3D OBJECT RECOGNITION, LOCALIZATION AND TREATMENT OF *RUMEX OBTUSIFOLIUS* IN ITS NATURAL ENVIRONMENT

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ABSTRACT

Rumex obtusifolius is one of the most highly competitive and persistent sorts of weed in agriculture. An automatic recognition and plant-treatment system is currently under development as an alternative treatment technique.

An infrared-laser triangulation sensor and a high-resolution smart camera are used to generate 3D images of the weeds and their natural environment. In a segmentation process, contiguous surface patches are separated from one other. These 3D surface patches are compared with different criteria of a plant database containing surface parameters such as shape, state of surface, etc. When individual objects are extracted and confirmed as possible leaves or parts of leaves, their texture is analyzed by comparing the information of simultaneously taken 2D images with database criteria. If an object is recognized as a dock leaf, its coordinates in the vehicle coordinate system are computed and the leaves are sprayed with herbicide.

The surface analysis in space can boost segmentation performance under conditions where state-of-the-art 2D recognition systems are not successful, e.g. low contrast, green-on-green images, noisy images, or images taken from inappropriate positions.

Initial results have been promising. System development focuses on a more robust imaging-sensor technique and refinement of the different algorithms. Looking to the future, the system design allows for the flexible integration of other plant species.

Keywords: plant recognition, plant localization, 3D image processing, segmentation, texture analysis

INTRODUCTION

Rumex obtusifolius, also called broad-leaved dock, is one of the most competitive and persistent weeds in agriculture (Fig. 1). The plant is very robust, and its dispersion, especially in grassland, is difficult to control.
Currently used methods such as time-intensive manual trumping of the plants, manual treatment of individual plants with herbicides, and non-specific broad surface spraying do not produce satisfactory results. Finding an effective technique for controlling this weed is difficult, especially in organic agriculture where chemical plant treatments are banned.

The development of a reliable single-plant recognition and localization system is one of the key drivers for automatic treatment systems in agriculture.

In the past, scientific work focused on the classification of leaves by 2D analysis of binary gray-scale or color images with feature recognition. Novel methods such as species identification using elliptic Fourier shape analysis (Neto et al. 2005) work well with clearly projected complete leaves. There are also commercial products on the market that use frame-by-frame video analysis (Dürr et al., 2004). A major disadvantage of all two-dimensional solutions is that they work on the projection of the natural landscape, and interpret the three-dimensional world by applying the data to models.

In geodesy and photogrammetry, data processing follows a different approach. Collected data are three-dimensional, whilst products and interpretations, e.g. topographic maps, are two-dimensional. When it comes to extraction and recognition of plants in their natural environment, analyzing and processing 3D point clouds has several advantages over 2D-image-processing approaches.

Fig. 1. Broad-leaved dock (*Rumex obtusifolius*)

Segmentation is the crucial part of data analysis, and ranges from simple binarization of images to complex analysis of multispectral images, multidimensional data, etc. The challenges of real-time data analysis lie in a reliable and fast segmentation of raw data. An initial step of the segmentation is edge extraction. A variety of algorithms have been published and evaluated in machine-vision literature. One of the most comprehensive evaluations compares different edge-detection algorithms and proposes a novel evaluation method for comparing edge-detection algorithms on gray-scale images (Heath, 1997). Although the possibilities for applying 2D-image-processing approaches to 3D data are rather limited, one interesting proposal was identified (Borkowski, 2004). Several real-time edge-extraction solutions (Basano et al., 1988; Sarkar and Boyer, 1990; Wunderlich et al., 1993; Hsiao et al., 2005) and one context-free approach (Giannarou and Stathaki, 2005) are described. Interesting watershed segmentation of triangle meshes was also examined (Sun et al., 2002; Mangan and Whitaker, 1999). A 2D *Rumex obtusifolius* recognition system requiring powerful computing resources for the segmentation of high-resolution images is described in various papers (Gebhardt et al., 2006; Gebhardt, 2007; Gebhardt and Kühbauch, 2007).

The main benefit of using the third dimension is that, with the help of height information, it actually enables the segmentation of plant leaves in very cluttered and complex environments such as can be found in overgrown fields. With the background of these technical facilities for 3D detection, an automatic recognition, localization and treatment system for *Rumex obtusifolius* was developed. The high-resolution 3D ground-data segmentation approach enables real-time plant recognition and the application of herbicides to the plant leaves.

SENSOR EVALUATION

The acquisition of three-dimensional data is mostly bound up with the type of application and the budget available for the equipment. Numerous sensors are available their quality ranging from non-utilizable to unaffordable.

The first sensors evaluated – *Sick LMS 400 (Time-of-flight laser scanner)* and *CSEM SwissRanger SR-2 (Time-of-flight range camera)* – did not meet requirements in terms of resolution (2mm) and reflection characteristics.

The tests with a *Sick Ranger C55* and a near-infrared (NIR) laser were successful. Vegetation perfectly reflects NIR light with a wavelength of 780 nm (Lorenzen and Jensen, 1987). In Fig. 2, the difference between measurements taken by the LMS 400 and the Ranger C55 is obvious. The modular setup of the Ranger system is combined with a high-resolution smart camera with 1536 x 512 pixels. The high-speed sensor with an on-camera FPGA processor allows for high-speed frame processing and can deliver up to 20,000 lines per second at a high quality. The measurement principle of C55 is laser triangulation. It computes ground contours by processing the line projected by the laser beam. The sensor delivers the contours at a rate of 1 kHz to the image-processing computer. A 70-mW infrared laser is used (laser class 3B).

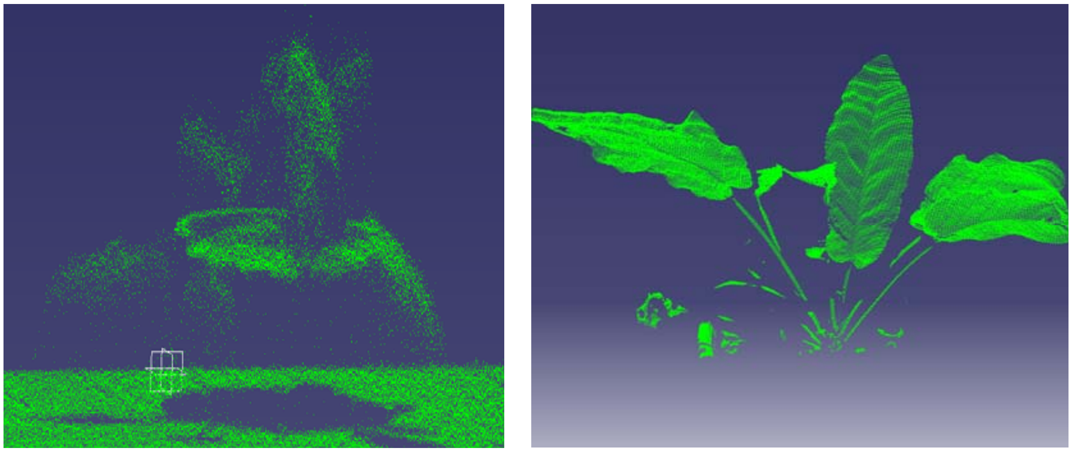

Fig. 2. Plant data acquired with LMS 400 (left) and with Ranger C55 (right). (Seatovic and Grueninger, 2007)

Despite the high resolution and speed of the Ranger C55, the accuracy of the system was unknown. Outdoor-application issues required special attention.

The camera is calibrated using the classic Tsai calibration procedure (Tsai, 1987). Tsai's procedure was supplemented with an additional routine to determine the position and orientation of the laser plane relative to the principle point of the objective. The system is calibrated manually. Initial calibration tests showed that an accuracy of 1 pixel could be achieved, bearing in mind that the measurement data is approximately 2-4 mm per measurement point (pixel). An automatic calibration procedure will reduce this value to 1 mm per measured point. Exhaustive calculations revealed that the calibrated system allows observation of the ground with a maximum error of 2.4 mm per pixel.

SYSTEM DESIGN

The system design incorporates two components: a real-time (RT) system consisting of a computer with a QNX real-time operating system, and a detection system comprising an image-processing computer running on Windows XP Professional (Fig. 3). Both systems are linked by an Ethernet peer-to-peer connection.

The RT system delivers a unique time for the whole system, calculates the navigation data, and triggers image acquisition on the ranger camera. The non-real-time system acquires and processes 3D data. The 3D data processing consists of the following steps:

- Data acquisition
- Data pre-processing (segmentation)
- Data processing (leaf detection)
- Data post-processing (location computation)

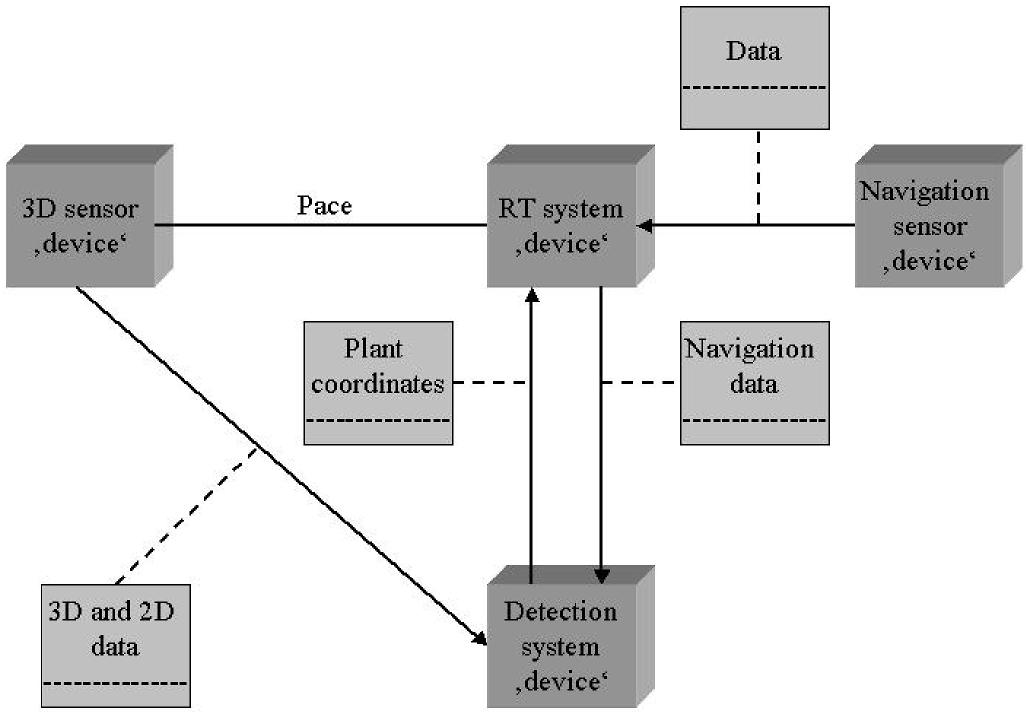

Fig. 3: System design, main components, and data flow

The center-point coordinates of each dock leaf detected and the bounding cube assigned to it are entered in the vehicle coordinate system. This information is passed on to the RT system via a network that also controls the herbicide nozzles for spraying the detected leaves.

SYSTEM PROTOTYPE

The vehicle prototype (Fig. 4) comprises the following components:

- Sick Ranger C55 with near-infrared laser (780nm). (Sick AG, Waldkirch, Germany)
- Two Baumer Electric MDFK 08T7105/N16 encoders (Baumer, Frauenfeld, Switzerland), mounted on the wheels.
- Carrier (vehicle) with security box, spraying boom and supporting devices.

Vehicle speed during recognition and treatment is 1 ms^{-1}. Data collection is continuous, and the system extracts the plant leaves out of the collected data in real time. In a subsequent step, the coordinates of the leaves or leaf parts in question are computed and transferred to the treatment device that applies herbicide to the plants. The system has roughly 0.6 seconds to process 1 m^2 of meadow. Some data facts are as follows:

- On 1 m^2 of meadow, the system measures 1536 x 1000 = 1 536 000 points.
- Every measurement point has single-word (16-bit) precision.
- High-resolution gray-scale row of C55 produces 3072 x 1000 = 3 072 000 8-bit pixels per 1 m^2.

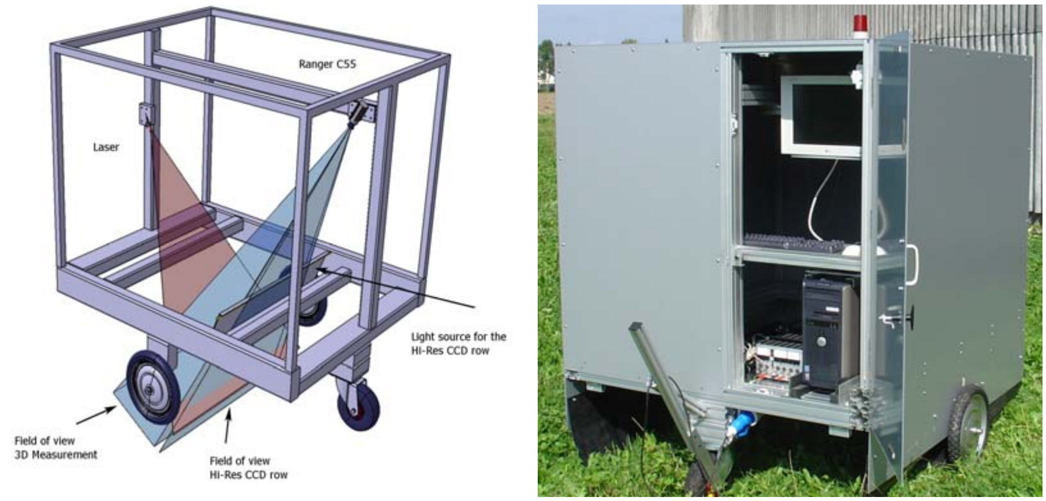

Fig. 4. Left: Drawing of towed vehicle. Right: Test vehicle.

Thus, the processing unit must process 2.9 MBs^{-1} of 3D data and the same amount of gray-scale textures within one second. Under these conditions, fast and reliable segmentation algorithms – for raw data, ideally – are essential. A highly efficient segmentation procedure is therefore required.

OBJECT EXTRACTION

Several plant-recognition and classification approaches have been published to date. The most recent and comprehensive of these is found in Gebhard, 2007. Nevertheless, vision systems, especially passive ones, can fail when environmental conditions change during the data-acquisition process. Failure can also result from insufficient contrast in a given input image, so that additional image-processing steps are necessary to extract the objects from the scene.
Further recognition results depend strongly on the angle between the object and the optical axis of the camera. In extreme cases there is no way to distinguish between blades of grass and broad leaves. All these problems are partly resolved if the acquired data is three-dimensional. The other side of the coin is that the complexity of processing algorithms is growing by increasing amounts of data.
Although there is an additional dimension in 3D data, the algorithms are less complex than their 2D computer-vision counterparts. Edges exist in the data, and need not be derived from the shadows, texture or projection parameters (Seatovic, 2008).

Edge detection is the first step in the segmentation procedure. An edge point can be described as a discontinuous place on the curve in the cutting plane π (Fig. 5): the intersection of surfaces (red and blue) and plane p creates one intersection curve on each surface patch. Traveling along the curves from the beginning until the end, the ambiguous position will be hit at point P. The distance between these points and the direction of their connection vector determine whether or not there is an edge between these two surface patches.

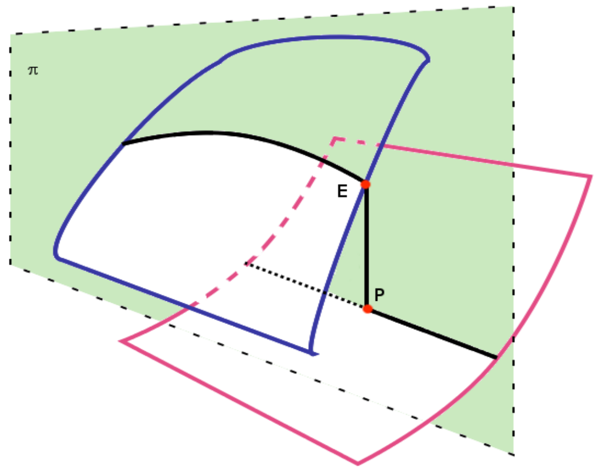

Fig. 5. Edge-etection principle. Point E is an edge point, point P is not. At point P, however, the curve branches in two directions.

SURFACE ANALYSIS AND SEGMENTATION

Acquired data is discrete and skewed in all three dimensions. Since rectification of the raw data would take far too much processing time, all segmentation algorithms process raw data (Seatovic and Grueninger, 2007). This is challenging, because the threshold varies according to the direction of the intersection plane and the heights of the surface patches.

Edge-point examination takes place in the 9-point neighborhood. The system tests whether the center point is on the edge or not. Together with its neighbors, Point P forms a regular triangulated mesh. Analysis of the surface patch is reduced to a vector analysis of the normals: see green lines in Fig. 6.

Once a surface patch has a complete and closed boundary that contains only edge points, it will be marked and labelled for further processing. Currently, the segmentation procedure only computes the approximate area of the object. If the computed area is greater than 9 cm^2, the object will be transferred to the recognition task for further analysis. Red dots in the segmentation result represent these objects recognized as large areas. White squares represent the missed patches. These errors are caused by laser failure (Fig. 7).

Field tests have shown that the recognition vehicle in this state of development can detect and extract large surfaces in the required time frame. The experiments enclose 100 m natural meadow; no artificial grassland was processed. Manual checks have shown that 62-91% of the large areas was detected and marked for treatment. Up to 25% of the objects were missed, however, owing to a weak laser signal, or too-complex or extremely fragmented scenes in overgrown areas.

At this stage of the project, position accuracy stands at 10 cm. The treatment system has twelve nozzles spraying a spot within a 10-cm radius, so that only a few recognized leaves per plant are needed for successful application of the herbicide.

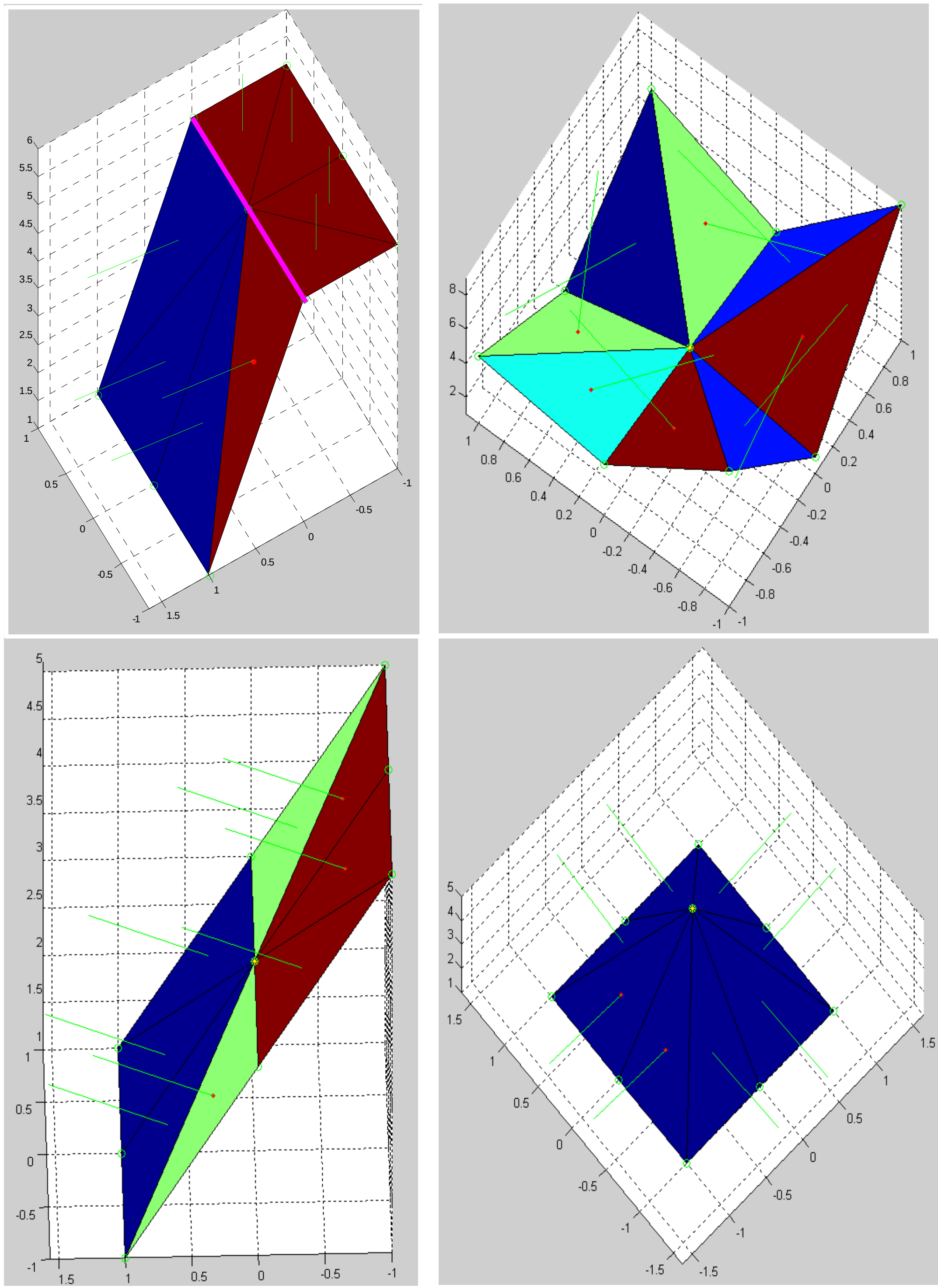

Fig. 6. Top left: Edge detection in the 9-point neighborhood. The center point is an edge point. Upper right: No edge: the center point is in the diffuse vector field. Bottom left: No edge: all vectors point in same direction. Bottom right: The center point is a node, and there are multiple edges gathering in the center of the patch.

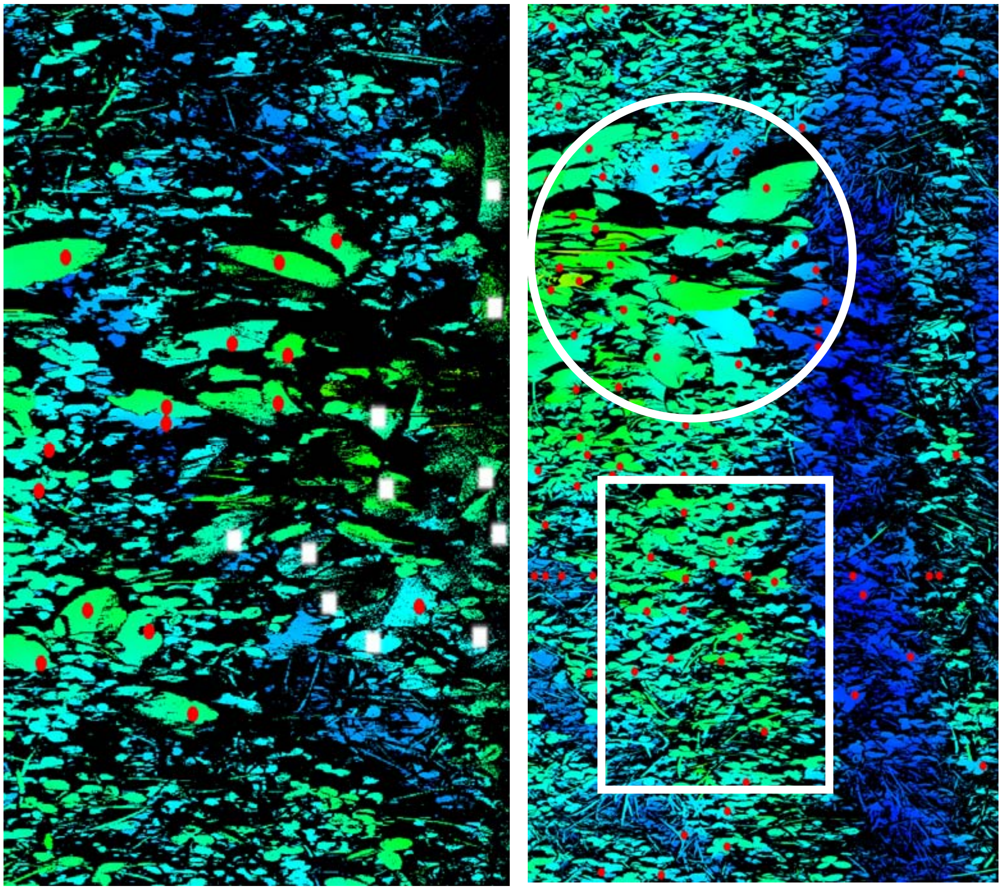

Fig. 7. Segmentation results. Height is color-coded, with warmer colors implying higher points. Areas recognized as large surfaces that are transferred to the recognition task are marked with red dots. Missed leaves owing to laser error are marked with white squares. White circle: Correctly recognized large surfaces of broad-leaved dock. White rectangle: Clover leaves recognized as large surfaces.

CONCLUSION

The solution shows that a 3D segmentation procedure has greater potential than 2D approaches described in the literature. Robustness and speed of edge detection and object extraction are the main benefits of the third dimension. The approach shows that 3D data processing is between 30 and 50% faster than 2D solutions: however, the procedure must still be refined, and there is still room for improvement. Object extraction is inefficient and in the worst-case scenario is ten times slower than required for reliable real-time processing.

The next project step is the implementation of analysis algorithms for the extracted surfaces in the recognition task. Object classification makes the final decision as to whether or not the extracted surface is a dock leaf. For this purpose, shape analysis in 3D space will be combined with texture-analysis algorithms such as the one described in Gebhardt, 2007.

REFERENCES

Basano, L. et al., 1988: Edge-detection schemes highly suitable for hardware implementation. J Opt Soc Am A 5(7) (Jul 1988), pp.1170-1175.

Borkowski, A., 2004: Modellierung von Oberflächen mit Diskontinuitäten. PhD thesis, Fakultät für Forst-, Geo- und Hydrowissenschaften der Technischen Universität Dresden, Deutsche Geodätische Kommission, Marstallplatz 8, D-80539 Munich.

Dürr L. et al., 2004: Machine vision detection and microwave based elimination of rumex obtusifolius L. on grassland. 5th European Conference on Precision Agriculture, Uppsala/Sweden. 5 pages.

Heath, M.D. et al., 1997: A robust visual method for assessing the relative performance of edge-detection algorithms. In: IEEE Transactions. Number 12 in IEEE Transactions on Pattern Analysis and Machine Intelligence, IEEE, IEEE (December 1997), pp. 1338-1359.

Hsiao, P.Y. et al., 2005: An fpga architecture design of parameter-adaptive real-time image processing system for edge detection. In: Emerging Information Technology Conference, 2005 (15-16 Aug. 2005), 3 pages.

Gebhardt, S. et al., 2006: Identification of broad-leaved dock (rumex obtusifolius l.) on grassland by means of digital image processing. In: Precision Farming. Number 3 in Precision Agriculture, Institute of Crop Science and Resource Management - Crop Science and Plant Breeding, University of Bonn, Katzenburgweg 5, D-53115 Bonn. Springer Netherlands (July 2006), pp. 165-178.

Gebhardt, S., 2007: Automatic classification of grassland herbs in close-range sensed digital colour images. PhD thesis, Mathematisch-Naturwissenschaftliche Fakultät, University Bonn (2007).

Gebhardt, S. and Kühbauch, W., 2007: A new algorithm for automatic rumex obtusifolius detection in digital images using colour and texture features and the influence of image resolution. In: Precision Farming. Number 1-2 in Precision Agriculture, Institute of Crop Science and Resource Management - Crop Science and Plant Breeding, University of Bonn, Katzenburgweg 5, D-53115 Bonn, Springer Netherlands (April 2007), pp. 1-13.

Giannarou, S. and Stathaki, T., 2005: Edge detection using quantitative combination of multiple operators. In: Signal Processing Systems Design and Implementation, 2005. IEEE Workshop, (2-4 Nov. 2005). pp. 359-364.

Lorenzen B. and Jensen A., 1987: Reflectance of blue, green, red and near infrared radiation from wetland vegetation used in a model discriminating live and dead above ground biomass, New Phytol.

Mangan, A.P. and Whitaker, R.T., 1999: Partitioning 3d surface meshes using watershed segmentation. In: IEEE Transactions. Number 4 in IEEE Transactions on Visualization and Computer Graphics, IEEE (October-December 1999), pp. 308-322.

Neto, J. C. et al. 2005: Plant species identification using Elliptic Fourier leaf shape analysis. Elsevier, Computers and electronics in agriculture.

Sarkar, S. and Boyer, K., 1990: Optimal, efficient, recursive edge detection filters. In: Pattern Recognition, 1990. Proceedings, 10th International Conference on Pattern Recognition. Volume 1 (16-21 June 1990), pp. 931-936.

Seatovic, D. and Grueninger, R., 2007: Smartweeder: Novel approach in 3d object recognition, localization and treatment of broad dock in its natural environment. In: RAAD 2007: Programme and Book of Abstracts, RAAD 2007 (June 2007).

Seatovic, D., 2008: A Segmentation Approach in Novel Real Time 3D Plant Recognition System. In print: Proceedings of the 6th International Conference on Computer Vision Systems, Santorini.

Sun, Y. et al., 2002: Triangle mesh-based edge detection and its application to surface segmentation and adaptive surface smoothing. In: Image Processing. 2002. Proceedings. 2002 International Conference on Image Processing. Volume 3 (24-28 June 2002), pp. 825-828.

Tsai, R, 1987: A versatile camera calibration technique for high-accuracy 3d machine vision metrology using off-the-shelf tv cameras and lenses. In: IEEE Proceedings. Number 4 in Robotics and Automation, IEEE Journal of [legacy, pre - 1988], IBM T. J. Watson Research Center, Yorktown Heights, NY, USA, IEEE, IEEE (August 1987), pp. 323-344.

Wunderlich, W. et al., 1993: Optimizing edge detection in quantitative coronary arteriography: problems and proposals. In: Computers in Cardiology 1993. Proceedings (5-8 Sept. 1993), pp. 583-586.