ELSEVIER Computers and Electronics in Agriculture 15 (1996) 41-55

Computers and electronics in agriculture

Computer vision system for on-line sorting of pot plants using an artificial neural network classifier [1]

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Accepted 6 December 1995

Abstract

A flexible grading system for pot plants is described. The system consists of a colour camera, an image processing system and specially developed software. It can be applied to several types of pot plants because of its implementation of learning techniques. Experiments are described for classification of a flowered plant and a cactus plant. Statistical discriminant analysis and a neural network (NN) classifier are used as techniques for pattern recognition. NNs gave for less complex applications at least equal results as linear discriminant analysis (LDA) or quadratic discriminant analysis (QDA). For more complex applications the NN classifier showed better results. Complexity for the described classification tasks can be associated with the distribution and shape of groups in the multi-dimensional feature space.

Keywords: Image processing; Computer vision; Pattern recognition; Discriminant analysis; Neural network

1. Introduction

Practical topics in plant raising are quality monitoring and improvement of the process efficiency in the greenhouse. A high-quality product with a low cost price is the solution to handle increasing competition. In future greenhouses the role of human labour will be limited, because of further mechanisation and computerisation. Judging product quality and the physical sorting of the plants is one of the few tasks that still has to be performed by humans. Labour costs for sorting and product handling are a substantial part of the cost price.

Besides the high costs, another big disadvantage of human grading is the

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[1] This paper is a revised version of research presented at IFAC/IFIP/EurAgEng Workshop on Artificial Intelligence in Agriculture, Wageningen, The Netherlands, May 1995.

SSDI 0168-1699(95)00056-9

subjectivity of the judgement. The human eye is very good in recognising different patterns but has limited capabilities to perform objective estimates of, for example, size and shape. When grading on size humans have a tendency to compare the plants in a group and select the extreme plants and put them in the class of small and big plants. The grading criteria can be set completely different when a group with another size distribution is examined. Considering the fact that quality of plants is determined by numerous plant features like size, height, colour, shape, symmetry, etc., it is not surprising that humans have problems in maintaining the same objective decision criteria.

Computer vision techniques have proven to be successful for objective measurement of agricultural products. Some research projects have been described on applications of machine vision for analysis of plants and plant material. Cardenas-Weber et al. (1988) suggested techniques for measuring plants and implemented an automatic grading of strawberry plants based on the diameter and number of roots. Suh and Miles (1988) successfully used machine vision to measure morphological properties of tree seedlings. Dijkstra (1991) presented a technique to grade begonia cuttings by estimating leaf area and analyzing the plant structure with digital image processing. Brons et al. (1991) investigated the use of neural network (NN) techniques to judge the quality of cyclamen. Dijkstra and Meuleman (1994) describe an on-line sorting system for flowered plants. The literature shows that the field of image processing and machine vision in plant analysis has evolved in less than ten years from relatively simple laboratory projects to successful on-line applications.

In this paper a flexible computer vision system for grading pot plants developed at ATO–DLO is presented. The system is based on a framework of universal software tools for colour image processing, feature extraction and pattern recognition. Therefore the same software package can be used for grading of different types of pot plants. As with most image processing systems the camera and lighting configuration is optimised for each application. In the next section the complete image processing system is described. The objective of the research described in this paper is to examine the performance of different pattern recognition techniques for clustering of colour data and product classification. The applied pattern recognition techniques are statistical discriminant analysis and simulated NNs. The experiments are performed on two real applications with different level of complexity.

2. Pot plant sorting system

2.1. System configuration

The intelligent part of the plant sorting system is a machine vision unit. The hardware of the machine vision unit consists of a high resolution 3-CCD colour camera (Sony DXC-930P) with a 7.5–97.5 mm zoom lens (VCL-713BX), an industrial Intel 486 computer and an MFG colour frame grabber (Modular Frame Grabber, Imaging Technology Inc.). An illumination chamber with high-frequency tube lighting (Philips) and transparent diffusors is used to illuminate the plants. The image from the colour camera is digitized into a 24 bit image with a resolution of 768×256 pixels. Since the camera is read out in an interlaced mode only the even frame is used for further processing. In cooperation with a horticultural mechanisation company an on-line prototype has been built with electronics and mechanical parts to transport and separate plants. The image processing system has a theoretical maximum capacity of 10,000 plants per hour, but in most practical cases performance is lower because of mechanical limitations. Performance of the image processing system is dependent on the region of interest that is processed and the number and type of measurement features. In its most complex case and at full image resolution a measurement cycle is about one second per plant.

The software for the overall program control, the classification process and user-interface is implemented in Microsoft ANSI-C7.0 and runs under MS-DOS. The image processing functions are implemented on the TMS34020 processor (Texas Instruments) that is present on the MFG. The configuration of the camera(s), the colour of the conveyor belt and position and spectrum of the tube lighting depend on the type of plant. In general, for flowering plants a colour camera looks downward at the plants and the conveyer belt is seen as background. In some cases a second monochrome camera is positioned on one side to measure the height of the plant. With the MFG a maximum of four cameras can be connected to the same frame grabber.

2.2. Product knowledge

The knowledge about grading full grown plants is partly described in quality rules that are defined by, for example, the Dutch auction organisation. Most information, however, is stored in the minds of growers and product quality experts. In research projects dealing with building expert systems based on human knowledge the bottleneck was in many cases the knowledge acquisition process. In general it is difficult and laborious to extract explicit knowledge rules from experts. This is definitely true for expert knowledge on ornamentals. It is difficult for experts to explain what are the relevant criteria for inspecting plants and what is the ranking on importance. Another factor is that the consistency in decisions of experts individually and correlation between different experts for judging pot plants is not high (Brons et al., 1991; Dijkstra and Meuleman, 1994).

To translate product knowledge into information that can be processed by a computer it is necessary to derive the set of features that is relevant to classify a type of plant and to define the discriminating values for the different classes. Numerous different plant types exist and a major functional demand was that the system could handle as many types of products as possible. Because of the difficulty to extract knowledge from experts and the number of different plant types a flexible tool is necessary to incorporate product knowledge. A software platform based on techniques of learning by examples and the possibility to select measurement features from an extensive feature set was developed to include product knowledge.

2.3. Software platform

In Fig. 1 the universal software platform is displayed. The left column shows the normal measurement procedure. In the right column the corresponding selection and learning inputs are indicated. The process of determining the quality group of the plant is composed of two stages, a feature extraction stage and a classification stage.

The feature extraction process is split in two successive operations. In the colour recognition module the 24 bit image colours are reduced to meaningful groups. For a flowering plant the groups are for example: background, leaves, and flower area. The colour recognition module can be trained by selecting pixels in example images. Using a pattern recognition technique the colour space is separated into non-overlapping clusters.

After the data-reduction step the quality features of the segmented objects can be measured. The software contains in total 25 features that can be measured for each object. These features include area, flower area, size, colour, width, diameter, height, and a number of shape and symmetry descriptors. The relevant variables can be selected from a list.

The selection of an optimum subset of features, from the initial set of 25, is an important and difficult step. The relevancy, discriminatory power and ease of computation of the various features define the quality of the classification process. Extensive research has taken place on the development of reliable methods for feature selection. Statistical methods like regression analysis (McCabe, 1975) and Principle Component Analysis (Brons et al., 1991), and techniques related to Artificial Intelligence, like branch and bound (Siedlecki and Sklansky, 1993a) and genetic algorithms (Siedlecki and Sklansky, 1993b), are proposed.

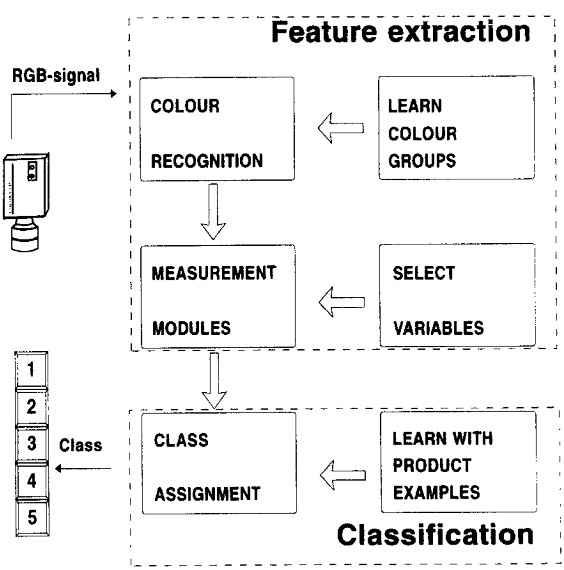

Fig. 1. Measurement procedure and training modules.

In this application a statistical method is used that is designed for a discriminant analysis. The optimal subset of variables is determined by a combination of a stepwise variable selection procedure using a statistical method described by McCabe (1975) and using general product knowledge. For any size an optimum subset is calculated. The subset is optimal in a sense that it produces the maximum U-statistic value. The U-statistic is a descriptive statistic which provides a measure of discrimination potential for the features considered. The determination of optimal subsets of variables is used as a basis for deciding what features to select. When talking with product experts or after looking at the different quality groups of plants it is obvious that some features must be included in the final subset. There can also be a computational reason to exclude a specific feature. The final selection of the subset is therefore based on a statistical analysis and practical considerations. Further research at this point will be necessary to develop an automatic feature selection method.

Finally in the classification stage the quality group of the plant is determined by applying pattern recognition techniques in the multi-dimensional feature space. The measurement data for the selected subset of features are used as input for the classification step. In the next section the pattern recognition techniques are described in more detail.

3. Pattern recognition

3.1. Introduction

For both the segmentation in colour clusters and the classification of the objects into a defined number of groups supervised pattern recognition techniques are used. Training sets for learning the colour classification are built using example products by selection of typical colours using the computer mouse. Training sets for product classification are built by creating product samples for the different quality groups. These products are measured by the image processing system and the feature vector is stored in combination with the group the object belongs to. Product experts build the training sets.

Several techniques are available for performing supervised classification. The methods can be divided into parametric and non-parametric classification. A parametric classifier assumes a functional distribution of given samples. Examples of parametric classifiers are the Bayes classifier and the discriminant analysis techniques. Non-parametric classifiers do not assume any functional distribution of the samples. The K-nearest neighbour rule, multi-class partitioning algorithms building decision trees and an NN classifier are examples of a non-parametric classifier (Talmon, 1986; Belkasim et al., 1992). For the plant classification application statistical discriminant analysis and NN techniques are used.

3.2. Statistical discriminant analysis

Discriminant analysis is a statistical technique to find the best way to distinguish between populations. For different classes probability density functions are calculated. From this discriminant axes are calculated so that the projections of the data points of the classes on the axes are separated maximally. Two different versions of this technique are used: linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA). For LDA the classes are assumed to be normally distributed. Furthermore, covariance matrices of the classes are equal. When covariance matrices are not assumed to be equal quadratic terms are introduced. The resulting multivariate classification method is called QDA. Algorithms to implement discriminant analysis are described by Fukunaga (1972) and Van der Voet and Hemel (1988).

3.3. Neural networks

A simulated NN is created to develop a computer model that matches functionality of the brain in a fundamental manner. NNs offer several potential advantages over statistical classification techniques. They are relatively robust and fault tolerant. Neural computing systems possess the capability to generalize information and get reasonable results with noisy or incomplete input (Masson and Wang, 1990; Neuralware, 1991). Practical advantages of NNs are easy implementation and prototyping. For some applications NNs get better or at least equal classification results as statistical classifiers (Brons et al., 1991; Lo and Bavarian, 1991; Rath, 1995).

3.4. Implementation

The statistical algorithms for feature selection and discriminant analysis are implemented in ANSI-C based on the algorithms described in the references (Fukunaga, 1972; McCabe, 1975). Since they are now available in a software library, they can be linked directly to the image processing software. Application of discriminant analysis is straightforward, because no adjustment of parameters is necessary.

All experiments with and implementations of the NN are done with the NeuralWorks Professional II/Plus software shell. With this toolbox fast prototyping and testing of several structures is possible (Neuralware, 1991). Training of the network is done off-line, but after training C-code for on-line classification can be derived. These algorithms can be linked with the image processing software.

4. Experiments

Numerous experiments with several types of plants have been done to examine the performance of the developed prototype. Ten types of flowered plants, three green plants, one half grown plant and five types of seedlings have been analyzed with the camera system. In this chapter two experiments for applications with a different degree of complexity are described.

4.1. Experiment 1: Sorting of saintpaulia plants

4.1.1. Problem description

This section describes an application where full grown saintpaulia (African violets) plants are sorted on colour, size and flowering stage. In the greenhouse plants with flowers of four different colours are grown. Full grown plants are sorted in three quality groups: stage 4, stage 2 and unacceptable plants. Plants are unacceptable if their size is below a specific value or when there are less than two open flowers. These plants will be put back in the greenhouse for further growth. Stage 4 plants have more open flowers than stage 2 plants. The discriminating functions for the different classes are different for specific customers of the plants and change during the growing season. Therefore a flexible and easily adjustable method for defining quality groups is necessary. For automatic filling of the plant trays according a specified colour palette the plants are also sorted on flower colour.

A colour camera was placed downward in an illumination chamber with five tube lights in a horizontal position on both sides of the belt. Philips tube lights type TLD-HF83 (warm white) were used to get maximum contrast between the different flower colours. The conveyer belt was white, because this colour was not present in the plants.

4.1.2. Colour clustering

For colour recognition the red, green and blue (RGB) images were segmented into seven meaningful colour groups (1 = background; 2 = leaves; 3 = pink flower; 4 = light blue flower; 5 = red flower; 6 = blue flower; 7 = yellow). The training set was built by selecting pixels using the computer mouse in example images of plants with different flower colours. The training set consisted of RGB values for 200 pixels, the test set contained RGB values for 240 pixels.

For the NN the RGB values were used as input, divided by 256 to get values in the range from 0 to 1. For each colour class an output neuron was defined. For learning the relevant output neuron was fed with the value 1, all others with 0. When classifying, each image pixel was assigned to the class connected with the output neuron having the maximum output value. Several fully connected feedforward networks with a backpropagation learning schedule have been tested. Variations were made in the number of hidden layers (one or two), the learning rule (delta rule, perceptron rule and cumulative normalised delta rule) and the transfer functions (linear, sigmoid and tanh). Also the number of neurons in the hidden layer were changed, starting with one up to maximally the total number of inputs and outputs.

4.1.3. Product classification

The plants are sorted into three quality groups based on the total projected area and the flower area. The total plant area is calculated by adding all pixels classified as non-background pixels in the region of interest. The flower area is determined by adding all pixels classified as one of the flower colours. Both the total area and flower area are converted to mm^2 using a geometric calibration. Finally the flower

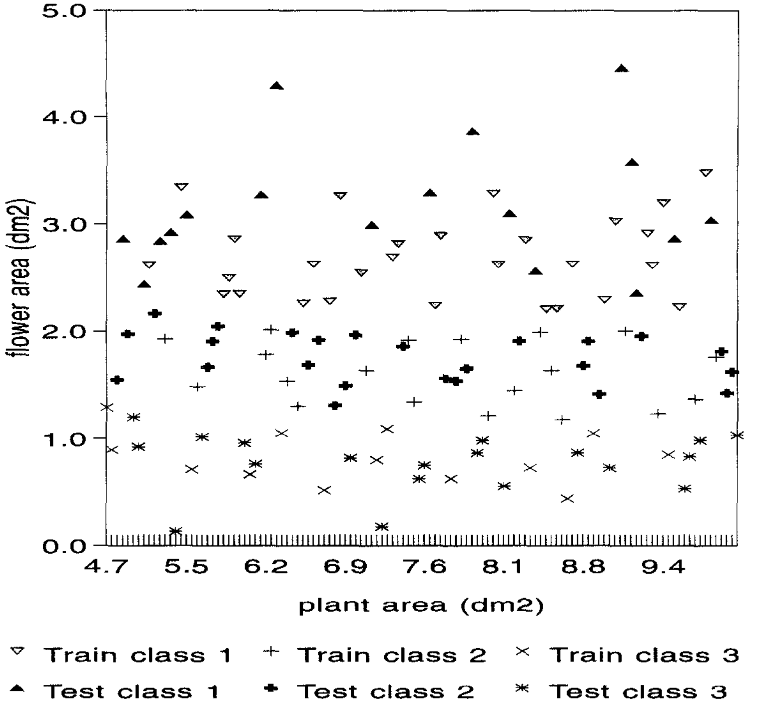

Fig. 2. Classification space with training and test set for saintpaulia quality.

colour is derived from the maximum number of pixels in one of the flower colour classes. Both the training and test set enclosed 60 examples of plants and were selected by a product expert. In Fig. 2 the distribution of the training and test set is displayed. An NN structure with two input neurons, a hidden layer with three neurons and three output neurons was used. The scaled values for the total plant area and the flower area were used as input. For each class an output neuron was specified.

4.2. Experiment 2: Sorting of cactus plants

Experiment 2 describes a sorting application of cactus plants (cactaceae). The classification of the specific type of cacti is based on the number of shoots and the area of the shoots. The plants are sorted into six classes according to criteria defined by a product expert. Table 1 gives a summary of the criteria. The most important criteria for classification is the number of shoots. Cacti with one, two and three or more shoots have to be separated. Each group is also separated in two classes based on the size of plant. For classification in size, for plants with more than one shoot, not only the total area is important, but also the size distribution of the individual shoots.

The same camera and lighting configuration as for experiment 1 was used. The camera was looking downward and the background had a light blue colour. The

Table 1
Cactus classification criteria

Class	1	2	3	4	5	6
No. shoots	1	1	2	2	≥ 3	≥ 3
Size	small	big	small	big	small	big

colours of the cactus parts were between light and dark green, with white prickles. Because there was a high colour contrast between background, pot, ground and cactus area the LDA method was appropriate for colour segmentation. Less than 1% of the image was misclassified.

For the classification in six quality groups five parameters were used: total projected area (mm^2); length/width ratio (maximum/minimum diameter through the optical centre); shape factor (4π area/squared perimeter); polygon shape (polygon contour area/total area); and convex hull shape (convex hull area/total area). The training set contained 60 plants, the test set 61. An NN structure with five input neurons (one for each parameter), one hidden layer and six output neurons (one for each class) was built. The backpropagation learning schedule was used with the delta rule for weights adjustment and a tanh transfer function. The number of neurons in the hidden layer varied between 2 and 11.

5. Results

5.1. Experiment 1: Sorting of saintpaulia plants

5.1.1. Colour clustering

In Tables 2, 3 and 4 the classification results for the colour recognition are displayed for LDA, QDA and the NN classifier. From the tested NN structures a fully connected network with one hidden layer containing eight neurons, with application of the delta learning rule with a tanh transfer function, gave the lowest error. Fig. 3 shows the network structure.

Table 2
Colour classification with LDA

Colour	Classified colour class						
	1	2	3	4	5	6	7
1	39						
2	2	51	1		2		
3		1	16	8			
4			12	40		2	
5				1	21		
6					1	15	
7	1						27

Total errors: 12.9%.

Table 3
Colour classification with QDA

Colour	Classified colour class						
	1	2	3	4	5	6	7
1	37	2					
2	2	51			3		
3		1	20	4			
4			3	51			
5					22		
6						16	
7		1					27

Total errors: 6.7%.

Table 4
Colour classification with NN

Colour	Classified colour class						
	1	2	3	4	5	6	7
1	37	1					1
2		55	1				
3			24	1			
4			4	50			
5		1			21		
6				1		15	
7	1						27

Total errors: 4.6%.

For this experiment QDA was superior to LDA and the performance of the NN was better than QDA. For building the training and test set proportionately many pixels close to overlapping areas were selected. Doing so the edges of the colour clusters were better defined. An error percentage of 4.68 for the training set means that less than 1% of the total image is misclassified. Misclassification of the colours has effect on the estimate of the flower area and the flower colour. An error rate of 1% for the total region of interest is more than acceptable for the total system performance.

5.1.2. Product classification

Nearly no mistakes are made at determining the overall flower colour. The system is now implemented in a Dutch greenhouse and the false recognition rate of the plant colour is less than 0.1%. This means that during normal operation at a speed of 3000 plants per hour less than three plants are misclassified on colour in one hour.

As can be noticed in the two-dimensional classification space (Fig. 2) the clusters can be separated with a linear function. In Table 5 the classification results for the LDA, QDA and NN are displayed. From the experimental results it can be noticed

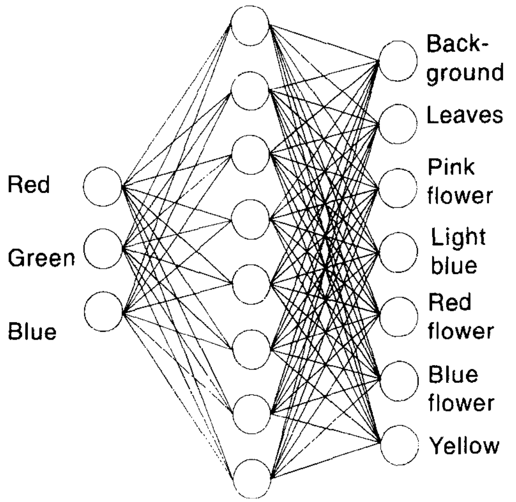

Fig. 3. NN structure for colour classification of saintpaulia plants.

Table 5
Classification with LDA, QDA and NN

	LDA [a]			QDA [b]			NN [c]		
Class	1	2	3	1	2	3	1	2	3
1	17			17			17		
2		24		1	23			23	1
3			19			19			19

[a] Errors: 0.0%.
[b] Errors: 1.7%.
[c] Errors: 1.7%.

that for a classification problem with low complexity there is hardly any difference in performance between the tested pattern recognition methods.

5.2. Experiment 2: Sorting of cactus plants

In Tables 6, 7 and 8 the classification results with LDA, QDA and NN are displayed. An NN with seven neurons in the hidden layer gave the lowest error after training. For the classification two types of errors are defined. Since the primary separation is based on the number of shoots an error is rated as critical when the number of shoots is classified wrong. The critical errors with LDA, QDA and NN are, respectively, 9.6, 6.6 and 1.6%.

This classification problem is relatively complex, because the clusters cannot easily be separated in the classification space. For this reason the NN gives better results than LDA and QDA, because an NN can also model non-linear relations. This experiment was used in the feasibility study as a prototyping method. As results

Table 6
Cactus classification with LDA

Class	Classified class					
	1	2	3	4	5	6
1	5	1				
2		7				
3			12			
4				6		
5			1		12	1
6			3	2	2	9

Total errors: 16.4%. Critical errors: 9.8%.

Table 7
Cactus classification with QDA

Class	Classified class					
	1	2	3	4	5	6
1	5	1				
2		7				
3			12			
4				6		
5			1		12	1
6			2	1	1	12

Total errors: 11.5%. Critical errors: 6.6%.

Table 8
Cactus classification with NN

Class	Classified class					
	1	2	3	4	5	6
1	5	1				
2		7				
3			12			
4				5		1
5					14	
6					1	15

Total errors: 4.9%. Critical errors: 1.6%

of the NN classifier were promising it could be concluded that implementation was possible. Finally the cactus sorting procedure was implemented using structural shape recognition techniques. All individual cactus shoots were recognised, their sizes calculated and classified with LDA.

6. Discussion

The classification technique that gives the best results depends on the complexity of the application. As can be expected, applications with low complexity level can satisfactorily be implemented with a linear classifier. For applications with low complexity levels different quality groups can easily be separated in the feature or colour space. The plant classification in experiment 1 is a good example of such a low complexity classification problem.

The QDA technique gave better results than LDA for more complex situations. From experiment 1 it can be noticed that QDA is better as LDA for the colour classification and the NN gives only a minor improvement over QDA. To train the colour recognition an on-line procedure has to be available, because of the regular switch between learning and testing. The learning procedure can be stopped when the majority of the pixels is classified correctly, or when no improvement is achieved with further learning of points. Learning of an NN structure takes longer computing time. Because of this QDA is in general chosen for colour classification.

NNs gave for less complex applications at least equal results as LDA or QDA. For more complex applications the NN classifier showed better results. For the cactus classification in experiment 2 only the NN gave acceptable results.

Performance of a certain classifier for a specific application is not the only reason to prefer a specific technique to be applied in practical situations. Robustness of the learning technique, easiness to adjust and learn, verification and visualisation possibilities, education level of the end-user are important aspects to consider when taking the decision what classification technique to use. A disadvantage of applying NN classifiers is the optimisation process of the structure. There is no universal network structure or general recipe that can solve all possible classification problems. The construction of the training set is for a network more important than for discriminant analysis. When applying discriminant analysis the classification space can be visualised. The structure of an NN is more or less a black box. For objects that are not covered by the product examples, sometimes classification results are unpredictable and not acceptable with an NN.

7. Conclusions

ATO–DLO has built a flexible sorting system for pot plants. The brain of the machine is a colour image processing system. In cooperation with industry the system is completed with conveyer belts and is commercially available.

Product knowledge is incorporated in the feature extraction and classification step. In the first step of the feature extraction the colour images are compressed into meaningful object groups. This classification procedure is trained by showing product examples. In general a discriminant analysis method is chosen to separate colour groups. In the second step of the feature extraction relevant features are measured of each object.

The set of variables is optimised for each type of plant using product knowledge and a special statistical subset analysis tool. After extraction of the measurement variables from the image the object is classified into a product group using pattern recognition tools. Statistical discriminant analysis (linear and quadratic) and NN techniques are used for pattern recognition. The system is trained by showing product examples to the camera.

The system has been successfully tested on several types of full grown plants, half grown plants and seedlings. The selection of the best pattern recognition technique depends on the complexity of the application. LDA and QDA have only limited capabilities to segment the feature space into clusters. Deformed or separated groups cannot be separated with the selected discriminant analysis methods. With an NN structure it is possible to construct deformed clusters and therefore NN is superior for more complex problems. For these types of classification problems complexity can be associated with the distribution and shape of groups in the multi-dimensional feature space.

The performance of the NN classifier is at least as good as the LDA or QDA classifier. A disadvantage of applying the NN is that the building and learning of the network is up to this moment a task for experienced system developers.

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