change, depending on the expert, the time between judgements, and the group of plants. The multiple r values between features and expert judgement are higher for the ordered blocks than for the random placed blocks. The experts mentioned that the plants in the ordered blocks develop more homogeneously. Therefore they can be judged better.

Growth experiments also have been performed to test whether a grading system, based on DIP, is able to grade plants into uniform growth groups. Uniformity is determined by calculating the size ratios of the growth groups. The size ratio indicates the average size and distribution of plants in a growth group. The differences in size ratio between the growth groups are used to evaluate the effect of grading.

The ordered Begonia plants show an increase of the size ratio for the 'larger' (larger projected leaf area in the unrooted stage) growth groups. The size ratios of the random placed plants do not differ much. The same effect is seen for the Dieffenbachia plants. It is concluded that grading of plants at a young stage results in groups of plants of similar size at an older stage.

Simulating the grading of the Dieffenbachia plants after six weeks or after nine weeks, shows that the uniformity of the growth groups in the eleven week stage has been improved if this is compared with the effects of grading only at the young stage.

The Begonia and Dieffenbachia growth experiments show a difference in response in both ordered blocks as well as the random placed blocks. Correlation coefficients between expert judgement in the final stage and the leaf area in the start stage are higher for the ordered blocks. This means that the development of the plants in the ordered blocks is better determined by the features at a young stage than is the case with the plants in the random placed blocks. Besides putting plants of the same size into one group, the effect of grading leads to the development of more uniform plants.

Judgement experiments have been done to test whether a grading system based on DIP is able to grade plants into groups in the same way as a human grader does. The performance of the grading system is determined by looking at the percentage of plants where both computer decision model and the human expert agree on the grade.

In the Begonia judgement experiments using four week old plants, the maximum achieved agreement with a regression equation model is 81 percent. The Dieffenbachia judgement experiments with eleven week old plants show a maximum agreement of 84 percent. For both case studies, a neural network decision model gives a better performance than the regression equation model (Begonia 87 percent, Dieffenbachia 87 percent). A neural network better handles the non-linear relations in the decision model.

A problem with expert judgements is the possibility contradictory opinions. The judgement experiments with four week old Begonia plants shows that one expert uses the development of the second and third leaf as grading features while the other expert uses the total height of the plant. The judgement experiments with eleven week old Dieffenbachia plants show that the expert changes his standards during judgement. This means that when a learn set is created to teach the decision model, consideration has to be given to the fact that expert judgement is not always consistent.

Samenvatting

De hoofdvraag van dit onderzoek is: is het mogelijk om potplanten te sorteren in meer homogene groepen met behulp van Digitale Beeldverwerking (DB). De algemene doelstelling van de potplantenteelt is het produceren van planten van een bepaalde (wel)omschreven kwaliteit. Dit brengt sorteerhandelingen met zich mee.
Het sorteren in de diverse groeistadia heeft diverse voordelen:

- Slechte planten kunnen reeds in een jong stadium worden verwijderd. Dit betekent dat zij geen onnodig beslag leggen op kasruimte en geen voedingsstoffen en energie verbruiken. Verder hoeven deze planten niet tijdens of aan het eind van de teelt te worden verwijderd.
- De groei van de planten kan worden geoptimaliseerd. De interactie tussen de planten is van meer gelijkmatige aard omdat groepen planten van ongeveer gelijke grootte opgroeien.
- Er treedt een arbeidsbesparing op tijdens de oogst van de planten doordat een gehele groep in één keer geoogst kan worden. Dit houdt ook in dat de kasruimte beter benut kan worden. Om het oogstproces te kunnen automatiseren, is het belangrijk dat een partij planten uniform is.
- De productie van potplanten kan beter beheerst worden. Door het sorteren is het bekend hoeveel planten er zijn en in welk ontwikkelingsstadium zij zich bevinden.

Sorteren zoals dat nu wordt gedaan heeft nadelen. Het veroorzaakt extra handelingen en het vertraagt de verwerkingssnelheid. Sorteren zorgt ook voor een herverdeling van planten in meerdere partijen wat extra transport inhoudt. Vanuit een logistiek en economisch oogpunt gezien is het beter om een sorteerhandeling uit te voeren op het moment dat er ook andere fysieke handelingen op de plant worden uitgevoerd zoals tijdens planten, wijderzetten, verpotten en oogsten.

Op dit moment wordt het sorteren voornamelijk door de mens gedaan. Zijn oordeel is gebaseerd op een complexe set planteigenschappen die op het oog bepaald worden. Sorteren is arbeidsintensief en vraagt veel concentratie. De menselijke sorteerder is niet in staat om gedurende de gehele dag volgens dezelfde criteria te sorteren. Zijn prestatie is afhankelijk van zijn ervaring, zijn fysieke en mentale gesteldheid, zijn werktempo en zijn motivatie. De sorteercriteria zijn gebaseerd op specifieke, persoonlijke ervaringen die moeilijk objectief over te brengen zijn naar ander mensen. Door dat gebrek aan objectiviteit gaat iedere sorteerder zijn eigen criteria hanteren.

Het veranderen van de sorteercriteria tijdens het sorteren door de mens is getoetst met behulp van consistentietesten. Dit houdt in dat dezelfde plant diverse malen in drie verschillende groepen moest worden ingedeeld (klein, middel en groot). Experimenten met onbewortelde Begonia stekken geven aan dat bij de tweede keer sorteren 66 procent van de stekken dezelfde beoordeling krijgt. Van de halfwas Begonia planten (vier weken oud) wordt 87 procent in dezelfde groep ingedeeld tijdens de tweede beoordeling. Na vijf beoordelingen is deze score voor de onbewortelde Begonia stekken gezakt naar 48 procent en voor de halfwas Begonia plant naar 68 procent. Eenzelfde test is gedaan met

Dieffenbachia planten. Na een tweede beoordeling zijn 76 procent van de Dieffenbachia stekken en 66 procent van de halfwas planten in dezelfde groep ingedeeld. Na vijf beoordelingen zijn deze scores 29 procent voor de stekken en 47 procent voor de halfwas planten. Hieruit is geconcludeerd dat de criteria die gebruikt worden door de mens veranderen gedurende de dag. De criteria voor de halfwas planten zijn gemakkelijker vast te houden dan die voor de stekken.

De hedendaagse potplantenteelt vraagt om uniformiteit tijdens de teelt om voordeel van de automatisering te kunnen hebben. Vanuit de handel is er een toenemende behoefte aan uniforme en gestandaardiseerde, volgroeide planten. Daarom is er een behoefte ontstaan aan een automatisch sorteersysteem om de uniformiteit te verhogen en de kwaliteit te standaardiseren. Verder zijn de arbeidskosten in Nederland erg hoog en is het moeilijk om goed personeel te vinden voor het sorteerwerk. Het gebruik van DB wordt gezien als een interessant alternatief voor de oog-hersens combinatie van de mens. Een sterk punt van DB is het vermogen om (combinaties van) relevante kenmerken op objectieve wijze te meten.

Een belangrijk deel van het ontwikkelen van een sorteersysteem is het onderkennen van kenmerken die gemeten moeten worden en hoe deze kenmerken gecombineerd moeten worden om tot de classificatie van een plant te komen. Deze kenmerken en regels zijn onbekend in de potplantenteelt, mede omdat de beoordeling van planten door de mens wordt gedaan en ieder mens anders indeelt. Sorteerkenmerken worden geïdentificeerd aan de hand van de literatuur, door interviews met telers en door het uitvoeren van groei- en beoordelingsexperimenten.

Het type sorteerkenmerk dat gemeten moet worden hangt af van het groeistadium. In het jonge stadium zijn de kenmerken die gemeten moeten worden gedetailleerd zoals de grootte van de individuele bladeren en stengels. Daarom is kennis gestuurde segmentatie toegepast die gebruikt maakt van de beschrijving van de structuur van de plant. Kennis gestuurde segmentatie houdt in dat de objecten in het beeld worden geïdentificeerd op basis van een model of van regels.

Volgens de literatuur en de experts is in het jonge stadium het bladoppervlak een belangrijk sorteerkenmerk. Het bladoppervlak van de onbewortelde Begonia en Dieffenbachia stekken is geschat aan de hand van een correctie op het geprojecteerde bladoppervlak. De correctiemethode is gebaseerd op de lichtdoorlatendheid van de bladeren. De correctie wordt geschat aan de hand van de minimalisatie van de variatie in het geprojecteerde bladoppervlak van dezelfde stek in verschillende natuurlijke rustposities. Hierbij wordt gebruik gemaakt van de grijswaarde histogrammen. De consistentie van het gecorrigeerde bladoppervlak is niet beter dan die van het geprojecteerde bladoppervlak (onbewortelde Begonia stek gecorrigeerd bladoppervlak 94.1%; geprojecteerd bladoppervlak 94.6%; onbewortelde Dieffenbachia stek gecorrigeerd blad oppervlak 96.7%; geprojecteerd bladoppervlak 97.0%). De correlatie met het werkelijke bladoppervlak is beter voor het gecorrigeerde bladoppervlak dan voor het geprojecteerde bladoppervlak (Begonia: r is 0.87 respectievelijk 0.82).

In het halfwas stadium is het type sorteerkenmerk dat gemeten moet worden minder gedetailleerd dan in het jonge stadium. Dit wordt ondermeer veroorzaakt door de opbouw van de plant en het aantal onderdelen. Om de individuele onderdelen van een vier weken oude Begonia plant te identificeren is een model ontwikkeld van de stengel-blad structuur. De meting van de kenmerken is minder consistent dan in het jonge stadium. De bladeren staan loodrecht op het beeldvlak en de stengels zijn niet altijd volledig zichtbaar. De zes weken oude Dieffenbachia planten en de zes weken oude Saintpaulia planten zijn gemeten met behulp van globale kenmerken zoals het geprojecteerde bladoppervlak in boven- en zijaanzicht. Hiervoor wordt geen gebruik gemaakt van kennis gestuurde segmentatie.

Volgens de literatuur en de experts is in het volgroeide stadium het geprojecteerde bladoppervlak in bovenaanzicht belangrijk. Dit kenmerk kan gemeten worden met een hoge consistentie (Begonia 98.5%, Dieffenbachia 97.7%, Saintpaulia 99.1%) omdat deze meting niet beïnvloed wordt door de oriëntatie van de plant. De metingen van kenmerken in zijaanzicht worden wel beïnvloed door de oriëntatie van de plant. Deze invloed kan worden gereduceerd door het gebruik van meerdere opnames. Wanneer twee beelden worden gebruikt die opgenomen zijn onder een hoek van 90 graden in het horizontale vlak neemt de consistentie van de meting van het bladoppervlak in zijaanzicht toe van 93.7% naar 96.3%. Hetzelfde is gevonden voor de hoogtemeting van de plant wanneer er twee tegenoverelkaar liggende beelden in het horizontale vlak worden gebruikt.

De planten in de groeiexperimenten waren ingedeeld in twee blokken. Één blok waarin de planten groeien temidden van planten van ongeveer dezelfde grootte (geordend blok: homogene plant interactie) en een ander blok waarin de normale groeiomstandigheden worden gerepresenteerd wat inhoudt dat de plant opgroeit tussen planten van diverse groottes. (willekeurig blok: heterogene plant interactie). De groeiexperimenten met de Begonia planten laten zien dat het gecorrigeerde bladoppervlak in het onbewortelde stadium de beste correlatie vertoond met de expert beoordeling in het vier weken oude stadium.

Het gecorrigeerde bladoppervlak in het onbewortelde stadium is ook gevonden in de groeiexperimenten met Dieffenbachia planten als zijnde het best gerelateerde kenmerk met de expert beoordeling in het elf weken oude stadium. In de zes en negen weken oude stadia hebben het geprojecteerde bladoppervlak van zij- en bovenaanzicht de sterkste correlatie met de expert beoordeling in het elf weken oude stadium.

In de groeiexperimenten met de Saintpaulia planten vertonen het bladoppervlak en het totale oppervlak in het onbewortelde stadium de beste correlatie met het aantal dagen dat de plant nodig heeft om het veilingrijpe stadium te bereiken. In het zes en elf weken oude stadium heeft het geprojecteerd bladoppervlak in bovenaanzicht de sterkste correlatie met de lengte van deze periode.

Verder is gebleken dat de kenmerken die soms door de expert worden genoemd niet altijd iets te maken hoeven te hebben met de ontwikkeling in een later stadium. Ook kan het zijn dat ze niet meetbaar zijn met DB en dan moet er gezocht worden naar vervangende kenmerken.

De beoordelingsexperimenten met de halfwas Begonia planten laten zien dat de ontwikkeling van het tweede en derde blad en de totale hoogte van de plant de kenmerken zijn die het best relateren aan de expert beoordeling in halfwas stadium. Voor de elf weken oude Dieffenbachia plant is gevonden dat het geprojecteerde bladoppervlak in zij- en bovenaanzicht de best gecorreleerde kenmerken met de expert beoordeling zijn. De correlatie veranderde afhankelijk van de expert, de tijd tussen de beoordelingen en de groep planten. De correlatie tussen de kenmerken en de expert beoordeling is hoger voor de geordende blokken dan voor de willekeurige blokken. De expert merkte op de planten in de geordende blokken zich meer homogeen ontwikkelden. Daarom konden ze gemakkelijker beoordeeld worden.

De groeiexperimenten zijn ook gedaan om te toetsen of een sorteersysteem, dat gebaseerd is op DB, in staat is om planten in uniforme groeigroepen in te delen. De uniformiteit wordt bepaald aan de hand van het grootte-getal van een groeigroep. Het grootte-getal is een indicatie voor de gemiddelde grootte en de verdeling van groottes van planten in een groeigroep. Het wordt per groeigroep bepaald aan de hand van het percentage planten dat als respectievelijke klein, middel en groot wordt beoordeeld door de expert. Een groot verschil in grootte-getal tussen twee groeigroepen duidt op een groot verschil in grootte tussen die groeigroepen. Dit verschil wordt gebruikt om het sorteereffect te evalueren.

De geordende Begonia planten laten een toename van het grootte getal zien voor de 'grotere' groeigroepen (groter geprojecteerd bladoppervlak in het onbewortelde stadium). De grootte getallen van de willekeurig geplaatste planten zijn niet verschillend voor de verschillende groeigroepen. Deze effecten worden ook teruggevonden bij de Dieffenbachia planten. Geconcludeerd is dat het effect van sorteren van planten in een jong stadium terug te vinden is in een ouder stadium. Dit uit zich in het feit dat de groepen planten bevatten van ongeveer dezelfde grootte.

Het simuleren van het sorteren van Dieffenbachia planten na zes of negen weken laat zien dat de uniformiteit in de groeigroepen in het volgroeide stadium toeneemt ten opzichte de situatie dat er alleen in het jonge stadium wordt gesorteerd.

De Begonia en Dieffenbachia groeiexperimenten laten een verschil in response zien voor de geordende en de willekeurige ingedeelde blokken. De correlatie coëfficiënten tussen de expert beoordeling in het eindstadium en het bladoppervlak in het jonge stadium zijn hoger voor de geordende blokken. Dit houdt in dat de ontwikkeling van de planten in de geordende blokken beter bepaald wordt door de kenmerken in het jonge stadium. Naast het samenvoegen van planten van dezelfde grootte in één groep, leidt het sorteren tot de ontwikkeling van meer uniforme planten.

Om te testen of een sorteersysteem gebaseerd op DB in staat is om planten in groepen in te delen op dezelfde wijze als de mens dat doet, zijn er beoordelingsexperimenten gedaan. De prestatie van het sorteersysteem is bepaald door het percentage planten te bepalen waar het computer beslissingsmodel dezelfde beoordeling geeft aan de plant als de mens.

Voor de Begonia planten van vier weken oud is een prestatie bereikt van maximaal 81 procent met een model gebaseerd op een regressie vergelijking. Voor de Dieffenbachia planten van elf weken oud is een prestatie bereikt van maximaal 84 procent met het regressie model. Voor beide case studies geldt dat een neural netwerk een betere prestatie geeft dan het regressie model (Begonia 87 procent, Dieffenbachia 87 procent). Een neural netwerk is beter instaat om de niet-lineaire relaties in het beslissingsmodel te beschrijven.

Een probleem van de expert beoordeling is het mogelijke verschil in mening tussen de experts. De beoordelingsexperimenten met de vier weken oude Begonia planten lieten zien dat de ene expert de ontwikkeling van het tweede en derde blad belangrijk vindt, terwijl de andere expert de totale hoogte van de plant gebruikt. De beoordeling van de elf weken oude Dieffenbachia plant laat zien dat de expert zijn criteria veranderde gedurende het experiment. Dit houdt in dat er enige voorzichtigheid is geboden bij het creëren van een leerset voor een beslissingsmodel.

Als eindconclusie kan gesteld worden dat DB een goed hulpmiddel is bij het sorteren van potplanten. Het is vooral geschikt voor het vervangen van repeterend sorteerwerk waar de mens niet in staat is om gedurende enige uren dezelfde criteria te gebruiken. De fouten die het sorteersysteem maakt omdat het niet instaat is om de plant van alle kanten te bekijken wordt gecompenseerd door het objectieve en constante karakter van de meting.

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Curriculum vitae

Jouke Dijkstra werd geboren op 30 september 1961 te Finkum (Friesland). In 1980 behaalde hij het Atheneum diploma aan de Rijksscholengemeenschap in Leeuwarden en startte aansluitend zijn studie aan de toenmalige Landbouwhogeschool in Wageningen. Het kandidaatsdiploma werd behaald in 1984 en het doctoraaldiploma in 1988. Het doctoraal diploma omvatte de vakken Landbouwwerktuigkunde, Informatica en Bedrijfskunde.

Op 1 september 1988 is hij in dienst getreden als AIO bij de Landbouwuniversiteit bij de toenmalige vakgroep Landbouwtechniek. Na een fusie met de secties Natuurkunde en Meet-, Regel- en Systeemtechniek van de vakgroep Natuur- en Weerkunde is de vakgroep Landbouwtechniek per 1 januari 1989 opgegaan in de vakgroep Agrotechniek en -fysica. Tot 1 september 1992 is gewerkt aan het project: 'Het gebruik van digitale beeldverwerking bij het sorteren van agrarische produkten'. Vanaf 1 september 1992 is hij werkzaam bij het bedrijf Meuleman Automation B.V. waar hij verder werkt aan de ontwikkelingen op het gebied van het toepassen van beeldverwerking bij sorteersystemen in de tuinbouw.