Flourish – A robotic approach for automation in crop management

Ein Robotikansatz zur Automation im Kulturpflanzenmanagement

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Abstract: The goal of the Flourish project is to bridge the gap between the current and desired capabilities of agricultural robots by developing an adaptable robotic solution for precision farming. Thereby, combining the aerial survey capabilities of a small autonomous multi-copter Unmanned Aerial Vehicle (UAV) with a multi-purpose agricultural Unmanned Ground Vehicle (UGV), the system will be able to survey a field from the air, perform targeted intervention on the ground, and provide detailed information for decision support, all with minimal user intervention. The system can be adapted to a wide range of farm management activities and different crops by choosing different sensors, status indicators and ground treatment packages. The gathered information can be used alongside existing precision agriculture machinery, for example, by providing position maps for variable rate fertilizer application.

The presentation will introduce the Flourish consortium and the concept of this project using the results of the first year field campaign. Two key parts of the project will be shown in more detail: first, the field mapping by means of an UAV. Particularly, the field 3D reconstruction approach (KHANNA *et al.* 2015) and the use of multi-spectral camera data to derive weed pressure or crop property maps (LIEBISCH *et al.* 2014) with examples for subsequent crop management decision support. The second part will show the automated image acquisition by the UGV and a subsequent plant classification with a four step pipeline differentiating crop from weed in real time (LOTTES *et al.* 2016). The presentation will close with a short outlook on not shown project packages like automated orientation and movement of the UAV and UGV and the project's time line.

Keywords: precision farming, agriculture, multispectral camera, UAV, UGV, 3D reconstruction, trait detection

Zusammenfassung: *Das Projekt Flourish zielt darauf ab die Lücke zwischen den derzeit vorhandenen und den gewünschten Möglichkeiten landwirtschaftlicher Roboter zu schließen. Dafür werden die luftgestützten Erkundungsfähigkeiten von kleinen autonomen Multikopter-Drohnen (UAV) mit unbemannten landwirtschaftlichen Mehrzweck-Fahrzeugen (UGV) kombiniert. Das System soll fähig sein ein Feld aus der Luft zu erkunden, zielgerichtete Kultivierungsmaßnahmen im Feld durchzuführen und detaillierte Informationen zur Entscheidungsunterstützung zur Verfügung stellen, alles mit minimalem Benutzer-Input. Das System kann durch geeignete Wahl der Sensoren, Statusindikatoren und Feldbehandlungs-module der UGV an viele Kultivierungsmaßnahmen und verschiedene Nutzpflanzen angepasst werden. Die gesammelten Informationen können auch mit gängigen landwirtschaftlichen Maschinen genutzt werden, zum Beispiel für das bedarfsgerechte Ausbringen von Dünger.*

Die Präsentation stellt das Flourish-Konsortium und dessen Konzept anhand von Versuchsergebnissen aus der ersten Feldmesskampagne vor. Zwei wichtige Unterprojekte werden genauer betrachtet. Gezeigt wird zuerst die Feldkartierung mittels UAV, insbesondere die 3D-Rekonstruktion (KHANNA et al. 2015) und Multispektralmessung der räumlichen Verteilung von Unkraut-Druck oder Nutzpflanzeneigenschaften (LIEBISCH et al. 2014) mit einer anschließenden Entscheidungshilfe für Feldinterventionen. Der Zweite Teil befasst sich mit der automatischen Bilderfassung am UGV und der daraus resultierenden Pflanzenklassifizierung zur Unterscheidung von Kulturpflanze und Unkraut mittels eines Vierschrittverfahrens in Echtzeit (LOTTES et al. 2016). Die Präsentation schließt mit einem kurzen Ausblick auf nicht gezeigte Teilprojekte wie die automatische Orientierung und Bewegung der UAV und UGV und der geplanten Projekt-Zeitlinie.

Deskriptoren: *Präzisionslandwirtschaft, Multispektralkamera, UAV, UGV, 3D-Rekonstruktion, Eigenschaftserkennung*

1 Introduction

Today's agriculture needs to improve its resource use efficiency for farm inputs like fertilizers and pesticides, and thereby reducing costs and detrimental effects on the environment. Precision farming is a technical approach to facilitate such needs. Many applications today improve single field management tasks such as precision fertilizer application in form of variable rate application according to tractor based sensor information or for large field areas based on satellite information. However, there is a gap between close to the crop and far away sensing level and in flexibility and applicability of systems. Unmanned aerial vehicles (UAV) might help to bridge the remote sensing gap, because they allow monitoring the fields with relatively high detail without relying on a machine driving in the field and thereby collecting data before the actual intervention in the field starts. Their relatively high flexibility should also allow frequent monitoring necessary for short-term reactions for field management and intervention.

To build autonomous robots for farming applications, several challenges need to be addressed, among them robust perception for on-field operation. This paper will focus on information derived from sensors within an exemplary robotic crop management chain on the example of sugar beet. Early weed detection and control is a very important step during the cultivation of this cash crop because of its low competition potential against weeds during early growth.

2 Flourish project

The goal of the Flourish project is to bridge the gap between the current and desired capabilities of agricultural robots by developing a flexible and adaptable robotic solution for precision farming. Thereby, combining aerial survey capabilities of small autonomous multi-copter UAV with a multi-purpose agricultural UGV, such a system should be able to survey a field from the air, perform targeted intervention on the ground, and provide detailed information for decision support to the farmer, all with minimal user intervention (**Figure 1**).

2.1 The flourish concept

To build autonomous robots for farming applications, several challenges need to be addressed, among them robust perception for on-field operation and information retrieval for agronomic tasks or decision support. The flourish projects aims to investigate two main scenarios: 1) weed detection and subsequent control measures in the field and 2) detection of crop nitrogen status from UAV. Additional scenarios such as crop disease infestation or water status are being investigated as they occur.

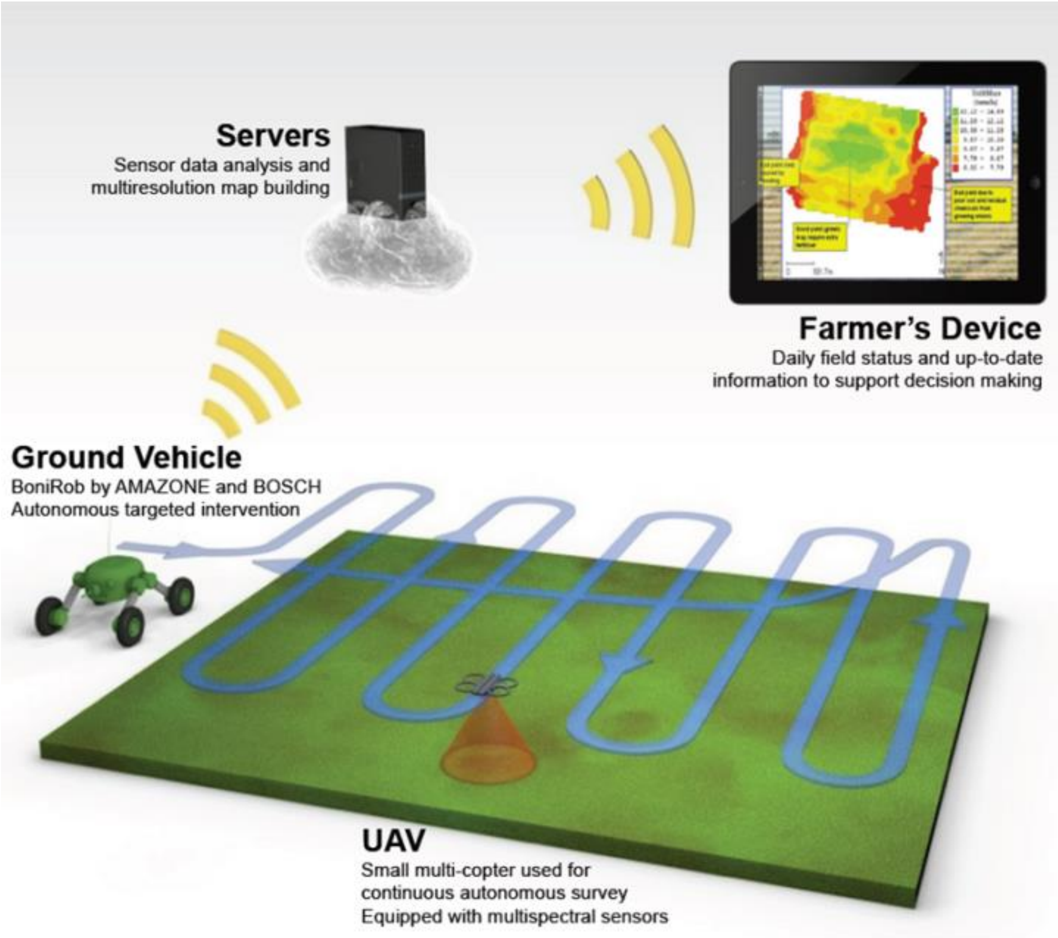

Figure 1: Visualization of the Flourish concept

2.2 The consortium

The Flourish consortium consists of seven highly qualified partners with know-how from robot design to crop management. The involved partners are the Autonomous Systems Lab and the Crop Science Lab of ETH Zurich, the department for Photogrammetry and Remote Sensing at University of Bonn as part of the Faculty for Agriculture and the Institute for Geodesy and Geoinformation, The Bosch Group and their subsidiary Deepfield robotics, the French Centre National de la Recherche Scientifique (CNRS), Sapienza Università di Roma, Department of Computer and System Sciences and the ASSAM - Agency for Agro-food Sector Services of Marche region (Italy). More information can be found under http://flourish-project.eu/.

3 Used sensors and robots

In this study two low cost unmanned aerial vehicles (UAV) were used with two different sensor setups. UAV one used for the 3D reconstruction tests was a DJI Phantom equipped with an 11 megapixel GoPro Hero R 2 camera (GoPro, Inc., USA) with a fisheye lens mounted. The second UAV used for the multispectral mapping was an

IRIS+ (3DR, Inc., USA) equipped with a Gamaya OXI VIS NIR multispectral camera set consisting of two 2 megapixel snapshot multispectral imagers 16 band VIS (450 - 670 nm), 25 band NIR (600 - 900 nm), and an integrated x 86 computer. This imaging system has a weight of 250 g, and the dimensions are 9 x 6 x 4 cm.

The UGV was a Deepfield Robotics Bonirob V3 equipped with a JAI AD 130 camera for weed detection. This camera is a two CCD 1/3" -multi-spectral-camera, with the first being a color interline transfer CCD sensor with a Bayer filter and the second a monochrome interline transfer CCD sensor with a narrow band-pass NIR filter. The resolution is 1296 (H) x 966 (V) pixels. The pixel size is 3,75 µm and the active sensor area 5.05 mm x 3.66 mm. It was used at a frame rate of 30 full images/s.

4 First results

4.1 Field information derived from multi-spectral images

The aim of this project part is to derive information about field and crop status such as weed pressure or leaf greenness maps (LIEBISCH *et al.* 2014) by using multispectral sensors adding more channels to the above mentioned measurement capability. By combining indicators we aim to facilitate and improve crop management decision support. This can be by delivering weed pressure maps, variable rate application maps for fertilizers and pesticides (fungicides and herbicides) but also by improved path planning for information retrieval and intervening machinery in the field.

Canopy cover is a well-established crop growth indicator, which can be measured with several sensors from several remote sensing levels (LIEBISCH *et al.* 2014, 2015 and Constantin *et al.* 2015, GRIEDER *et al.* 2015). Thus it may serve as a standard indicator linking *in situ* data to growth potential by using simple or complex growth models (**Figure 2**). In this way it can be used to classify values into three classes: 1.) optimal coverage reflecting a healthy crop, 2.) sub-optimal values indicating growth reduction caused by biotic or abiotic stresses or 3.) superior to the growth curve coverage indicating a high risk of weed to be present.

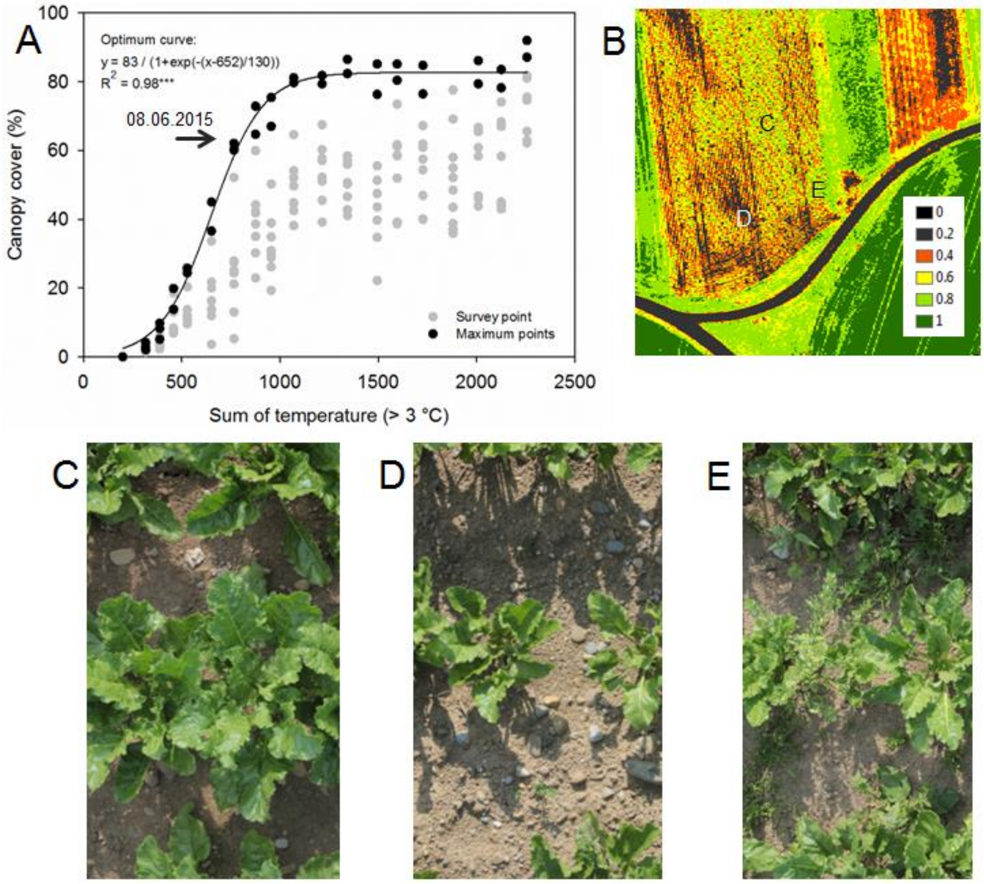

Figure 2: A) Field derived canopy cover development, B) NDVI map of the sugar beet field, C) optimal grown field plot, D) suboptimal grown field plot and E) weed infested field plot.

Once this classification is done additional information can be retrieved by involving other analysis or data acquisition steps. Other spectral indicators may involve leaf greenness as indicated by the triangular vegetation index (TGI) or nitrogen nutrition status as indicated by the photochemical reflectance index as shown by CONSTANTIN *et al.* (2015). Crop architectural information can be derived by 3D reconstruction (see details in section 4.2). Follow up flight planning might be necessary when the obtained data is not sufficient for deriving a specific management decision. In such cases the information retrieval path for the UAV might be re-planned (in real time) to follow uncertain information points getting information with higher ground resolution or even close up images of regions with high weed pressure to achieve information about weed species and leaf symptoms.

4.2 Field 3D reconstruction from UAV images: height estimation pipeline

The data was collected with a GoPro Hero R 2 with a fisheye lens mounted. The combination of a wide angle lens with a high resolution sensor gives a small ground sampling distance (1~5 cm) while maintaining a high overlap (about 80%) between consecutive images which are essential in order to obtain satisfactory 3D reconstructions. The images were post processed using the software Pix4D (http://www.pix4d.com/) to obtain 3D point clouds such as the one shown in **Figure 3**. For this purpose, the software searches for points or features that are recognized in several images in order to estimate their 3D coordinate. It further takes into account the positions of these points in the single images in order to estimate the calibration of the camera. The camera model in turn is then used to optimize the 3D map. In particular it corrects for the radial distortion introduced by the wide angle lens.

Figure 3: Left: Dense point cloud of a winter wheat genotype trial generated from aerial images using Pix4Dmapper by Pix4D. The numbers indicate the plot indices used for referencing. Right: Segmented point cloud generated using automated thresholding based on the excess green index and Otsu's method. Green points represent winter wheat and pale brown represents background.

In order to extract the plant height, soil points must be distinguished from plant points. The segmentation was based on RGB data using the excess green index introduced in Gitelson (2004) to determine an green intensity value (I) for each point i in the point cloud: I (i) = 2G(i) - R(i) - B(i). In the resulting intensity point cloud, green plants have a high intensity value in contrast to a low value for the background including soil surface, shadows, stones and plant debris. Once this intensity value is determined, we use Otsu's method (1975) to determine a global threshold and extract a binary point cloud from the colored one. This method has the advantage of being fully automated while giving accurate segmentation for images and point clouds collected under varying illumination conditions or with different cameras. An example of such segmentation is shown in **Figure 4**.

Figure 4: Image overlaying the automatically segmented vegetation (bright green) onto the original image.

For approximation of the ground level a linear regression surface is fitted through all vertices corresponding to the ground points A as determined by segmentation. The resulting approximation is shown in **Figure 5** left. All vertices of the point cloud are expressed in a new frame of coordinates B via a vector transformation using a rotation matrix (KHANNA *et al.* 2015). The new frame of coordinates is chosen such that the x_B-y_B-plane corresponds to the mean ground level. In order to analyze the plots, a tessellation was performed to subdivide each plot into smaller rectangles of size 0.1 m * 0.1 m containing enough green points to be representative of the geometry. The plant height can then be calculated as the distance between the upper vertices within a small tile and the ground. Additionally, a more detailed representation of the soil geometry, based on the soil vertices directly below the plants, is needed. To model the ground surface based on the vertices within a plant's neighborhood, a multinomial regression for the points within each plot is carried out. Here, a second order two-dimensional polynomial function is fitted to the vertices **Figure 5** right. The method can be adjusted to other functions. The plant height is finally calculated as the 99th percentile to exclude potential outliers as used for height extraction from terrestrial laser scan (FRIEDLI *et al.* 2016) and UAV derived point clouds (KHANNA *et al.* 2015).

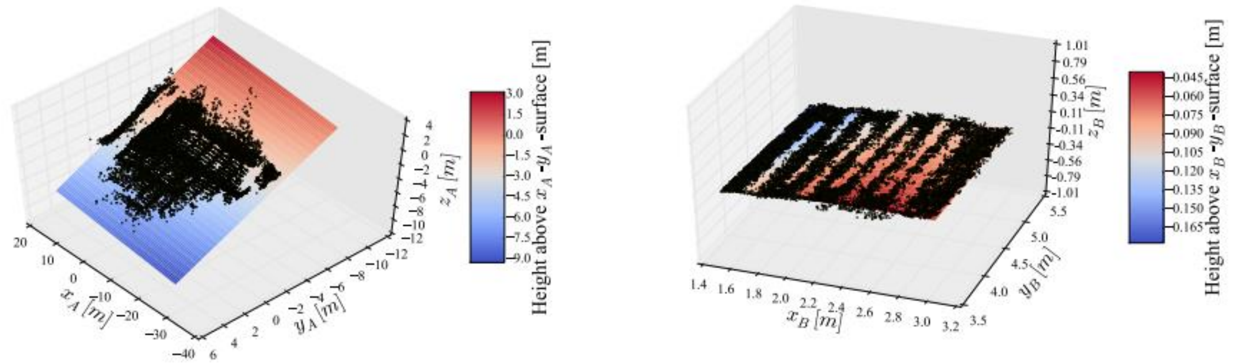

Figure 5: Left: Linear approximation of the ground surface to determine a scene's global orientation. One can observe the large variation in z coordinates creating the need for local regression surfaces for accurate height estimation. Right: Local regression surface along with the corresponding ground points from the point cloud for one plot. From KHANNA *et al.* 2015.

4.3 Automated crop-weed classification by the ground unit

The here shown vision-based classification system for mobile robots is targeted to separate sugar beets from weeds and therefore executes four principal steps. The method is described in detail by LOTTES *et al.* (2016). It first separates the vegetation from the remaining parts of the image, i.e., mostly soil by making use of a NDVI threshold (**Figure 6**). Then, a series of spectral and object based features are computed in the image regions corresponding to vegetation. A random forest decision tree approach is used for performing the classification based on the computed features. In a last step, the neighborhood information between classified regions is taken into account through Markov random fields to improve the individually computed classifications of the random forest.

The approach can also exploit spatial priors, for example, if value crops were roughly planted at a known distance.

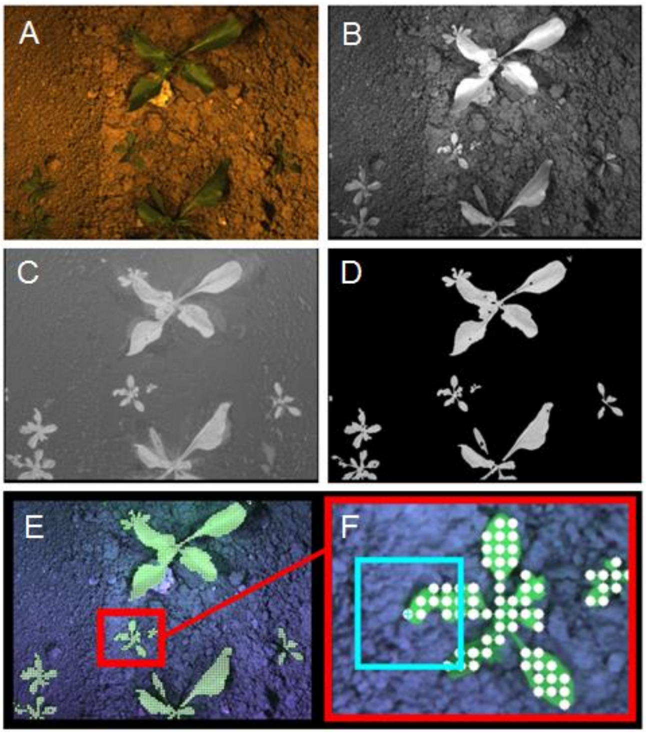

Figure 6: RGB (A) and NIR image (B), NDVI (C) and masked NDVI image according to the vegetation detection (D). Key points (white) for classification at a 3 mm distance on the object and an example neighborhood (E+F). Blue represents the region that is considered for the feature computation.

The approach was evaluated on sugar beet plants at two to four leaf growth stage and weed plants that grew on test fields near Stuttgart, Germany. The system provides accurate classification results (**Figure 7**). In this precision farming scenario, it is important to keep the number of false negatives, i.e., the number of sugar beet plants that are classified as weeds, small. This type of misclassification should be avoided as this would lead to the elimination of the value crop by the robot. In contrast, not detecting a weed is less critical than destroying the crop. The evaluation of this approach suggests that the majority of weed plants get correctly classified while the number of false positives remains small.

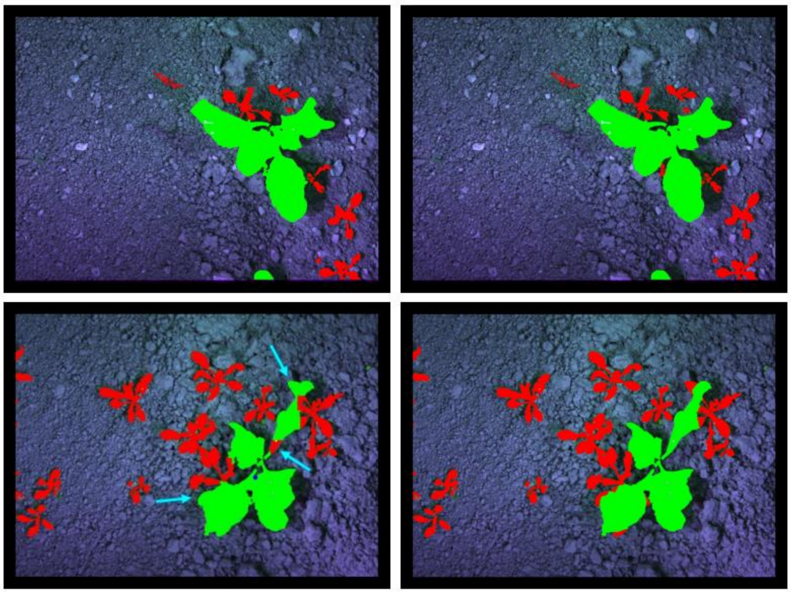

Figure 7: Example results of value crop/weed classification system based on UGV data. In green value crop (sugar beet) and weeds in red. From LOTTES *et al.* (2016)

5 Conclusion and outlook

An aerial information retrieval pipeline has been developed including spatial information and crop height estimation. The maps of crop coverage or pigment information can be used for variable rate application of fertilizers. Crop height information may be interpreted independently and may deliver information about crop vitality. The developed weed perception system includes vegetation detection and feature extraction; the classification performance obtained so far is good. All systems have to be tested and adjusted to different, likely more complicated, field situations, containing different weed species and earlier and later growth stages of sugar beet.

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