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Image Processing for Plant Determination Using the Hough Transform and Clustering Methods

Bildverarbeitung zur Pflanzenbestimmung mit Hilfe der Hough-Transformation und Cluster-Methoden

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Summary

One important goal of future crop production is to reduce the usage of herbicides. In many circumstances automatic detection and determination of weeds and crops is necessary for feasible weed control. Previous approaches in the area of computer vision based plant classification in a natural environment have only limited success, especially under variable field conditions with overlapping plants.

The objective of this study was to apply a technique to cluster objects classified by a computer vision system in order to recognise not only single leaves but also whole plants.

Images of the crop were obtained using a device that blocked out the natural light to provide controlled artificial lighting conditions. The crop rows were calculated from the determined plant positions. Plants which were not located in the row were labelled as weeds. It has been investigated, whether information on the row position can be used to reduce the classification errors.

With this approach plant classification under field conditions can be improved and a plant classification accuracy of over 90 % for cabbage and 70 % for carrots has been obtained. The results clearly depended on the growing stage of the crop, on specific parameters of the row identification process and on the question whether the type 1 error (not identified crops) or the type 2 error (weed classified as crop) should be minimised.

Zusammenfassung

Eines der herausragenden Ziele des modernen Pflanzenbaues ist die Verringerung des Herbizid- und Pestizideinsatzes. In vielen Situation und Anwendungen ist eine automatische Erkennung und Differenzierung von Unkräutern und Kulturpflanzen Grundvoraussetzung für eine effektive Unkrautbekämpfung.

Ziel der hier vorgestellten Arbeiten ist es, neue methodische Ansätze zu beschreiben, bei denen die bildanalytische Pflanzenklassifikation nicht nur auf der Klassifikation von Pflanzeneinzelblättern sondern auf der Analyse der Gesamtpflanzen und der Pflanzenreihen beruht. Die Einzelpflanzen wurden mit Hilfe eines Clusterverfahrens aus aufbereiteten Bestandesbildern (aufgenommen mit einem mobilen Kamerasystem) zusammengesetzt. Anschließend erfolgte die Bestimmung der Pflanzenreihen aufgrund der ermittelten Pflanzenpositionen mit Hilfe der Hough-Transformation. Die berechneten Pflanzenreihen wurden danach genutzt, um rückwirkend die bereits erfolgten Pflanzenklassifikationen noch einmal zu optimieren. Die Versuche wurden mit unterschiedlichen Verunkrautungen in Kohl- bzw. Möhrenkulturen unter Glas und im Freiland durchgeführt.

Es konnte gezeigt werden, dass mit diesem methodischen Ansatz die bildanalytische Pflanzenklassifikation (bzw. die Pflanzentrennung zwischen Kulturpflanzen und Unkräutern) bei Kohl- und Möhrenkulturen verbessert werden kann und eine Erkennungsgenauigkeit für Kohl von über 90 % und für Möhren von 70 % erzielt wird. Die Klassifikationsergebnisse hängen jedoch maßgeblich vom Wachstumsstadium der vorhandenen Pflanzen, von spezifischen Parametern der eingesetzten Algorithmen und von der Frage ab, ob der Fehler erster Art (nicht identifizierte Kulturpflanze) oder der Fehler zweiter Art (als Kulturpflanze identifiziertes Unkraut) minimiert werden soll. Zukünftige Arbeiten sollten die beschriebenen Ansätze zur Optimierung der bildanalytischen Pflanzenklassifikation von Reihenkulturen nutzen.

Introduction

Weed control is one of the most time-consuming activities in agriculture. At present, most herbicides are uniformly sprayed in the field, which can result in environmental pollution. With a large within-field variation in weed occurrence and density, precision mechanical control or precision spraying of weeds will lead to herbicide savings (HÄUSLER et al. 1998). Having detailed information about the plants and weeds will offer the possibility to implement such a system on a crop protection robot. Furthermore such a system could be used to generate a weed map of the field which perfectly integrates in the concept of Precision Farming. However, these techniques require the detailed information about plant positions which can be obtained by image processing techniques. Most open field crops are cultivated as row-crops. This offers the possibility to use the information about the row position to reduce the error of identifying weed plants as crops.

In the field of plant identification there have been numerous publications. The most often used approach



Fig. 1. The greenhouse test stand: (a) rack with cameras; (b) the rack covered with lightproof PE-film
Gewächshausversuchsstand: a) Träger mit Kameras b) Träger mit Lichtschutz (PE-Folie)

is to extract shape features from digitised images of plants and to use these features for identification models (PETRY and KÜHBAUCH,1989; TIAN and SLAUGHTER 1993; WOEBBECKE 1995; SÖKEFELD et al. 1996; PÉREZ et al. 2000). More recent studies also investigated colour and/or textural features of the objects. In the area of individual plant identification an average identification accuracy from 30 to 77 % (MEYER et al. 1998) for the discrimination of different weeds (laboratory conditions); 61 % for identifying tomato seedlings in the open field (TIAN and SLAUGHTER 1993) and up to 95 % for distinguishing weeds and cabbage plants in the open field (HEMMING and RATH 2001) were realised.

Several research groups successfully localised the plant rows by means of image processing. The Hough transform has been used most commonly (MARCHANT and BRIVOT 1995; BILLINGSLEY and SCHOENFISCH 1997; PLA et al. 1997; SANCHIZ et al. 1998). PÉREZ et al. (2000) computed the positions of the crop rows by defining a kind of histogram of a binary image so that the plant pixels were summed per column (in the row crop direction). TILLETT and HAGUE (1999) used an approach where the pixels of a grey value image are explored in relation to a threshold in both directions along a horizontal line. The developed system was able to operate in real-time under field conditions. SOUTHALL et al. (1999) were able to navigate a vehicle along the crop rows using a Kalman filter to fuse information from proprioceptive sensing (odometry and inertial sensors) with data from a vision system. They used a grid-like model representing the planting geometry of the crop to classify plants located outside the grid as weeds. In almost all other research projects carried out so far, the result of the row tracking was used to guide a vehicle or tools along the crop row but not as a plant classification tool.

Objective

Previous approaches in the field of computer-vision-based plant classification under natural conditions often had limited success because of the variable field and crop conditions. An improvement of the plant identification can be obtained by integrating the plant's microstructure (the single parts of the plant) or the macrostructure of the plant stand (e.g. plant rows). Plant classification systems based on the recognition of microstructures (e.g. leaves) need splitting algorithms, which segment the input images in regions of interest (ROI). After analysing these ROI, methods are needed to merge the corresponding regions to a full plant. For the integration of macrostructures special methods are required to filter and to extract this information from the available data.

The objective of the work presented here is to develop and to test algorithms and techniques for the differentiation of plants and weeds, which merge
1. Parts of a plant to a complete plant.
2. Single plants to a complete plant stand (plant rows).

Materials and Methods

The experiments described were carried out at the Institute for Horticultural and Agricultural Engineering at the University of Hanover, Germany. Two crops with different leave shape were used in greenhouse and open field experiments: Cabbage *(Brassica oleracea* L. conv. *capitata* var. *capitata)* and carrots *(Daucus carota* L.*)*.

Greenhouse and open field set-up

A mobile carrier rack was constructed to simulate a tractor drive inside a greenhouse. The rack carried three cameras, the video electronics and the illumination system. The rack was covered completely with lightproof PE-film to block out the natural light (Fig. 1). Using this system the problem of changing light conditions could be avoided. The crops were cultivated as in horticultural practice. For the greenhouse experiments extra weed seed was added to create a population with high weed density. For the open field experiments a tractor add-on unit was built. Comparable to the greenhouse test stand, lamps and cameras were mounted inside a steel-tube rack covered with lightproof PE-film (Fig. 2). The crops in the open field were also cultivated as in horticultural practice. No weed control has taken place. The main weed species emerged in the greenhouse and open field experiments were *Alopercus myosuroides, Galisonga ciliata,, Lamium amplexicaule, Matricaria discoidea,*

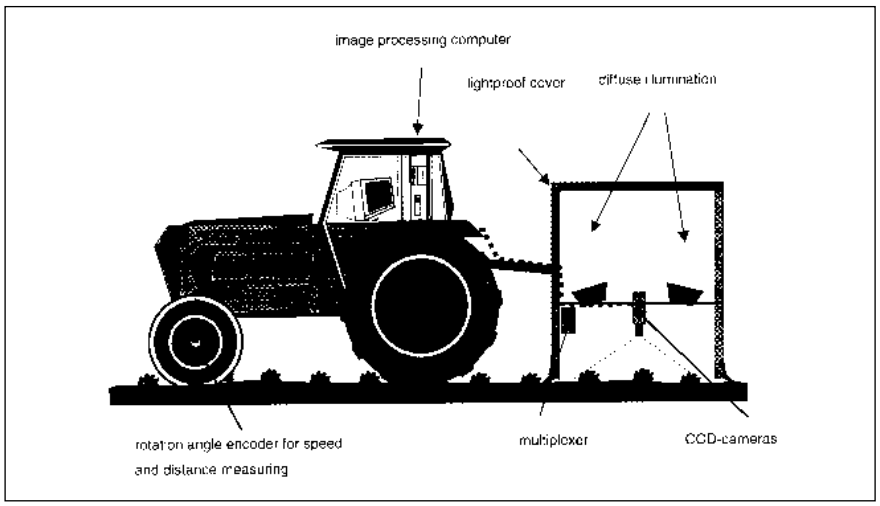


Fig. 2. Components of the open field image processing system
Komponenten des Freiland-Bildverarbeitungssystems

Oxalis corniculata, Ranunculus arvensis, Taraxacum officinale and *Urtica urens*. The positions of weeds were recorded and used for the experiments. The images of the plants were taken between 24 and 34 days after seeding to investigate different growth stages. Depending on the crop variety, the recording area per image was varied between 350 x 263 mm and 600 x 450 mm.

Computer vision system

A standard PC with 350 MHz PII processor was used for the digitisation and the analysis of the images. The images were captured with a Matrox Meteor red, green, blue (RGB) framegrabber card and analysed with the software package HALCON 5.01 (MVTEC 1998). Three 1/2"–3-chip colour charge coupled device (CCD) cameras (Hitachi, HV–C20) were used to achieve a satisfactory image resolution and a sufficient width of the recording area. The images were captured as 24-bit colour images with a resolution of 768 pixels by 576 pixels. A specially designed multiplexer was used to switch between the cameras during the drive. The cameras were mounted in such a way that a part of each image overlapped in the horizontal direction with the neighbouring images. The overlapping in the forward direction was achieved by the movement of the machine. A shift between the images which could be caused by a rotation or vibration of the vehicle always affected all images in a row and was tolerated for the experiments. In the open field determination of the distance covered by the machine was calculated by counting the impulses generated by a rotation angle encoder attached to the axis of the left front wheel. For the greenhouse experiments the distance covered could be computed via time due to the constant speed of the rack. The analysis of the images was carried out off-line.

Algorithm development

Binarization

For the separation of plants and background all images were transformed from the RGB to the hue, saturation and intensity (HSI) colour space. Threshold values for the plants for the channels H, S and I were determined by manually selecting areas containing the plants on sample images. By applying a three-dimensional threshold to the image, the regions of interest (the plants) were separated from the background. Due to the controlled lighting conditions it was not necessary to adapt the thresholds during the experiments.

Plant classification

After binarization of the images the single plant leaves were segmented as binary regions with morphological image processing operators. For every region (object) eight different morphological and three colour features were calculated and a joint feature space was built. Statistical analyses were carried out on the basis of sample data sets of each class to determine the features that were suitable for discrimination. A membership function based on statistical values is formed and used for the classification. The objects were divided into the two classes "crop plant" and "weed plant". A more detailed description of the classification procedure can be found in HEMMING and RATH (2001) and HEMMING (2000).

The result of the automatic classification was compared with the result of a manual classification (by a human) of the images to calculate the identification success. The type 1 error (percentage of not identified crop plant area) and the type 2 error (percentage of weed plant area classified as crop plant area) were computed.

Total plant recognition, cluster analysis

a) Basics
Cluster analysis methods divide the set of processed feature vectors into subsets (clusters) based on the mutual similarity of subset elements. Each cluster contains feature vectors representing objects that are similar according to the selected object description and similarity criteria (SONKA et al. 1993).

b) Application
In the experiments presented here a cluster analysis was computed with the regions (objects) identified as crop leaves in order to recognise not only single leaves but whole plants. The method used can be understood as

non-hierarchical cluster analysis which sequentially assigns each object to one cluster. Since the minimum distances between the regions precalculated by the image processing software are used, the clustering carried out is not a clustering analysis in the approved statistical sense.

The sequence of the total plant recognition was as follows. The minimum distance between the contour pixels of two regions each was calculated. The calculation is carried out by comparing all contour pixels, using the Euclidean distance. This was done for all regions in the image. The two regions that had the smallest distance were put into the same cluster if their distance was smaller than a threshold value. The threshold value was automatically set to the mean value of the maximum diameters of all leaves in the sample data set of the crop. Preliminary tests showed that the best results were achieved by using this distance. The procedure was repeated until no regions were closer together than the threshold value. After each step a convex hull (a surrounding envelope, see also Fig. 3. below) was laid around each cluster of objects. By this not only the leaves but also the (so far not recognised) stems of the

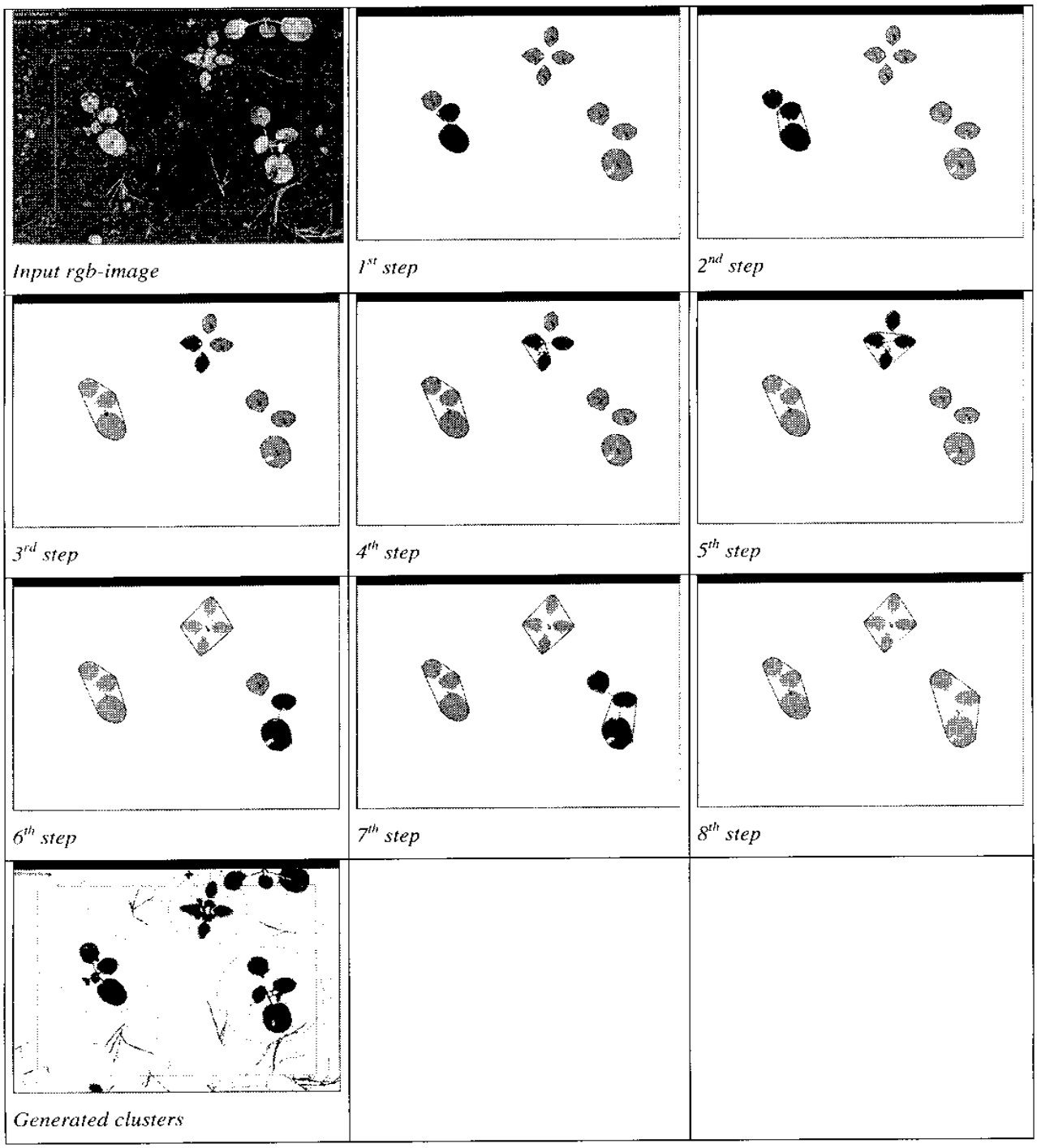


Fig. 3. Steps in the clustering procedure (description see text)
Berechnungsschritte innerhalb des Clusterverfahrens (Beschreibung siehe Text)

plants were assigned to the cluster. Finally, to determine the crop plant, the intersection between the area within the hull and the binary input image was calculated. To avoid the problem of getting different results for different start regions the procedure always started with the two regions that had the smallest distance Fig. 3. shows the whole process with a sample image. The input image contained 3 plants which were located within the analysed part of the image (marked by a rectangle). In the 1st step the two regions which were the closest together were determined (marked in black), put into the same cluster and surrounded by a convex hull (2nd step). The third region, which is marked black in this step was then the one with the minimal distance to other regions or already formed clusters. In step 3 it is therefore be added to the already existing cluster. At the same step two leaves of the plant located at the top of the image then represented the regions which were the closest together. In the following steps 5 to 7 the process was repeated. In step 8 there were no more regions on the image which were closer together than the threshold value. The clustering procedure was complete. If the image processing did not achieve to separate overlapping leaves completely, the overlapping structure is treated as one object. This has little impact on the procedure to leaves belonging to the same plant. Concerning leaves belonging to different plants this causes misinterpretation.

c) Localisation
The groups of regions computed by the cluster analysis represent the recognised individual plants. The positions of the area centres of these regions are the predicted plant positions. The sequence-number of the image was included in the calculations to determine not only the position within the individual image but also the position in the overall plant stand.

Hough transform for row structure detection

a) Basics
The Hough transform is a mathematical procedure used in a variety of related methods for shape detection. The methodology of the transform was laid down in a patent specification (HOUGH 1962). A comprehensive description of using the Hough transform in image analysis can be found in CASTLEMAN (1996) or HABERÄCKER (1987).

A straight line
$$y = ax+b \quad (1)$$
can be expressed in polar coordinates by their distance **d** to the origin and the angle φ between vector **d** and the x-axis (Fig. 4)

$$\mathbf{d} = x\cos(\varphi) + y\sin(\varphi) \quad (2)$$

Any line in the x,y-plane is represented by a point in the two-dimensional space **d** and φ. Transforming a set of lines in the x,y-plane through a certain point (Fig. 5) corresponds to a sinusoidal curve in the **d**, φ-space, the so called parameter space (Fig. 6). In the parameter space pixels for all features, which are on or near a straight line are accumulated. The **d**, φ-space histogram is searched for local maxima to obtain the parameters of linear boundary segments.

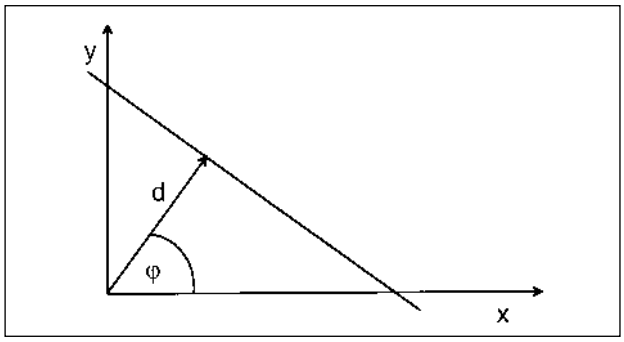


Fig. 4. Description of a straight line in polar coordinates
Beschreibung einer Geraden in Polkoordinaten

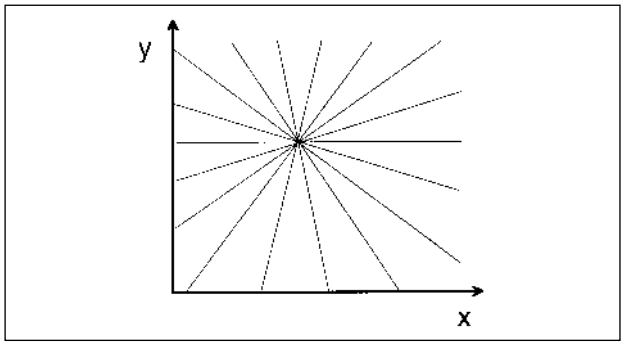


Fig. 5. Set of lines in the Cartesian x,y-plane through a certain point
Geraden in einem kartesischen x,y-Koordinatensystem

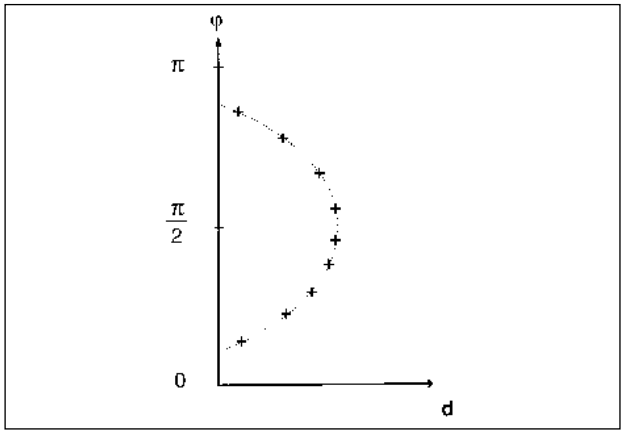


Fig. 6. The lines in Fig. 5 are represented as a sinusoidal curve in the d, φ-space
Die Geraden aus Fig.5 werden in dem d, φ-Koordinatensystem durch eine sinusförmige Kurve dargestellt

b) Application
For tracking the row structure the following parameters were given to the system:
– the number of rows to detect
– the minimal inter-row distance to be maintained
– the maximum angle of deviation from the travelling direction for the detected rows

Fig. 7a shows the detected crop plant positions of a 1 000 cm by 180 cm wide analysed plot of a cabbage crop. This artificial image merged 22 images per camera in the direction of travel, giving 22 x 3=66 individually analysed images, each marked by a rectangle in the figure. A trac-

tor drive over the plant stand is simulated. After a forward drive of 45 cm – which is equivalent to the width of 1 image minus the overlapping to the neighbouring images – a row detection is executed. For this the 10 last images per camera in travelling direction (corresponding to a 450 cm x 180 cm wide section of a bed) are used. An artificial image is generated in which the positions of the plants are marked as points (images labelled 1 to 10 in Fig. 7a). From this image the Hough transform is calculated and registered in the parameter space (Fig. 8). In this figure the sinusoidal curves described above (corresponding to the original plant positions) can be found back. Where numerous curves cross, dark spots are accumulated in the parameter space. Image processing techinques are used to determine the positions of these local maxima. Each maximum can be back-transformed and represents a straight line. The detected lines are retained, provided that they do not exceed the maximum deviation angle from the horizontal and that the minimal inter-row distance is maintained. The identified line sections are pieced together in the resulting image (Fig.7c).

c) Using row structure information for classification improvement

The detected row structure was used to improve the classification result. Plants which were located outside the plant row and therefore were very unlikely to be crop plants were excluded from the class of the crop plants. The smaller the search area, the more likely it will be that not only weeds but also crop plants not located exactly on the detected row will be excluded. This leads to a deterioration in the classification. Various extended search areas around the rows were examined.

Results and Discussion

Clustering methods and plant classification

Fig. 7a shows a typical result of a plant classification using the described cluster algorithms. On the one hand it is demonstrated that the plants can be merged from parts. On the other hand it becomes clear that errors

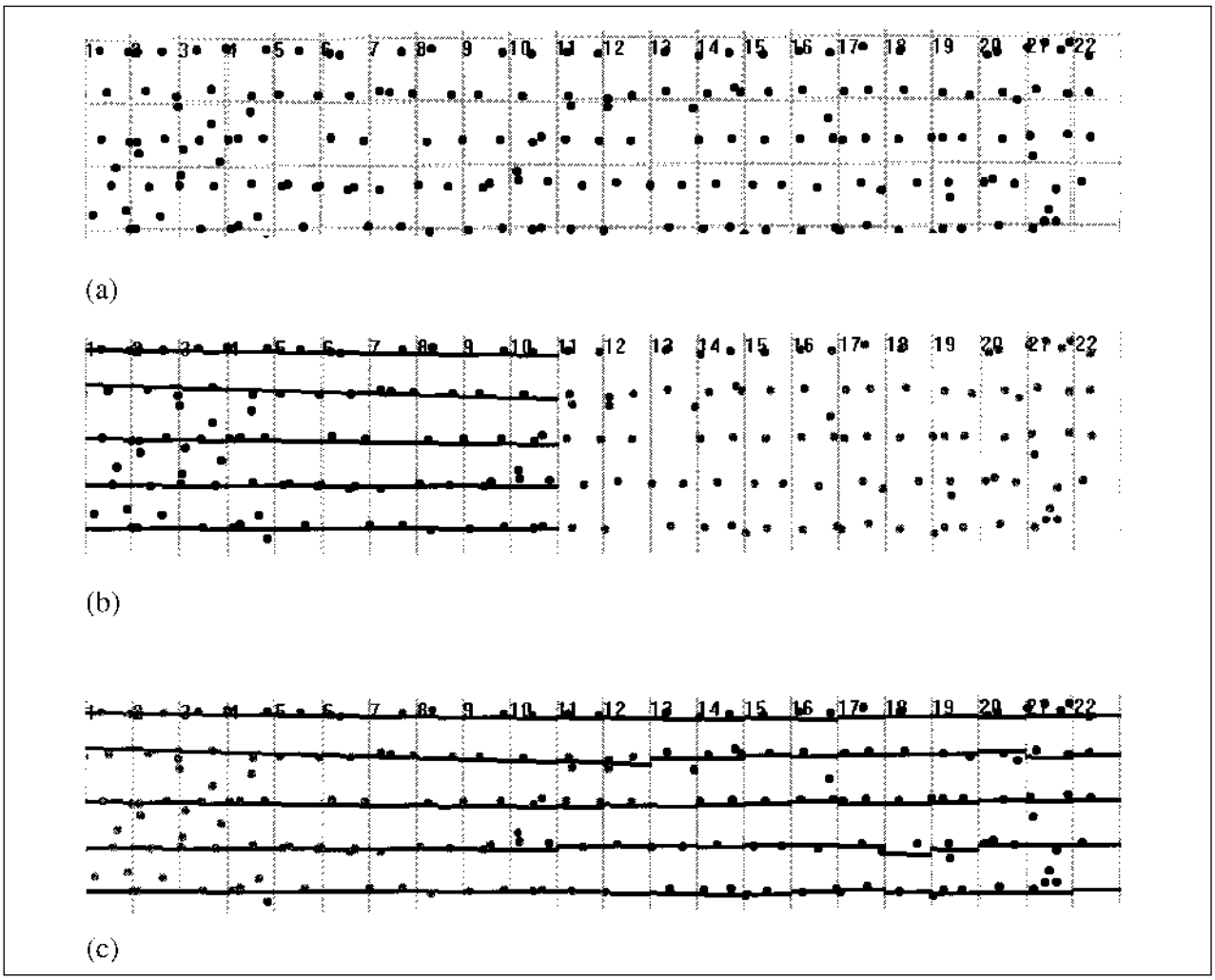


Fig. 7. Overall view of the experimental plot (cabbage, 36 days after seeding, greenhouse experiment). (a): Dots mark the detected crop plant positions, every rectangle represents one image; (b): Rows detected with the information of 10 x 3 images, (c): Completed row detection

Gesamtansicht der Versuchsparzelle (Kohl, 36 Tage nach Aussaat, Gewächshausexperiment) (a) die Punkte markieren die gefundenen Pflanzenpositionen, jedes Rechteck repräsentiert ein Aufnahmebild; (b) Reihen, die erkannt wurden nach der Auswertung von 10 x 3 Bildern; (c) erkannte Reihen nach vollständiger Überfahrt

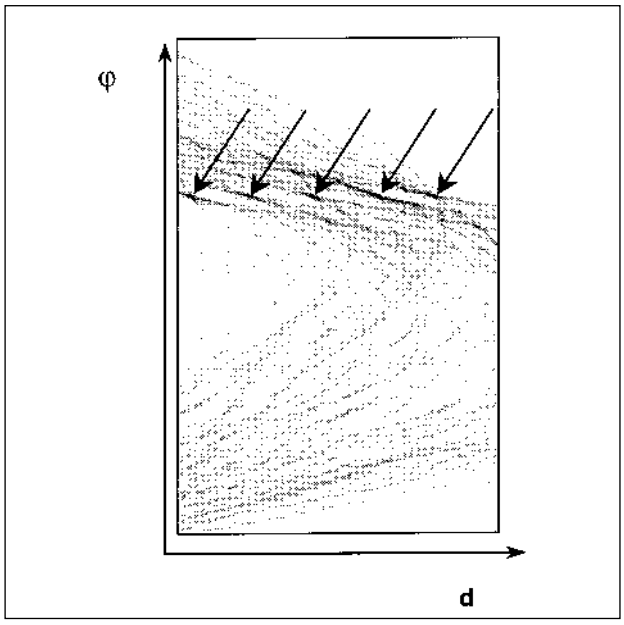


Fig. 8. Detail of a Hough-transformed image (arrows point to the spots where numerous curves cross, each spot represents one straight line in the original input image)
Ausschnitt aus einem hough-transformierten Bild (die Pfeile kennzeichnen Stellen an denen sich viele Kurven schneiden, diese Schnittpunkte repräsentieren gerade Linien im Originalbild)

exist which are caused by misclassification as well as incorrect clustering. Looking closer at the obtained classification results the following can be noticed. On average, 60 single images per evaluation day were analysed, containing about 100 (experiments with cabbage) to 300 (experiments with carrots) crop plants. Looking at all greenhouse and open field experiments, for cabbage a mean classification accuracy of 87 % correctly identified crop plants (83 to 91 %) was achieved while having a mean error of 11 % (3 to 28 %) for weeds identified as crops. For carrots a mean classification accuracy of 69 % correctly identified crop plants (58 to 73 %) was achieved while having a mean error of 33 % (14 to 49 %) for weeds identified as crops. Table 1 summarises the plant classification results for the experiments without additional crop row detection. These results are picked-up again in Fig. 10 and Fig. 11 to show the effect of the crop row detection (for more detailed information see HEMMING 2000).

Because nothing but the distances between the leaves were used for the calculation, the leaves of more than one plant were composed when having the plants close together in the bed. Since this problem did not occur too often, due to the fixed planting distances, there was only a minor effect on the experiments presented here. Nevertheless, the problem exists in other crops and at different growth stages and is not solved yet. It could be useful to have a method to determine the position of the leaf-stalk concluding thereof the orientation of the leaf. RATH (1997) developed this kind of algorithm based on morphological operations for the use with leaves of deciduous trees. However, with the segmentation procedure used in the work presented here, the

Table 1. Classification results for cabbage and carrots at different growing stages without additional crop row detection. Type 1 error (not identified crops) and type 2 error (weed classified as crop)
Klassifikationsergebnisse ohne zusätzliche Reihenerkennung bei Kohl und Möhren in verschiedenen Wachstumsstadien. Fehler erster Art (nicht erkannte Kulturpflanze) und Fehler zweiter Art (als Kulturpflanze klassifiziertes Unkraut).

	Age [days]	Type 1 error [%]	Type 2 error [%]
Cabbage	24	6.8	6.5
	27	12.3	5.4
	32	12.5	9.2
	34	8.1	16.7
Carrots	18	26.6	23.4
	25	20.8	34.8

stalks are already removed from the objects before classification. TIAN and SLAUGHTER (1993) used the orientation of the leave to overcome this problem indirectly. To locate the plant position they applied the rule that the stem of a tomato seedling is always in the line of the extended major axis of the cotyledons. This procedure will only work with oval or oblong shaped leaves which clearly show a major axis. A more universally applicable algorithm is not yet available.

Localisation, row structure detection and plant classification

Fig. 7a to 7c give an example of the row tracing process. The method used was very robust in the cases where only a few plants were missing (because of diseases, pests or other failures) or misclassified. If a larger number of plants were lost or misclassified then the row detection was incomplete. For the greenhouse experiments the procedure worked well and was very robust in respect of missing or not identified plants. For the open field experiments the applicability of the row detection was sometimes limited because the rows were not as consistent as in the greenhouse.

As an example Fig. 9 shows which plant positions were excluded from the different search areas for cabbage after 36 days in the greenhouse experiments. The identified crop plant positions are marked with black dots, the detected rows with black lines and the different width plant search areas are visualised by grey regions. All plants outside the search areas are labelled with a number. The smaller the search area the more objects are excluded.

The evaluation of the methods developed are demonstrated in Fig. 10 and 11 with respect to their applicability in the classification process. Fig. 10a/b and Fig. 11a/b show the effect of including the information of the detected rows in the classification process for two experiments. As expected in no case the type 1 error (not identified crop) was lowered. The major effect noticed was a decrease of type 2 error (weed identified as crop). The smaller the search area the higher was the amount of crop plants not identified correctly. Especially using the two smallest search areas (1/6 and 1/8 of the row-spacing) the rise in type 1 error was unacceptable. The results of the other search areas were promising in some cases.

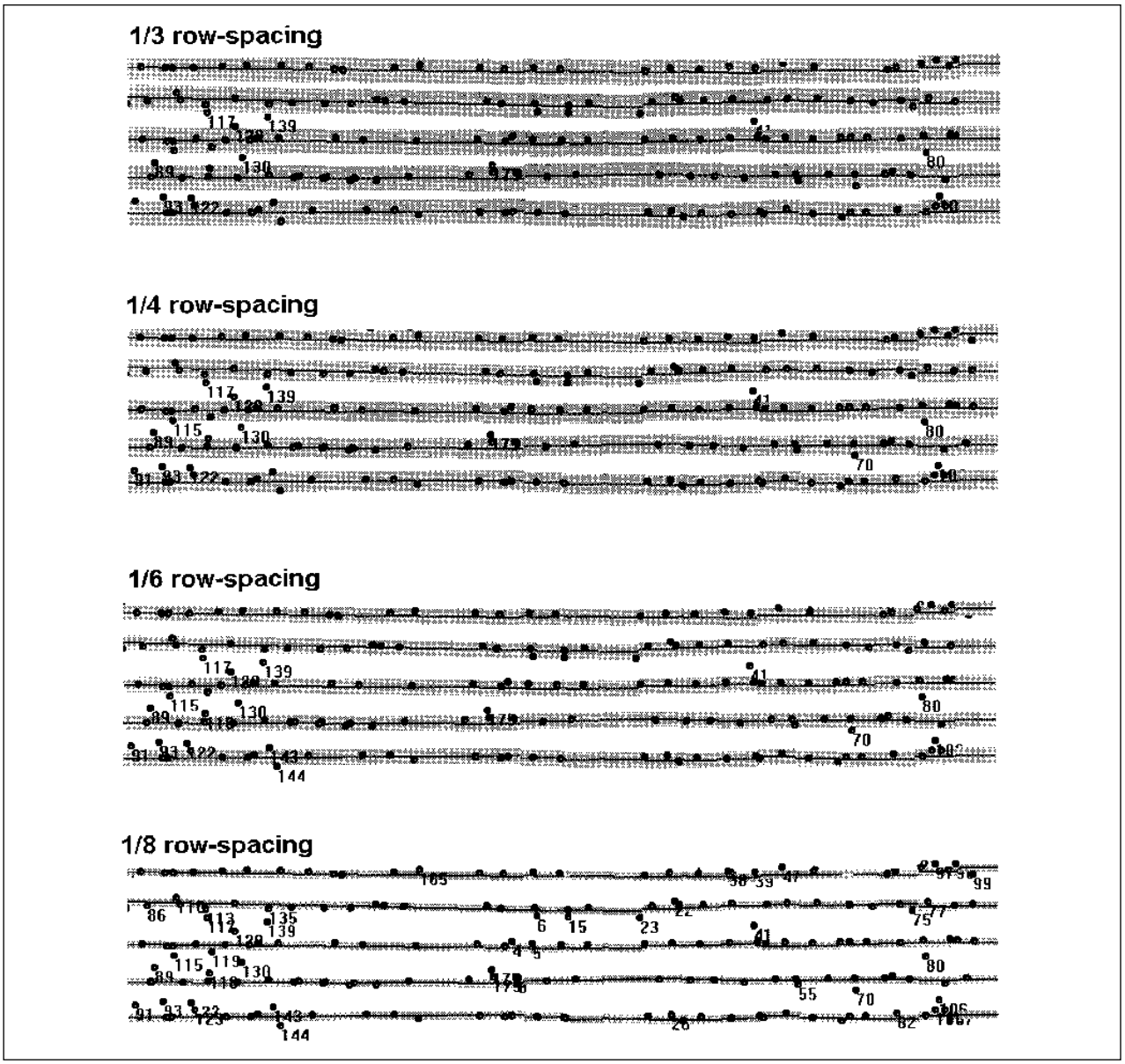


Fig. 9. Identified crop plants (black points), detected rows (black lines) and different width plant search areas (gray regions). Numbers label plants outside the search areas (cabbage after 36 days, greenhouse experiments)
Identifizierte Kulturpflanzen (schwarze Punkte), erkannte Reihen (schwarze Linien) und verschiedene Suchkorridore (graue Regionen). Nummerierten Pflanzen befinden sich außerhalb der Korridore (Kohl nach 36 Tagen, Gewächshausexperiment)

Summarising, no universally valid recommendation can be given. The result clearly depends on the question whether the type 1 error (not identified crops) or the type 2 error (weed classified as crop) should be minimised. The crop plants are not always located exactly in the row and furthermore the plant positions used as a reference are not necessarily the real positions because they are calculated as the centroids of the binary regions.

Using the Hough transform for row detection is different from the approach described by PÉREZ, et al. (2000). There the rows must follow a vertical course within the image and the result is only based on a single image. Gaps in the plant row(s) will have considerable impact on the result. The method used by TILLETT and HAGUE (1999) dealt with a different sort of input information. Whereas they analysed a perspective view of the crop obtained with a camera pointing towards the travelling direction of the vehicle, in the study presented here the input image for row detection was an image composed out of the analysis result of several images taken with cameras mounted parallel to the ground.

Although the methods presented here were used offline, speed is not the critical factor. Using different hardware it should be no problem to build a real-time system (see e.g. SANCHIZ et al. 1998).

Conclusions

For vision based classification of different plants in natural scenes with overlapping leaves in different growing stages it is necessary to separate single leaves and to classify these leaves with common used image process-

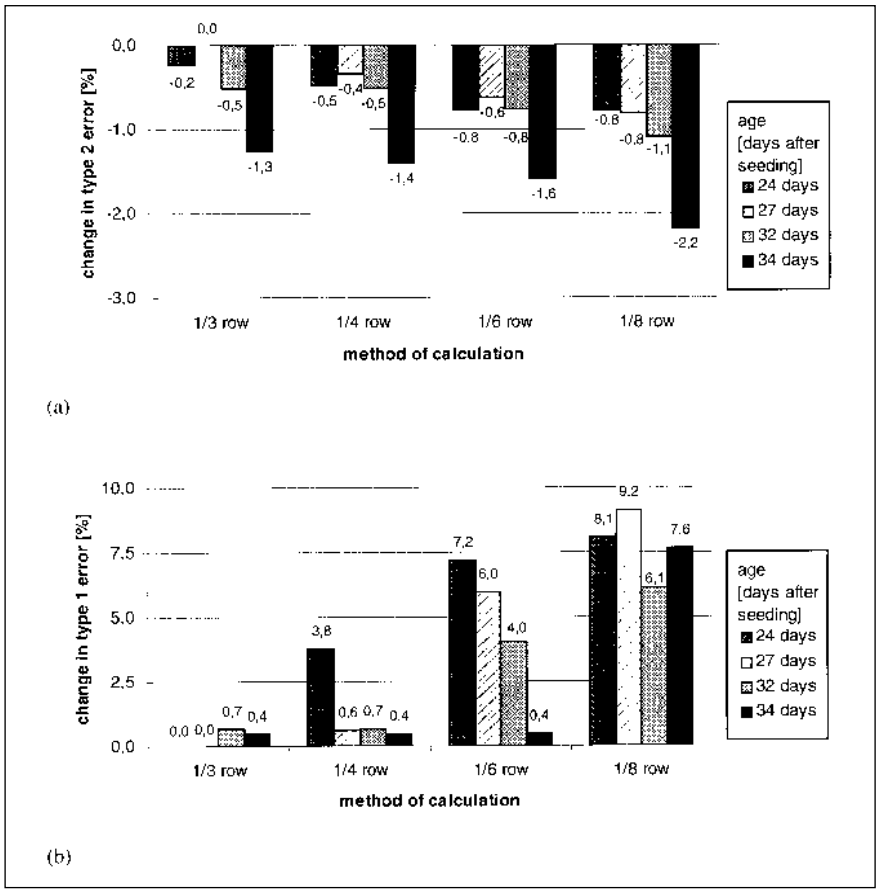


Fig. 10. Effect on classification errors when adding information of detected crop rows at different growing stages and using different search areas (1/3 up to 1/8 of the row-spacing). Cabbage, open field experiments: (a) type 1 error (not identified crops) , (b) type 2 error (weed classified as crop)
Einfluß auf das Klassifikationsergebnis durch zusätzliche Verwendung der Reiheninformationen bei verschiedenen Wachstumsstadien und Suchkorridoren (1/3 bis 1/8 des Reihenabstandes). Kohl, Freilandexperimente: (a) Fehler erster Art (nicht erkannte Kulturpflanze), (b) Fehler zweiter Art (als Kulturpflanze klassifiziertes Unkraut)

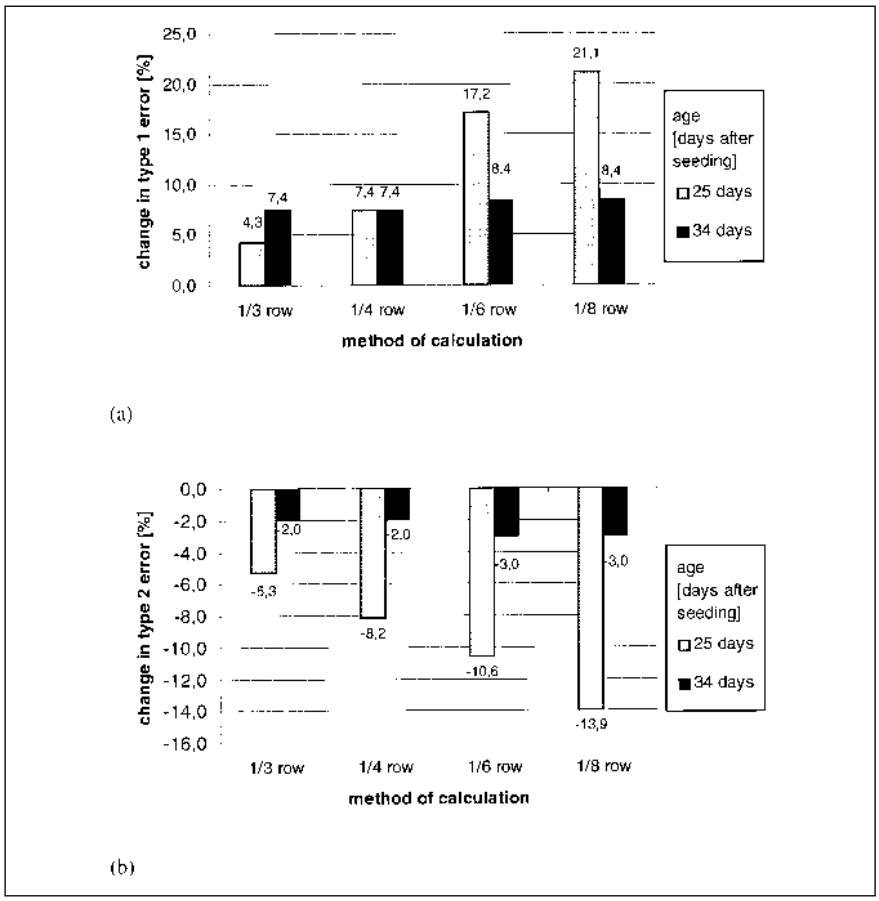


Fig. 11. Effect on classification errors when adding information of detected crop rows at different growing stages and using different search areas (1/3 up to 1/8 of the row-spacing). Carrots, greenhouse experiments: (a) type 1 error (not identified crops), (b) type 2 error (weed classified as crop)
Einfluß auf das Klassifikationsergebnis durch zusätzliche Verwendung der Reiheninformationen bei verschiedenen Wachstumsstadien und Suchkorridoren (1/3 bis 1/8 des Reihenabstandes). Möhren, Gewächshauexperimente: (a) Fehler erster Art (nicht erkannte Kulturpflanze), (b) Fehler zweiter Art (als Kulturpflanze klassifiziertes Unkraut)

ing methods. If special plant based actions should follow (e.g. precise spot spraying) or if the accurate localisation of the plants is expected, it is essential to cluster the leaves into groups representing the plants. In this work it was demonstrated that with the use of cluster analysis methods it is possible to solve this task of localisation, especially in complex open field situations. Nevertheless the methods are limited to situations where the overlapping areas of the plants are not extreme. Otherwise faults in leaf separation and later in the clustering process itself could take place. This results in insufficient localisation accuracy.

The advantage of using the Hough transform for crop row detection is that the technique is robust to uncertainty in the data. It is therefore suited very well for analysing scenes containing biological objects with high variability. Small gaps in the plant row were tolerated as well as plants not exactly positioned in the row by the system without losing the heading of the row. The information of the row structure can be used to correct the classification result in row-crops. However, the extend of the "safety zone" around the row, where plants are never classified as weeds, must be chosen carefully to prevent a loss in classification accuracy. The results clearly depended on the growing stage of the crop, on specific parameters of the row identification process and on the question whether the type 1 error (not identified crops) or the type 2 error (weed classified as crop) should be minimised.

The practical implementation of the methods presented here in an automatic weeding or spraying machine was not the objective of this work but would be the following step. In the future the methods described can be used to improve machine based plant determination in open field horticulture. Precision horticulture with less usage of pesticides but more usage of intelligent control becomes more and more reality.

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Literature

BILLINGSLEY, J. and SCHOENFISCH, M. 1997: The successful development of a vision guidance system for agriculture. Computers and Electronics in Agriculture. **16**, 147–163.

CASTLEMAN, K. R. 1996: Digital Image Processing. Prentice Hall, Upper Saddle River, New Jersey, USA.

HABERÄCKER, P. 1987: Digitale Bildverarbeitung. [Digital image processing]. Hanser, München.

HÄUSLER, A., NORDMEYER, H. AND P. NIEMANN 1998: Voraussetzungen für eine teilflächenspezifische Unkrautbekämpfung. [Suppositions for a site-specific-weed control.] Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz, Sonderh. **XVI**, 249–256.

HEMMING, J. 2000: Computer vision for identifying weeds in crops. Gartenbautechnische Informationen. Heft **50**. ISBN 3-926203-24-2. Inst. für Technik in Gartenbau und Landwirtschaft. PhD-Thesis, University of Hanover, Germany

HEMMING, J. and T. RATH 2001: Computer-Vision-based Weed Identification under Field Conditions using Controlled Lighting. Journal of Agricultural Engineering Research, **78**(3), 233–243.

HOUGH, P. V. C. 1962: Methods and Means for Recognizing Complex Patterns. U.S. Patent 3069654.

MARCHANT, J. A. and R. BRIVOT 1995: Real-Time Tracking of Plants Rows Using a Hough Transform. Real-Time Imaging. **1**, 363–371.

MEYER, G. E., MEHTA T., KOCHER, M. F., MORTENSEN, D. A. and A. SAMAL 1998: Textural imaging and discriminant analysis for distinguishing weeds for spot spraying. Transactions of the ASAE. **41**(4), 1189–1197.

MVTEC 1998: HALCON Reference Manual C++ Version 5.01. MVTec Software GmbH, München.

PÉREZ, A. J., LÓPEZ, F., BENLLOCH, J. V. and S. CHRISTENSEN 2000: Colour and shape analysis techniques for weed detection in cereal fields. Computers and Electronics in Agriculture. **25**, 197–212.

PETRY, W. and W. KÜHBAUCH 1989: Automatisierte Unterscheidung von Unkrautarten nach Formparametern mit Hilfe der quantitativen Bildanalyse. [Automated discrimination of weed species with quantitative image analysis.] J. Agronomy & Crop Science. **163**, 345–351.

PLA, F., SANCHIZ, J. M., MARCHANT, J. A. and R. BRIVOT 1997: Building perspective models to guide a row crop navigation vehicle. Image an Vision Computing. **15**, 465–473.

RATH, T. 1997: Methoden zur computerbildanalytischen Pflanzenidentifikation am Beispiel dendrologischer Bestimmungen. [Methods for plant identification by image processing demonstrated in the area of dendrological determinations.] Gartenbautechnische Informationen, Heft **42**. Institut für Technik in Gartenbau und Landwirtschaft. University of Hannover, Germany.

SANCHIZ, J. M., MARCHANT, J. A., PLA, F. and T. HAGUE 1998: Real-Time Visual Sensing for Task Planning in a Field Navigation Vehicle. Real-Time Imaging. **4**, 55–65.

SÖKEFELD, M., GERHARDS, R. and W. KÜHBAUCH 1996: Automatische Erkennung von Unkräutern im Keimblattstadium mit digitaler Bildverarbeitung. [Automated identification of weeds in the stage of cotyledon using image analysis.] KTBL-Arbeitspapier. Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V, Darmstadt.

SONKA, M., HLAVAC, V. and R. BOYLE 1993: Image Processing, Analysis and Machine Vision. University Press. Cambridge, UK

TIAN, L. and D. C. SLAUGHTER 1993: Computer vision identification of tomato seedlings in natural outdoor scenes. ASAE-Paper. 93–3608.

TILLETT, N. D. and T. HAGUE 1999: Computer-vision-based hoe guidance for cereals – an initial trial. J. agric. Engng Res. **74** , 225–236.

WOEBBECKE, D. M. 1995: Shape features for identifying young weeds using image analysis. Transactions of the ASAE. **38** (1), 271–281.

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