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Human vs Computer: Image processing to detect overlapping plants

In order to solve the overlapping problem that occurs when performing identification of single plants, a computer base pattern recognition system was implemented. The presented technique has 3 general steps: The recognition of overlapping or non-overlapping leaves using ellipse detection; an ellipse landmarking step that allows the creation of deformable models that define specific characteristics of the plants and the use of ASMs (Active Shape Models) that permit the identification of plantlets in complex situation without having to use the extracted color information. This method was tested using overlapping *Nicotiana tabacum* seedlings. Furthermore, a comparison between the recognition of the computer system and the human perception shows that in average the brain-eye system performs better. However, there are cases where the implemented algorithm has better identification results than the identification performed by student drop-outs. The presented methodology is being used is a Laser based weed control system.

Keywords
Image processing, overlapping problem, active shape model, plant production

Abstract
Landtechnik 67 (2012), no. 3, pp. 172–178, 11 figures, 2 tables, 20 references

Computer vision is one of the key technologies in the development of autonomous systems. Its use favors the development of highly automated production processes in the industrial production, as well as many technical systems in crop production such as the control of machinery or the quality control. In contrast to industrial applications, image processing in plant sciences often takes place under natural conditions that create non-standard unknown environments. A list of specific characteristics of image processing in plant production is shown in **Table 1**. Furthermore, a particular difficulty is the occurrence of overlapping and incomplete objects, which often leads to problems in the identification. Overlapping is defined as an object partially covered and therefore only partially visible [1]. This particular problem in natural and open field systems is of great relevance and until now has not being fully solved. Literature of the last decade demonstrates that the aforementioned statement is valid and up to date [2–9]. Due to the importance of this topic, “overlapping in the crop production”, it was included as a part of a research project at the Leibniz Univer-

Table 1

Specific characteristics of image processing in plant production

Besonderheit ***Specific characteristics***	**Ursachen** ***Reasons***
Komplexe und unterschiedliche Objekte *Complex and different objects*	natürliches Wachstum; offenes, unbek. System *natural growth, uncontrolled system*
Wechselnde Randbedingungen *Changing boundary conditions*	Wetter-/Lichteinflüsse; Freilandsystem *influences of weather, light and open field conditions*
Überlappende und unvollständige Objekte *Overlapped and uncomplete objects*	unbekannte Objektanordnung; Realsystem *real system with unknown object arrangements*

Fig. 1

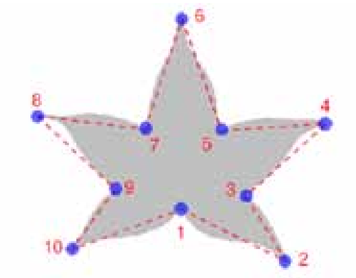
Demonstration of the overlapping problem using Nicotiana tabacum seedlings

Table 2

Image processing for pattern recognition

Analyseprozess ***Analytical process***	**Algorithmen-Beispiele** ***Algorithm examples***	**Wirkung** ***Effect***
Bildmanipulation auf der Basis von Punktoperatoren *Image manipulation using point operators*	Grauwertspreizung, Schwellenwertfilterung,... gray-scale enhancement, thresholding,...	Kontrastverstärkung,.../*enhancement,...* Pixelselektion,.../*pixel selection,...*
Bildmanipulation auf der Basis von lokalen Operatoren *Image manipulation using local operators*	Mittelwertfilterung, Sobel-Filterung,... *mean operator, Sobel operator,....*	Eliminierung von Bildstörungen,.../*image noise reduction,* Kantendetektion,.../*edge detection*
Bildtransformation *Image transformations*	Hought-Transformation, Fourier-Transformation,... *Hough-Transformation, Fourier-Transformation,...*	selektive Bilddatenverdichtung,... Rauschreduktion,... *selective data reduction, noise filtering,...*
Merkmalsgenerierung *Feature selection*	Binarisierung, „Landmarking"... *binarization, landmarking, ...*	Vermessung von Formen, Reduktion auf Konturen,... *shape analysis, contour extraction,...*
Objekt-Modellierung *Object/Shape modelling*	Diskriminanzanalyse, „Active Shape Modelling" (ASM),... *discriminant analysis, active shape modelling (ASM),...*	statistische Clustereinteilung... Formerkennung... *statistical clustering... shape recognition ...*

Fig. 2



Landmarks (blue) in a fixed order (red numbers) and the resulting model (red dashed line) of a sweet gum leaf Liqidambar styraciflua

sity of Hannover, with the purpose of developing computer image processing algorithms that solve the problem [10]. In order to solve the problem, overlapping seedlings of Nicotiana tabacum were used (**Figure 1**). The validation of the developed systems are difficult because no standard or reference study existed. Therefore, the accuracy of the algorithms was assessed on the base of a comparison between human "image processing capacity" and computer solution to the problem. The results of this comparison are presented below.

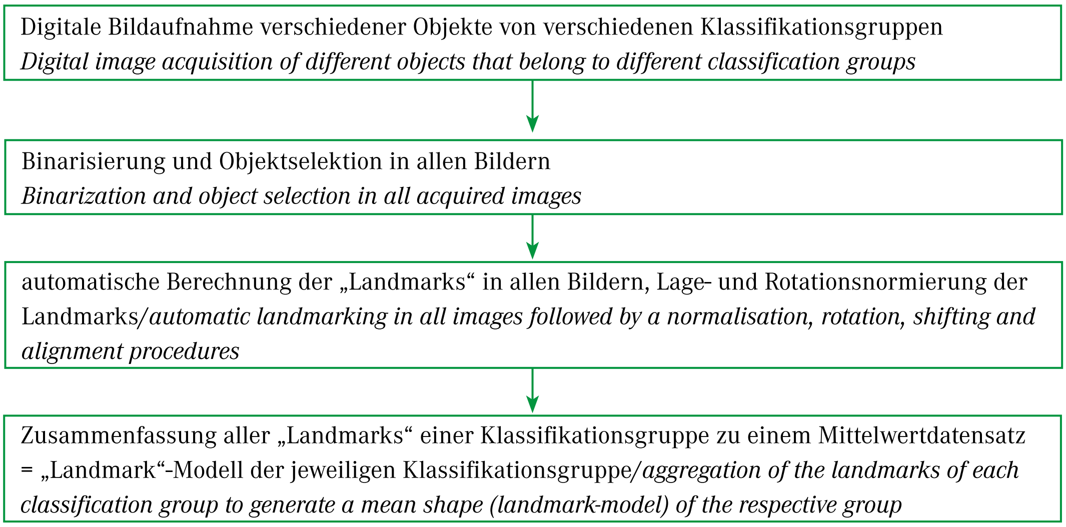
Basics

Image processing means the compression and analysis of pixel data, where despite of their high resolution, they do not provide numeric information that would allow the decision making nor the control of processes. The human visual perception is complex and not yet fully understood, however, it is believed that the learning process in the first years of life creates a model idea of the surrounding world [11, 12]. In contrast to this, computer based image analysis has specifically defined methods for data compression of real information to image points. **Table 2** presents the basic types of analysis involved.

Image manipulation leads essentially to image enhancement. Image transformation, feature extraction and object-modeling lead to data compression for the evaluation of the images [13]. With regards to the work presented here, particularly the landmarking process and the modeling using ASM, there are important aspects to be mentioned. Landmarking tries to bring out specific edge points of image shapes to characterize objects. **Figure 2** shows the landmarks of a leaf. There are several methods to do this automatically and also to bring the landmarks in a corresponding order [14, 15]. From **Figure 2** it is clear that the landmarking process ultimately produces a simplified model of the object. In addition to the landmarking process, Active Shape Modelling (ASM) is of great importance. This technique was first proposed by Cootes et al. [16, 17] and it allows statistically oriented pattern recognition. After identifying the landmarks of the objects in the training set, groups were created and then transformed (translation, rotation, scaling). Subsequently, an average model of each identified group was created. **Figure 3** summarizes the necessary computational steps.

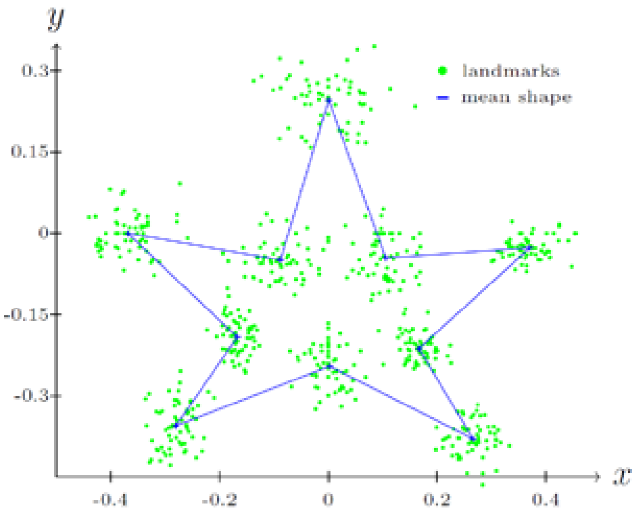
Figure 4 shows a resulting average model. One should note that this process is executed for each identified group. If an unknown shape is to be classified into a corresponding group it has to be compared with each generated mean shape, which was assigned to represent an object type or a group. The landmarks of the object in question have to be deformed until they overlap 100 % with the mean shape that is being compared to. The determination of the object type is done by selecting the group classification, in which the energy to bend landmarks is minimum. The calculation of the necessary deformation energy is based on statistical-algebraic calculation methods. Detailed information can be found at Pastrana [18]. **Figure 5** summarizes the basic procedure for the analysis of an unknown situation with multiple objects together.

Fig. 3



Modelling using the ASM-method (active shape modelling)

Fig. 4



Landmark-model of a sweet gum leaf Liquidambar styraciflua, green: normalized landmarks of different leaves; blue crosses: landmarks that identify the mean-shape; blue line: graph of the mean-shape (model); X,Y: Cartesian coordinates

Created image processing algorithms

To solve the overlapping problem in image processing and crop production, a 3-step algorithm system was developed. This method solves the problematic of identifying overlapping seedlings with reasonable precision, and at the same time it is transferable to other situations. The methodology is built on the following steps:

1. Detection of basic shapes or plant elements that permit the modeling and accurate identification in spite of overlapping. The ellipse was selected as the universal basic form, (**Figure 6**). With them, elongated, as well as, circular structures and all the intermediate forms can be represented. Moreover, by using the ellipse radii it is possible to include the direction in the models. **Figure 7** shows some examples from the plant domain. For the mathematical description and detection of ellipses, see Weisstein [19] and Pastrana [18].
2. Description of the basic pattern using landmarks and their aggregation to form a complete object: Each ellipse is characterized with 5 landmarks (**Figure 8**). The representation of a plant consists of several ellipses or leaves group together. A plant has an additional landmark: its center, which is used as an anchor in the rotation step. In the present study, seedlings with up to 4 leaves or cotyledons were taken into account.
3. Selection of the most probable pattern using ASM algorithms: **Figure 9** shows the developed ASM approach. It is essential to mention that the composite of ellipses into plants is based on an ASM concept. After all sorts of free and overlapping ellipses were detected in the image, the selected combinations were those in which the deformation energy to an existing model plant was minimum. The necessary calculations, boundary conditions and parameters are given at Pastrana [18].

Tests and applications

The developed algorithms have been used and successfully tested in various real scenarios. *Nicotiana tabacum* plants were sown with varying degrees of overlapping and then evaluated with image analysis. Naturally, the success and accuracy of the plant identification depends on the degree of the overlapping situation, and was between 100 % and 25 % accuracy.

These results include scenarios in which the overlapping area was more than 30 %. In a situation where the overlapping area is over 50 %, a theoretical detection is no longer possible because the objects are completely hidden and the information is insufficient. The algorithms described here were used in a laser-based weed control project for the determination of the target position, with highly accurate results [20].

Fig. 5

Digitale Bildaufnahme der zu analysierenden Situation, Bildbinarisierung und Objektselektion, automatische „Landmark"-Berechnung für alle selektierten Objekte/*digital image acquisition of the scene, binarization and object selection, automatic landmarking für all selected objects*

↓

Vergleich normierter „Landmarks" der unbekannten Objekte mit den „Landmark"-Mittelwertdatensätzen aller vorher erfassten Klassifikationsgruppen/*comparison of all possible landmark sets found in the unknown scene with mean shapes of the classification groups*

↓

Zuordnung der unbekannten Objekte jeweils zu der Klassifikationsgruppe, die die ähnlichsten „Landmark"-Konstellation aufweist (minimale „Landmark"-Verbiegungsenergie)/*assignation of each landmark set to its corresponding classification group using a minimal energy deformation heuristic*

Usage of the ASM-approach to analyse an unknown situation with multiple objects

Fig. 6

Ellipses as a powerfull model to approximate palnt leaves (first row left to right: Galium aparine, Amaranthus retroflexus, Chenopodium album; 2nd row left to right: Senecio vulgaris, Apera spica-venti, Beta vulgaris)

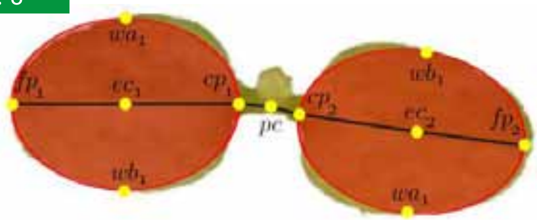
As aforedescribed, the precision of the procedure is highly dependent on the randomness of the natural growth. Therefore in further experiments the algorithms were tested on semi-real overlapping situations and also compared with human recognition ability. In this experiments images of non-overlapping plants were shown to 16 different individuals. By using image processing tools images of real plants were superimposed and distributed in various overlapping scenarios, which had range of overlapping area between 0 % to 32 % (**Figure 10**). All these scenarios were analyzed automatically with the implemented algorithms. At the same time, the different groups of people also carried out the identification analysis. One group was composed of academics over 25 years with college degree in the field of plant cultivation. The other group was composed of 15 to 16 year old pupils in a final year of a basic school.

In both cases, the subjects received black and white images of scenarios with overlapping plants. The machine was provided with the same scenarios, in which it had to solve the overlapping problem by counting and localizing the single plants. It is important to mention that before each person received the

Fig. 7

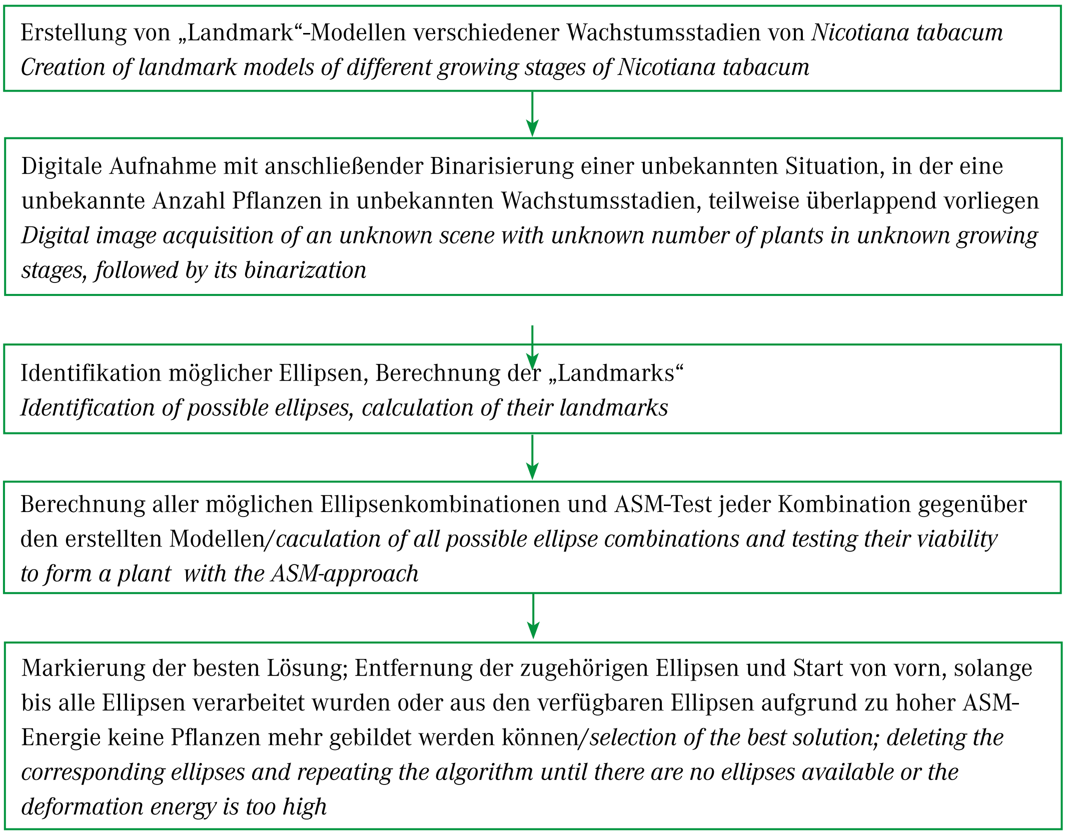
Ellipse detection in a simple overlapping situation

Fig. 8



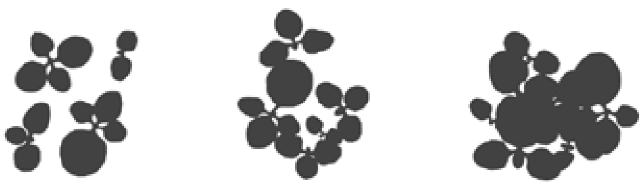
Ellipsen as a basic module in plant detection – 2-leaf seedling (Nicotiana tanbabum) with detetected ellipses and their corresponding landmarks

Fig. 9



Algorithm to detect plants based on an ASM-approach

Fig. 10



Examples of test scenarios for the evaluation of the algorithm accuracy with 0, 1 and 32 % (from left to right) overlapping area

overlapping cases, black and white images of single plants were shown to them, so that they had an idea of the plants they were looking for. Then, pictures with eight different difficult overlapping scenarios with defined overlapping areas were handed out (see **Figure 10**). The task was to highlight the matching plants, and there was no time limit.

The evaluation of the tests was carried out using a fixed scheme for both, the computer image analysis and the humans:

1. For each correctly detected plant one point awarded.

2. For recognized leaves, if they were not used in the formation of a plant, no point was awarded.

3. The detection of the leaves of a plant was right, but they were associated to the wrong plant, each plant properly allocated and assigned gave a point, each faulty plant deducted a point.

4. A leaf was detected with more than one ellipse, and faulty plants were assigned to these ellipses, for each wrong plant a point was deduced.

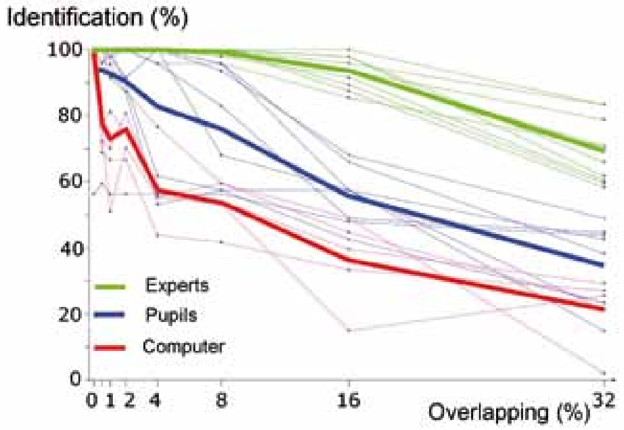
5. The calculation of the recognition was done with (total points / total number leaves) • 100 [%].

Results

Figure 11 shows the results in the form of a graph: single thin lines represent the values of the different persons and runs with the computer program. The bold lines show the respective mean of the group. It will be seen that the success of computer algorithms clearly depends on the scenario. Especially in milder overlaps the algorithms seem very susceptible to this trend.

If one is aware that the overlap in practice is below 10 %, the computer had very good results, with outcomes over 50 %. The comparison between the detection success rates shows that in all cases, the academics achieved significantly better recognition results than the computer. They identified overlapping situations with up to 8 % overlapping area without any errors. Nevertheless, something different can be seen in the results of the pupils: Within the test group there were large fluctuations in recognition task, this behavior can be explained with inhomogeneous structure of the class. On average the pupils executed the task better than the computer, but in some cases, the computer was better than the human brain. Furthermore, it was quicker than persons.

Fig. 11



Accuracy of the automatic identification prcocedure with image processing in comparison with human intelligence

In further developments, the algorithms were transferred to the 3-dimensional space. There instead of the ellipses, ellipsoids were used and all two-dimensional algorithms were extended to the 3-dimensional case. Because an overlap of objects in the 3-dimensional space is not possible, overlapping pores in substrates (recorded with a tomographic machine) were tested. Due to lack of visualization possibility the algorithm was better than human recognition.

Conclusions

The overlapping problem in agronomic oriented image processing was solved for first time, at least to some degree. This was done using ellipses as the basic shape, ASM methods to reconstruct shapes. The algorithms were successfully tested in real situations. Currently, the system is being used with great success to control a laser system. Improvements of the methods are planned in the future work, especially where stability and consistency is required. The comparison with human intelligence revealed on average a lower sensitivity and accuracy of the computer system. In some cases, however, the image processing algorithms was superior to some of the persons that were tested. This means that complex and difficult situations can be analyzed with the use of a computer that possesses an intelligent problem solving behavior. In principle, the developed approaches can be used, due to the good generalization, in crop production, harvesting and also in the control of plant protection measures or implements. A fully automated production in selective and complex situations gets more and more into the realm of possibility.

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